Neural Wiener Based MPC (NWMPC) for MTBE Catalytic Distillation

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Abstract: *Reactive distillation of MTBE has strong interaction between the variables and is highly nonlinear process. Here, nonlinear MPC was proposed to tackle the nonlinearity and the interaction in controlling tray temperature of MTBE reactive distillation. To improve the performance of the MPC, advanced nonlinear block oriented model known as Neural Wiener. The control study has been successfully simulated using Simulink (Matlab) which is integrated with Aspen dynamic model. Set point tracking, disturbances rejection and robustness tests were conducted to evaluate the Neural Wiener Based NMPC (NWMPC) performance. The results achieved show that the NWMPC is able to maintain the product purity at its set point of 99% with the Isobutene conversion over than 99.98%. NWMPC is also able to reject the disturbance which was introduced by changing the feed flowrate at 30% from the nominal value. It is also found to be robust towards column efficiency changes.*

Keywords: Reactive Distillation NMPC, Neural Wiener, SQP, Nonlinear Optimization

1. INTRODUCTION

The main purpose of reactive distillation (RD) of MTBE control is to maintain the MTBE purity at a desired range. The desired MTBE purity can be obtained by controlling tray temperature because MTBE purity can be correlated with tray temperature[1]. Temperature controller is more economical since the composition analyzer can be omitted. Due to highly variable interaction in the RD and its nonlinearity characteristics, in this work, the nonlinear MPC is proposed to control this system. Neural – Wiener (NW) model known to be as one of the powerful block oriented model which capable reduces the computational time has been selected to be embedded in the MPC. The NW model proposed is consisting of state space as a linear dynamic block followed by neural network as a nonlinear static block. The MPC with the NW model and SQP optimizer has been used to control the MTBE RD and is call as Neural Wiener Based MPC (NWMPC).

2. DEVELOPMENT OF MTBE REACTIVE DISTILLATION PROCESS MODEL

The most promising technique of producing MTBE is from methanol and isobutene, where the liquid-phase reaction is catalyzed by ion exchange resin (heterogeneous reaction). The reaction scheme is:

$$i\text{-}C4H8 + CH3\text{-}OH \rightleftarrows C5H12O \quad (1)$$

Butenes feed for MTBE synthesis consists of about 40% isobutene and 60% n-butene, which n-butene is an inert. Methanol is usually fed in excess to improve the conversion of isobutene into MTBE. MTBE forms azeotropes with methanol and isobutene, hence difficult to separate MTBE from it impurities. However, in reactive distillation the azeotropes are reacted in reaction section[6, 7]. The specification MTBE RD considered here can be found in[8].

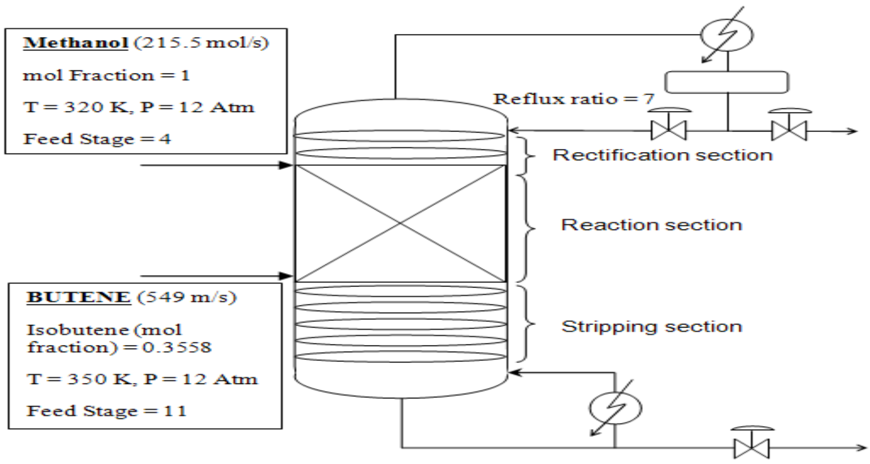

Fig. 1. MTBE Reactive Distillation Column

3. DEVELOPMENT OF NEURAL – WIENER MODEL

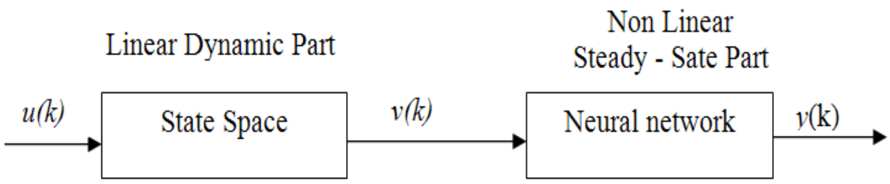

Fig. 2. Neural Wiener model configuration

Neural Wiener (N-W) model consist of linear block and nonlinear block as shown in Fig. 2. The linear block that used in this work is state space model. Using Matlab identification tool box, the state space model for multivariable MTBE Reactive distillation can be identified as shown below:

$$x_{(k+1)} = A\, x_{(k)} + B\, u_{(k)} \quad (2)$$

$$v_{(k)} = C\, x_{(k)} + D\, u_{(k)} \quad (3)$$

where :

$$A = \begin{bmatrix} 0.73897 & -0.042774 & 0.060387 & 0.02007 \\ -0.34542 & 0.7133 & -0.31961 & 0.30447 \\ -0.24956 & -0.44335 & 0.34634 & -0.7272 \\ -0.035443 & 0.059417 & -0.11259 & 0.61541 \end{bmatrix}, B = \begin{bmatrix} -1.3786 & 1.5398 \\ -4.2 & 4.1893 \\ 6.4984 & -5.8288 \\ 1.1353 & -0.38649 \end{bmatrix}$$

$$C = \begin{bmatrix} 0.20528 & 0.10429 & 0.10847 & -0.11637 \\ -0.0039021 & 0.0034986 & 0.0019554 & -0.00039005 \end{bmatrix}$$

where D, u and x are matrix zero with size (2x2), (4 x 2) and (4 x 1) respectively, G is discrete-time model.

Nonlinear Block of Neural – Wiener used in this work is Neural Network model and to represent the inverse of nonlinear block in N-W model. In this part, the MTBE reactive distillation was modeled using the MIMO (Multiple input Multiple output) feed forward Neural Network model which have 15 hidden nodes and 1 hidden layer. The output y(k) of the neural network is described below:

$$y_{(k)} = w_0 + \sum_{i=1}^{K} w_i^2 \phi \left(w_{i,0}^1 + w_{i,1}^1 v_{(k)} \right) \qquad (4)$$

where w_0 is bias, $w_{i,j}$ is weight of first layer, and w_i is weight of second layer, φ is a nonlinear transfer function (e.g. : hyperbolic tangent sigmoid transfer function or tansig), K is the number of hidden nodes[5, 9]. The output of the N-W model can be defined by substitute equation (3) into (4), as shown below:

$$y(k) = w_0 + \sum_{i=1}^{K} w_i^2 \varphi \left\{ w_{i,0}^1 + w_{i,1}^1 [C\,x(k) + D\,u(k) + e(k)] \right\} \qquad (5)$$

4. DEVELOPMENT OF NEURAL WIENER MPC (NWMPC)

The best control configurations with most suitable control variable, manipulated variable and disturbances have been identified[4, 5]. The empirical model developed and the optimizers proposed have been embedded in the Neural Wiener NMPC as shown in Fig. 3. The accuracy of controller is the main consideration taken in designing of the NWMPC.

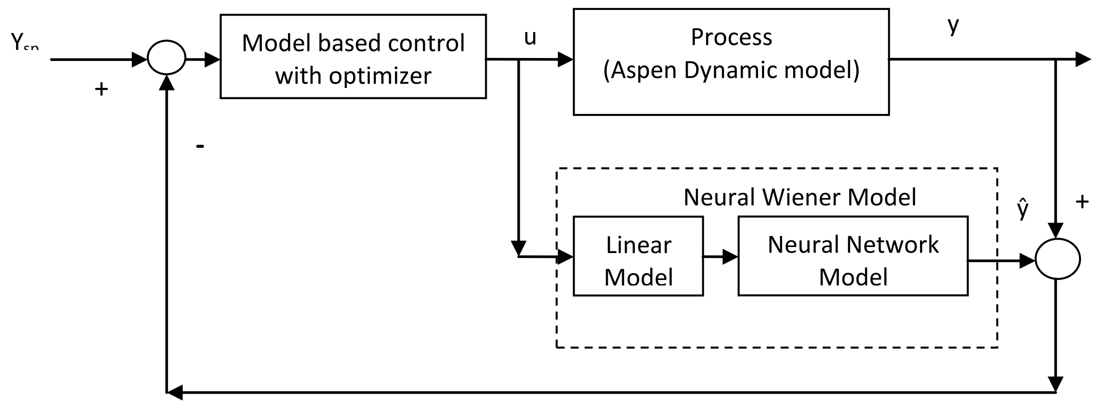

Fig. 3 General structure of NWMPC

The NWMPC objective function for the MIMO case consists of the quadratic error between each controlled variable and its set-point and the quadratic change of each manipulated variable. The MPC objective function for the 2 × 2 system is defined as follows:

$$j_k = \sum_{i=1}^{P} \left((y_{f1|k+i} - y_{sp1|k+i})^2 Q_1 + (y_{f2|k+i} - y_{sp2|k+i})^2 . Q_2 \right) + \left(\Delta u_{f1|k+i} \right)^2 . R_1 + \left(\Delta u_{f2|k+i} \right)^2 . R_2 \qquad (6)$$

where y_f is predicted future output, y_{sp} is set point, Q is error penalty, R is input change penalty, $\Delta\, u_f$ is future input change and *k* is current sampling time.

5. CONTROL STUDY

The controller performances heve been evaluated based on the results obtained from set point tracking , disturbance rejection and robustness tests andthe performance criteria used are integral absolute error (IAE), integral squared error (ISE), and integral of time absolute error (ITAE).

5.1 Set Point Tracking Test

In this test, the set point 1 value are 0, 5.4966, 4 and 5.4966, meanwhile set point 2 are 0, 0.424, 0.2708 and 0.424**,** were changed every 2 hours in order to bring MTBE purity from 95% (low quality), to 99% (high quality) and 97% (medium quality), respectively. The resulting CV profiles are shown in Fig 4. From the figure, the CV_1 profile can be tracked very well , however the CV_2 profile has shown slightly overshoot at the beginning of step changes (t = 2 2.3). The CV_2 also show small value of offset but the amount of error calculated is still very small with ITAE value at 1.55%.

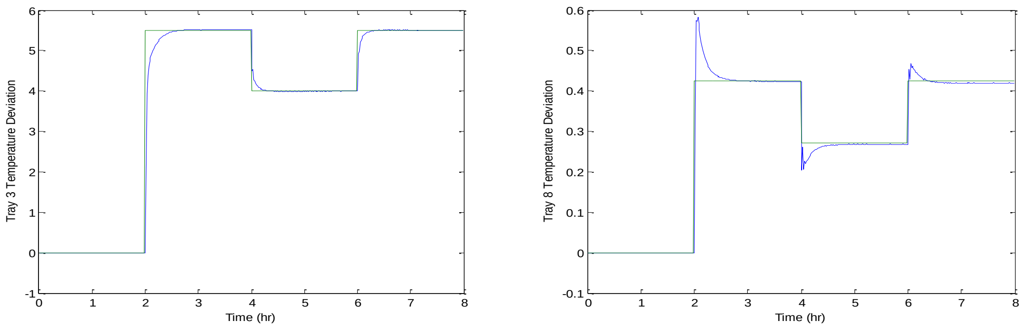

Fig. 4. Setpoint test profile of CV_1 and CV_2 using NWMPC

5.2 Disturbance rejection Test

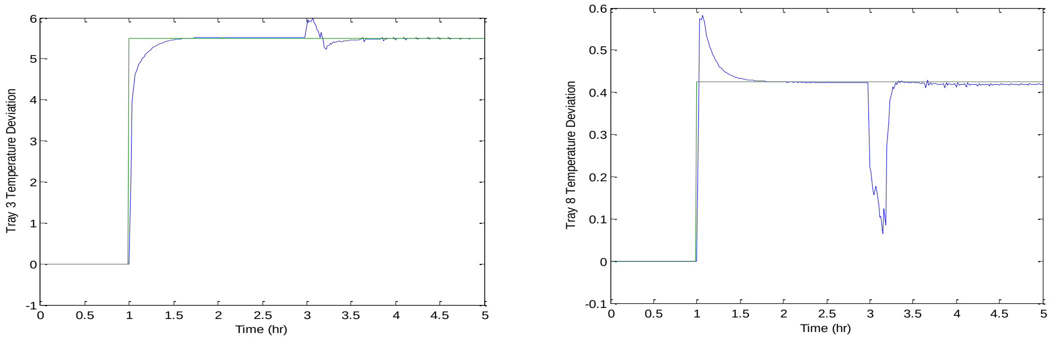

Fig. 5. Disturbance rejection test profile of CV_1 and CV_2

The disturbance rejection study is performed by changing the feed flowrate at 30% from the nominal value. The duration of the change is 0.2hour (3 until 3.2 hours). The result of CV_1 shows that NWMPC is able to reject the disturbance (within 0.5 hour) and bring back the CV_1 back to its original set point as shown in Fig. 5. On the other hand, for CV_2, the NWMPC needs longer time to reject the disturbance imposed. It can also be observed in Fig.5 that amount of the deviation occur for the CV_2 profile is quite big which caused by the reaction and separation process in this tray[1].

5.3 Robustness test

In this test, the column efficiency was change to 80%, without change the NMPC parameter. With the new initial conditions due to this efficiency change, at the steady state condition, the MTBE purity obtained is 95.24%, while the temperature of tray number 3 and 8 are 93.92 ^oC and 126.96 ^oC, respectively. In this test, set point step were varied from 0, 7, 4, and 7 for CV_1, meanwhile for CV_2 were 0, 0.75, 0.39 and 0.75 with switching time of 2 hours applied. For T_3 (CV_1) profiles, the NWMPC controller managed to bring the CV_1 to follow the set-point even though the tray efficiency of the column was reduced as shown in Fig. 8. Meanwhile the CV_2 profile shows an overshoot at the beginning of set point change and then converged to steady state. The performance criteria (error information) of CV_1 and CV_2 are tabulated in Table 2. The table shows that, overall, the NWMPC manage to control tray temperature of MTBE RD very well.

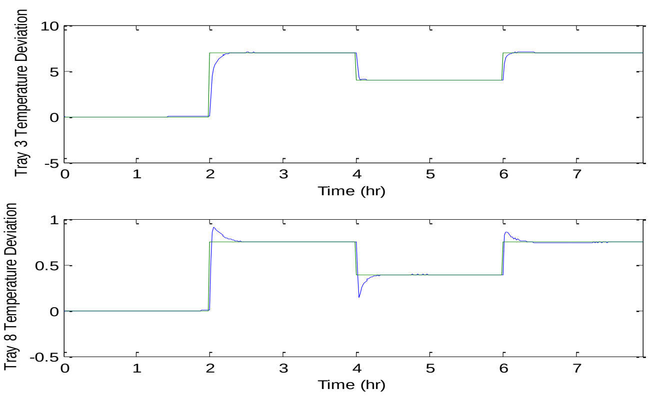

Fig. 6. Robustness test profile of CV_1 and CV_2

Table 2. Error calculation of Set Point Changing, Disturbances Rejection and Robustness tests

	NMPC NW					
	Set Point Changing Test		Disturbances Rejection test		Robustness test	
	Y_1	Y_2	Y_1	Y_2	Y_1	Y_2
IAE	0.5009	0.4958	0.4511	0.1072	0.6529	0.1029
ISE	0.6740	0.4872	0.2601	0.1986	0.3979	0.0570
ITAE	1.5627	1.5479	0.7502	0.2684	2.3473	0.4184

6. CONCLUSION

NWMPC using SQP optimizer has successfully applied to control tray temperatures in the MTBE reactive distillation. The NWMPC was then evaluated based on set point tracking, disturbance rejection and robustness test. The results achieved showed that NWMPC has successfully controls the CV_1 and CV_2 with small value of error.

7. ACKNOWLEDGEMENTS

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