Improved Multi-model Predictive Control to Reject Very Large Disturbances on a Distillation Column

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IMPROVED MULTI-MODEL PREDICTIVE CONTROL TO REJECT VERY LARGE DISTURBANCES ON A DISTILLATION COLUMN

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ABSTRACT

A multi model predictive control and proportional-integral controller switching (MMPCPIS) approach is proposed to control a nonlinear distillation column. The study was implemented on a multivariable nonlinear distillation column (Column A). The setpoint tracking and disturbance rejection performances of the proposed MMPCPIS were evaluated and compared to a proportional-integral (PI) controller and the hybrid controller (HC). MMPCPIS developed to overcome the HC's limitation when dealing with very large disturbance changes (50%). MMPCPIS provided improvements by 27% and 31% of the ISE (integral of square error) for feed flow rate and feed composition disturbance changes, respectively, compared with the PI controller, and 24% and 54% of the ISE for feed flow rate and feed composition disturbance change, respectively, compared with HC.

Keywords: Distillation; Multi-model; Predictive; Very large disturbance

1. INTRODUCTION

One prominent issue that must be resolved in process control is process nonlinearity, which becomes more prominent when operating in high purity products and high profitability zones (Mathur et al., 2008; Bachnas et al., 2014). Nonlinearity can be a dynamic, which causes strong fluctuation of disturbances, and static (gain) nonlinearity requires manipulated variable change (Gustafsson et al., 1995; Chan & Yu, 1995). A high purity product requires the ultimate in accuracy, while the need for high profit demands operating near constraints and high process efficiency. In reality, both aspects are reinforcing complexities of the control problems.

Among many control approaches, model predictive control (MPC) is considered qualified to deal with these problems (Dougherty & Cooper, 2003; Andrikopoulos et al., 2013). However, the performance of MPC controllers is highly dependent on the quality of the model used. For example, MPC based on linear model has limitations in handling nonlinearities, and its usage is restricted as a local MPC, in the region suited for the local linear model (Lundstrom et al., 1995; Qin & Badgwell, 2003).

An effective nonlinear MPC (NMPC) is the one that is supported by a model that can represent all the conditions of the process over a wider range of operations (Pearson, 2006). Under this

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condition, effective control can be established for nonlinear processes. Nevertheless, the use of linear MPC is broader than NMPC, because of two issues. First, the identification of a linear models based on process data is relatively easier. Second, linear models show good result when the plant is operating nearby the operating condition in which the model fitting was done. Due to these reasons, NMPC is only used in cases where the linear MPC is not adequate (Allgöwer & Zheng, 2012).

Wahid and Ahmad (2015) has successfully developed a HC by maximizing both controller output of MMPC and PI controller to reject disturbance changes in the multivariable nonlinear distillation column. Unfortunately, HC failed to reject the very large disturbance changes (+50% change). Therefore, this study intends to determine a means to improve this limitation. The aim of very large change in the disturbance is to know the controllability of the controller that has been designed (Skogestad, 1997; Luyben & Chien, 2010), so avoid the windup of the process (Åström, 2002). A very large disturbance could lead to an unsafe condition (Marlin, 2000).

2. CONTROLLER FORMULATION

In a nonlinear distillation column control, there are two kinds of input (u): reflux flow (L) and boilup flow (V), two outputs (y): distillate (y_D) and bottom (y_B) composition, two disturbances (d): feed flow rate (F) and feed composition (z_F), and set point tracking (w).

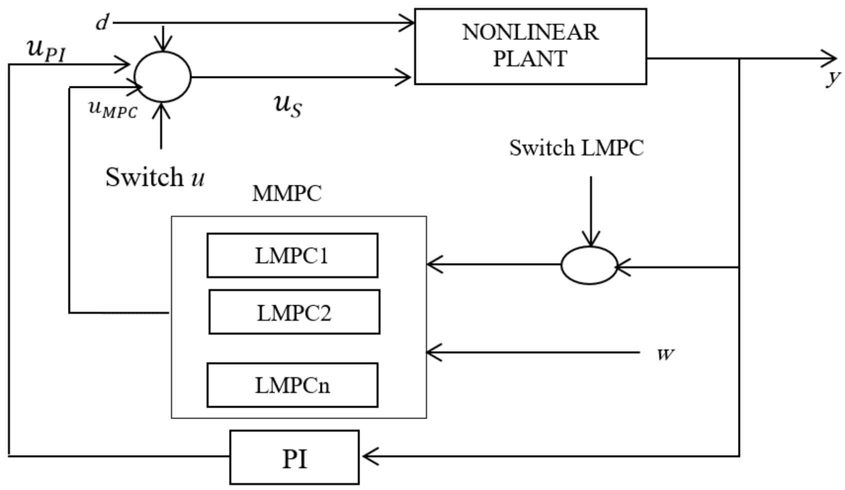

Figure 1 MMPCPIS controller algorithm

The proposed configuration is based on the idea of immediate switch of controller outputs in the presence of disturbances above specific threshold. The configuration is shown in Figure 1, and formulated mathematically as:

$$u_S = \begin{cases} u_{MMPC} & d_1 = d_{1i} \pm \varpi \cap d_2 = d_{2i} \pm \varpi \\ u_{PI} & d_1 \neq d_{1i} \pm \varpi \cup d_2 \neq d_{2i} \pm \varpi \end{cases} \tag{1}$$

where u_S is controller outputs switch (used), d_1 is feed flow, d_2 is feed composition, d_{1i} is initial feed flow, d_{2i} is initial feed composition, and ϖ is noise, respectively.

Equation 1 includes noise factor as a limiter to decide when controller switching is performed. In fact, a relatively small change (noise) always present in the process. Therefore, if the disturbance changes within a present limit, no switching is required.

3. SIMULATION/EXPERIMENTAL STUDY

As shown by Figure 1, MMPCIS used to control a nonlinear plant in the form of the nonlinear distillation model of Column A (Skogestad, 1997). It has 40 theoretical stages and separates a binary mixture with relative volatility of 1.5 into products of 99% purity. The mathematical model was coded in MATLAB, and building blocks were constructed in SIMULINK environments to facilitate dynamics and control studies.

The dynamic model of this process was developed based on the following assumptions: binary mixture; constant pressure; constant relative volatility; equilibrium on all stages; total condenser; constant molar flows; no vapor holdup; linearized liquid dynamics, but effect of vapor flow ("K2"-effect) is included. These assumptions may seem restrictive, but they capture the main important effects for dynamics and control studies (except for the assumption about constant pressure).

There are four output variables considered, i.e., the molar fractions of distillate and bottom product (y_D and y_B), liquid holdup in condenser and reboiler (M_D and M_B), and seven input variables, i.e., L (reflux flow), V (boilup flow), D (distillate product flowrate), B (bottom product flowrate), F (feed rate), z_F (feed composition), and q_F (fraction of liquid in feed). The dynamic response uses the LV-configuration, where reflux flowrate L and boilup V are considered as the independent variables for composition control and D and B are adjusted to establish level control. LV-configuration is known to be the common control strategy for one composition control (Skogestad, 1997) and the choice is bottom composition (y_B).

Two tests were conducted in the plant:

a. SP (set point) tracking uses staircase change in order to analize the effect of SP change based on scheduled setpoint tracking tests of the bottom distillate composition (y_B) at 0.01 to 0.02 (at t = 30 min.), 0.02 to 0.03 (t = 80 min.), and 0.03 to 0.02 (t = 200 min, while the disturbance changes in feed flow disturbance (F) or the feed composition (z_F) were scheduled in the 120th minute. The time between the disturbance change and the next SP change was made longer than the time of inter-SP in order to y_D has an enough time to return to its SP.
b. Disturbance rejection comes in three forms: normal (1%), large (20%) and very large (50%). A change of disturbance as much as 20% was also conducted by Skogestad (1997) in nonlinear distillation column (Column A) and also by Ogunnaike et al. (1983) and Luyben (2006) in C3-C4 distillation column. Luyben (2006) in the same process also made disturbance change of 50%, while Luyben and Chien (2010) made the same change in azeotropes distillation. Very large changes in feed flow rate will cause a drop in temperature at the feed tray and the tray underneath so that it will raise the reboiler heat input. Once heated by reboiler, vapor flow rate will be increased thereby increasing the heat removal as well. This tends to reduce pressure (Luyben, 2006). The aim of large change in the disturbance is for controllability analysis (Skogestad, 1997; Luyben and Chien, 2010), which is probably much larger than that to which an industrial column would typically be subjected (Luyben, 2006).

To see the effect of controller output switching between controller output of MPC and controller output of PI to the control performances, this switching must be applied in the single MPC (called as SMPCPIS) using MPC.02 (MPC at y_B = 0.02). After that, applying that strategy in the MMPC (called as MMPCIS). The control performance used in the study was the integral of square errors (ISE).

4. RESULTS AND DISCUSSION

4.1. Disturbance Change: Feed Flow Rate (F)

The results shown in Figures 2 to 5 indicate that the switching of controller outputs from MMPC to PI functioned efficiently. The process responses and controller outputs before disturbances corresponded well with the MMPC, while those after disturbances matched the PI controller, although different level of overshoot appeared moments after the emergence of the disturbance. MMPCPIS is considered generally better than other models in dealing with disturbances involving *F*. The results show that significant improvements were established in disturbance rejection, although the responses were not as good as that of the PI controller. As shown by Table 1, for ΔF disturbance of +0.1 kg-mole/min (+20%), the improvement (in ISE) of SMPCPIS against SMPC was as much as 42% at y_D and 28% at y_B. For ΔF disturbance of +0.25 kg-mole/min, larger value was obtained i.e. 50% at y_D and 63% at y_B.

Table 1 Controller performances based on switching MPC-PI at disturbance change (*F*)

No	Controller	ISE $\times 10^4$					
		ΔF = +1%		ΔF = +20%		ΔF = +50%	
		y_D	y_B	y_D	y_B	y_D	y_B
1	SMPC	1.285	6.272	5.419	14	28	54
2	SMPCPIS	1.495	7.313	3.157	10	14	20
3	MMPCPIS	0.958	1.620	2.765	2.563	14	8.74
4	PI	1.393	2.364	3.683	3.601	16	10

The MMPCPIS exceeded the performance of the SMPCPIS except on the very large ΔF disturbance of +0.25 kg-mole/min at y_D. As indicated by Figures 2 and 4, MMPCPIS also improved the performance of MMPC, resulting in outputs that were better that that of the PI controller with an average improvement of 24%. Substitution of LMPC used in MMPCPIS was equal to the change in F = + 20% and + 50%, as indicated by Figures 3 and 5.

4.2. Disturbance Change: Feed Composition (z_F)

As in the presence of *F* disturbance, in general the switching between MPC or MMPC and PI worked well with the z_F disturbance. However, the results show that the use of SMPCPIS was not able to improve the control performance, so that the control performance was still worse than the control performance of the PI controller. Neverthaless, the use of the switching can improve SMPC, significantly, especially at very large disturbance rejection. As shown by Table 2, for Δz_F disturbance of +20%, larger value was obtained i.e. 35% at y_D and 18% at y_B. Also, for Δz_F disturbance of +50%, larger value was obtained i.e. 84% at y_D and 64% at y_B.

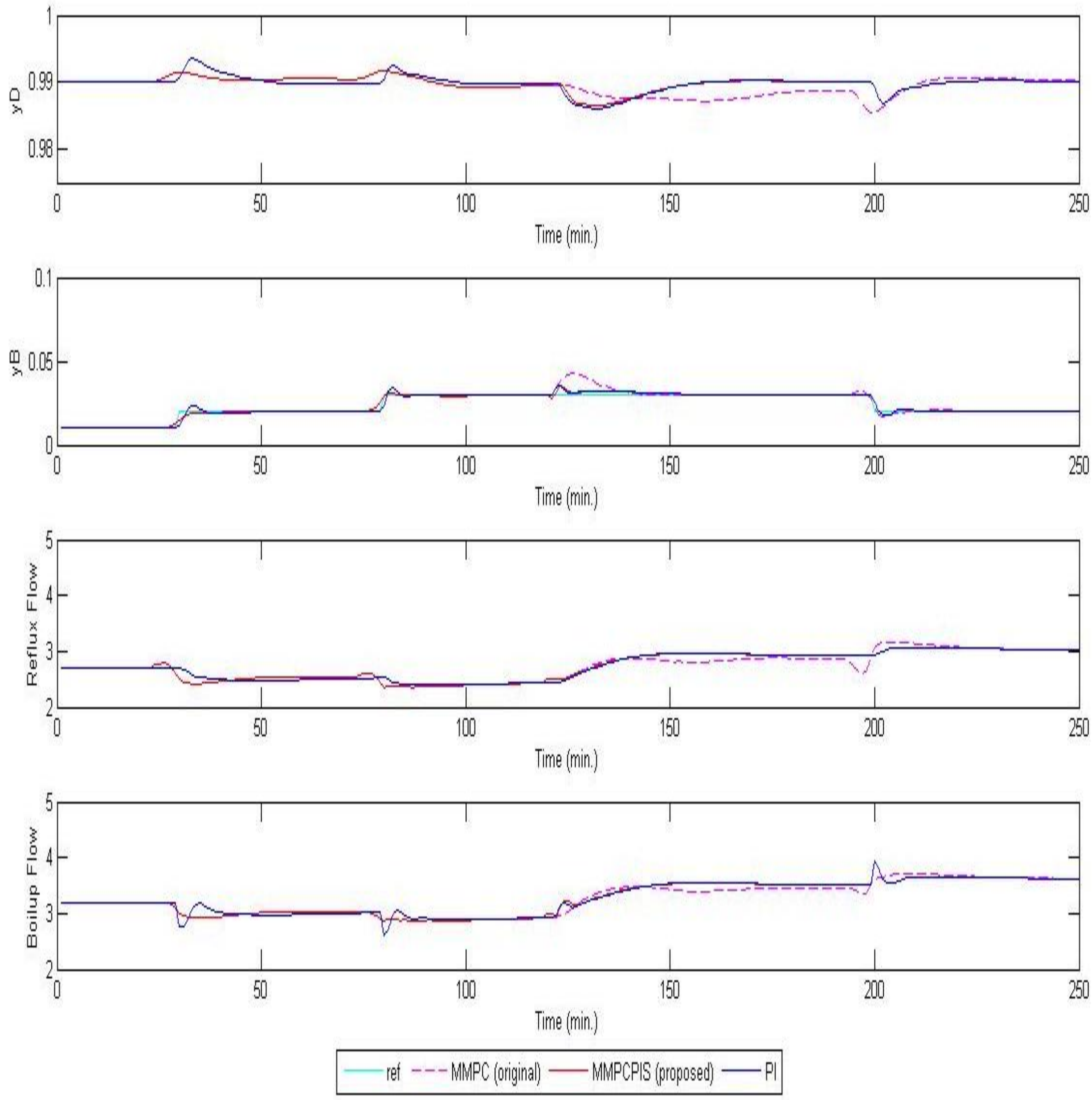

Figure 2 Controller performance of MMPCPIS and PI (ΔF = +20%)

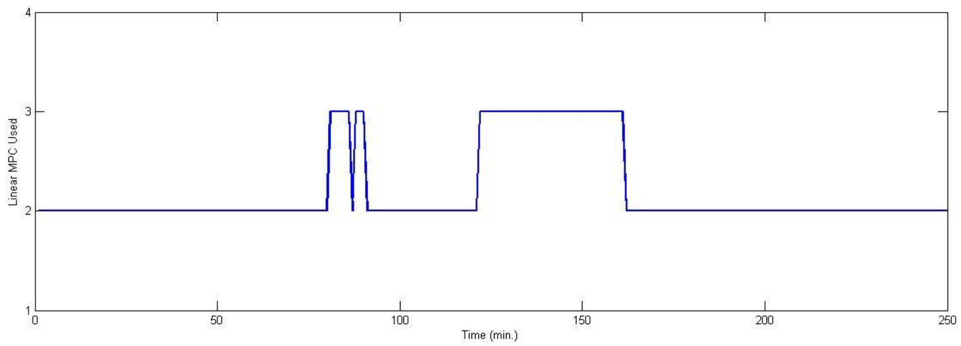

Figure 3 Switching of MMPCPIS (ΔF = +20%)

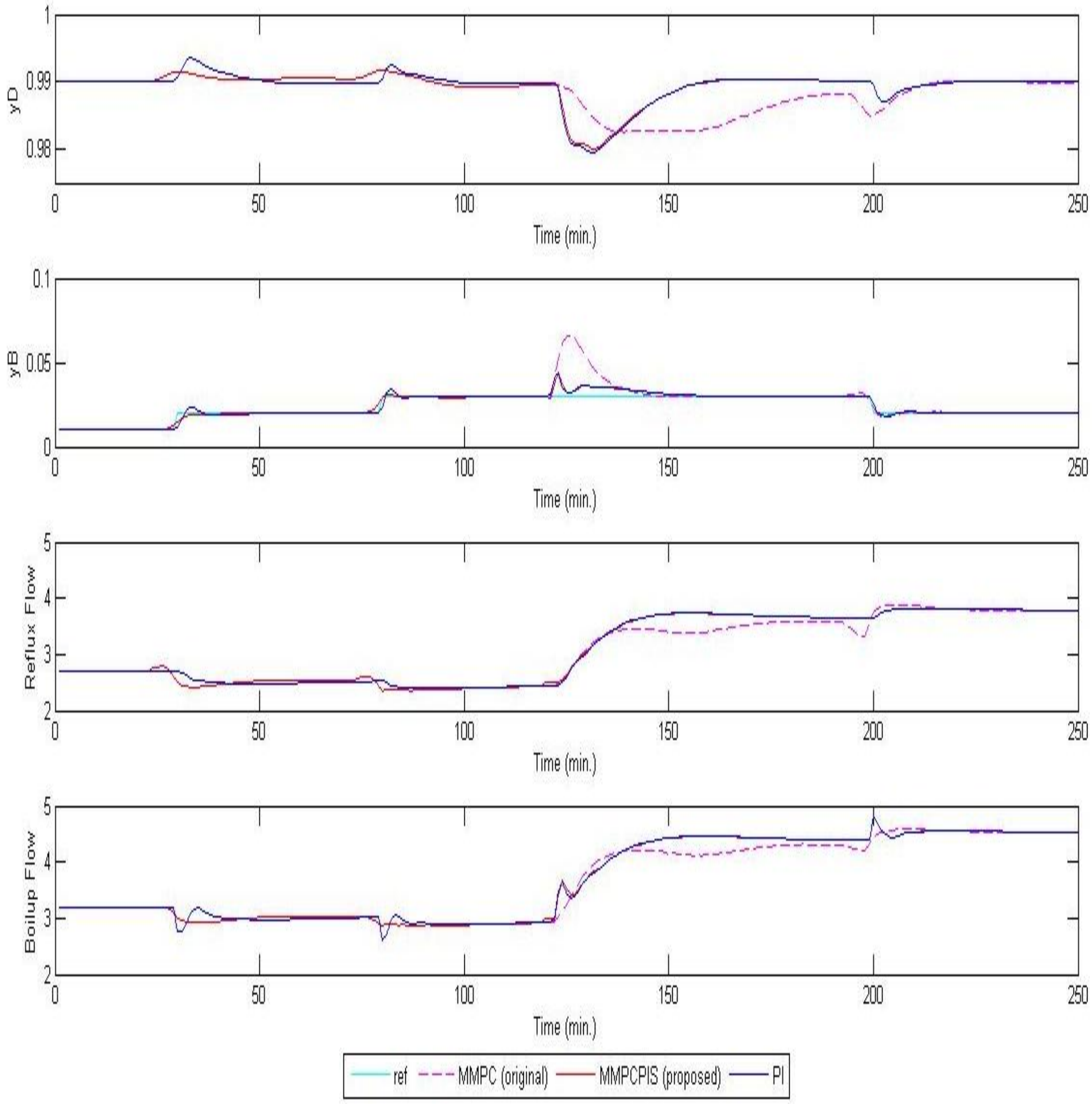

Figure 4 Controller performance of MMPCPIS and PI (ΔF = +50%)

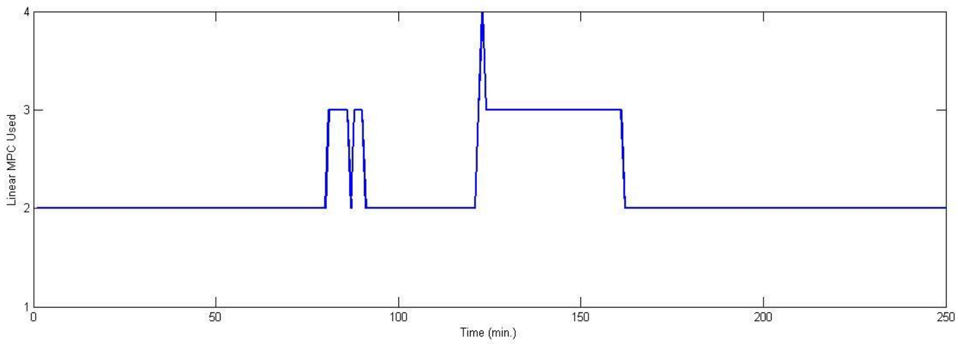

Figure 5 Switching of MMPCPIS (ΔF = +50%)

Table 2 Controller performances based on MPC-PI switching at disturbance change (z_F)

No	Controllers	ISE $\times 10^4$					
		Δz_F = +1%		Δz_F = +20%		Δz_F = +50%	
		y_D	y_B	y_D	y_B	y_D	y_B
1	SMPC	1.292	6.287	2.167	9.007	8.548	22
2	SMPCPIS	1.507	7.224	1.404	7.386	1.374	7.898
3	MMPCPIS	0.966	1.629	0.859	1.692	0.857	2.070
4	PI	1.379	2.361	1.290	2.444	1.275	2.836

The MMPCPIS exceeded the performance of the SMPCPIS for all the amount of Δz_F disturbance. As indicated by Figures 6 and 8, MMPCPIS also improved the performance of MMPC, resulting in outputs that were better that that of the PI controller with an average improvement of 31%. MMPCPIS also improved the control performance of HC (Wahid & Ahmad, 2015) at z_F disturbance of 50%, due to better performance of MMPCPIS against PI (see Table 2). Substitution of LMPC used in MMPCPIS was equal to the change in Δz_F = + 20% and + 50%, as indicated by Figures 7 and 9.

Tables 3 and 4 summarize the application of proposed algorithms in the control of a nonlinear distillation column. Both tables show that the percentage of ISE is decreasing due to MMPCPIS compared to other algorithms. Values listed in the tables is the value of performance compared to other controllers which is calculated using Equation 2. For example, SMPCPIS vs. HC means.

$$\text{ISE Reduction} = \frac{ISE_{SMPCPIS} - ISE_{HC}}{ISE_{HC}} x100\% \tag{2}$$

Table 3 ISE reduction (%) face to face HC and SWITCH algorithms based on F change

No	Controllers	ΔF = +1%		ΔF = +20%		ΔF = +50%	
		y_D	y_B	y_D	y_B	y_D	y_B
1	MMPCPIS vs HC	17	-7	-11	-24	-6	-19
2	HC vs PI	-33	-9	-3	-4	0	0
3	MMPCPIS vs PI	-22	-16	-13	-27	-6	-19

Table 4 ISE reduction (%) face to face HC and SWITCH algorithms based on z_F change

No	Controllers	Δz_F = +1%		Δz_F = +20%		Δz_F = +50%	
		y_D	y_B	y_D	y_B	y_D	y_B
1	MMPCPIS vs HC	23%	-7%	27%	-8%	-54%	-22%
2	HC vs PI	-37%	-8%	-42%	-7%	51%	11%
3	MMPCPIS vs PI	-22%	-15%	-26%	-15%	-31%	-13%

MMPCPIS provided improvements by 27% and 31% of the ISE for feed flow rate disturbance change and feed composition, respectively, compared with the PI controller, and 24% and 54% of the ISE for feed flow rate disturbance change and feed composition, respectively, compared with HC.

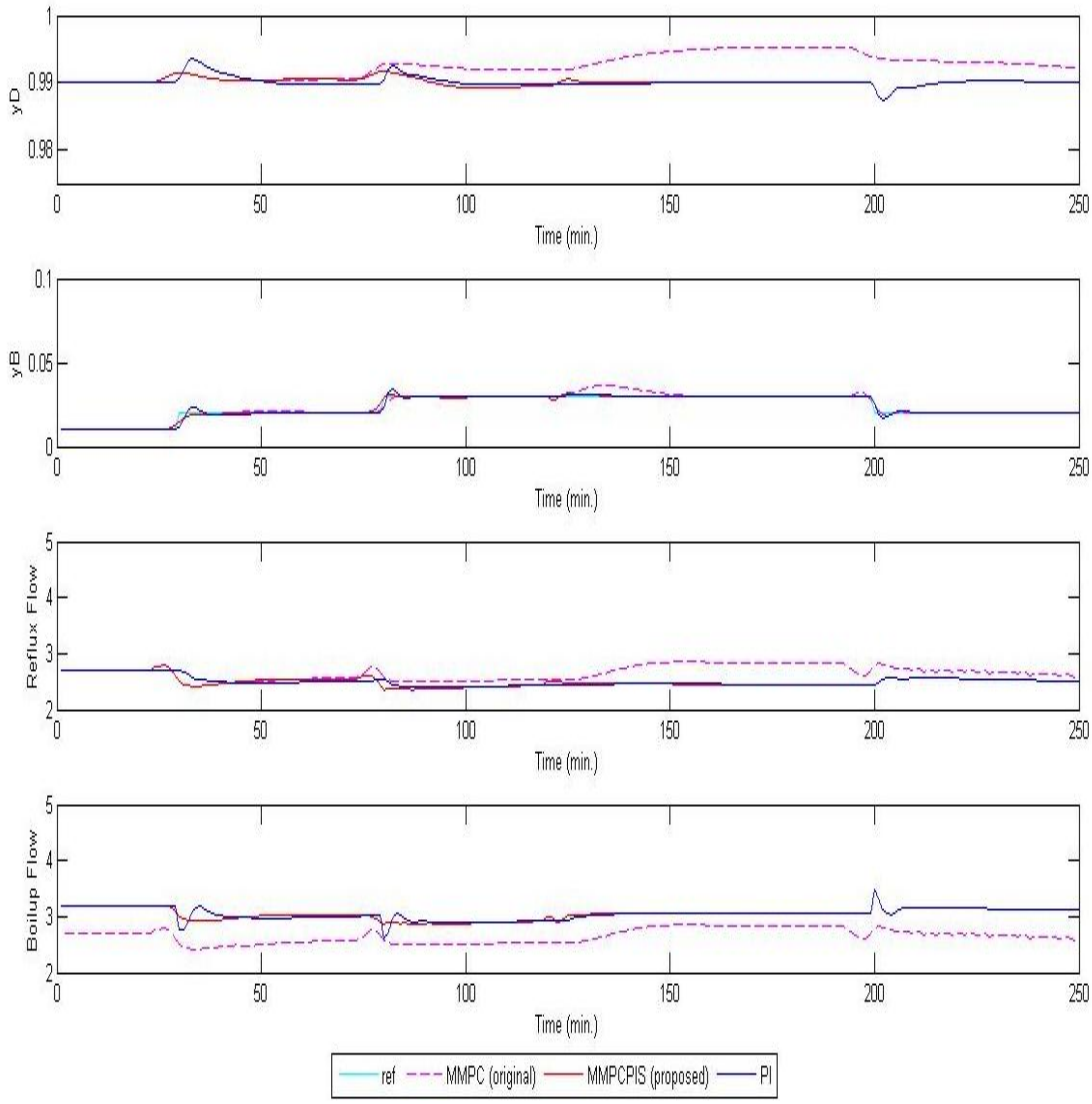

Figure 6 Controller performance of MMPCPIS and PI (Δz_F = +20%)

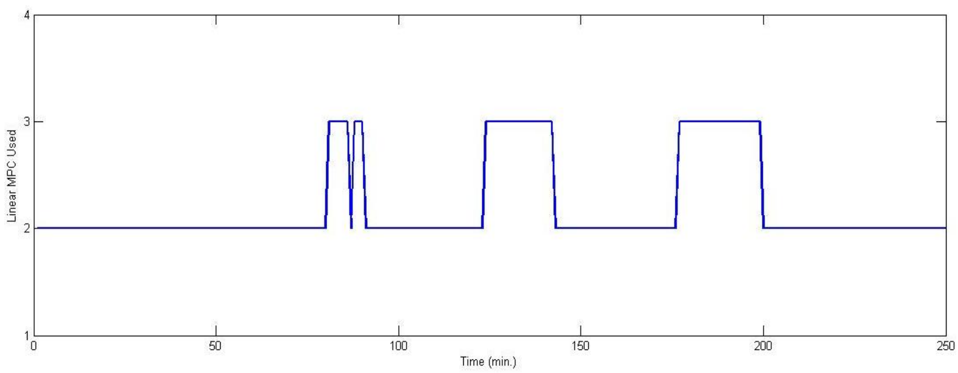

Figure 7 Switching of MMPCPIS (Δz_F = +20%)

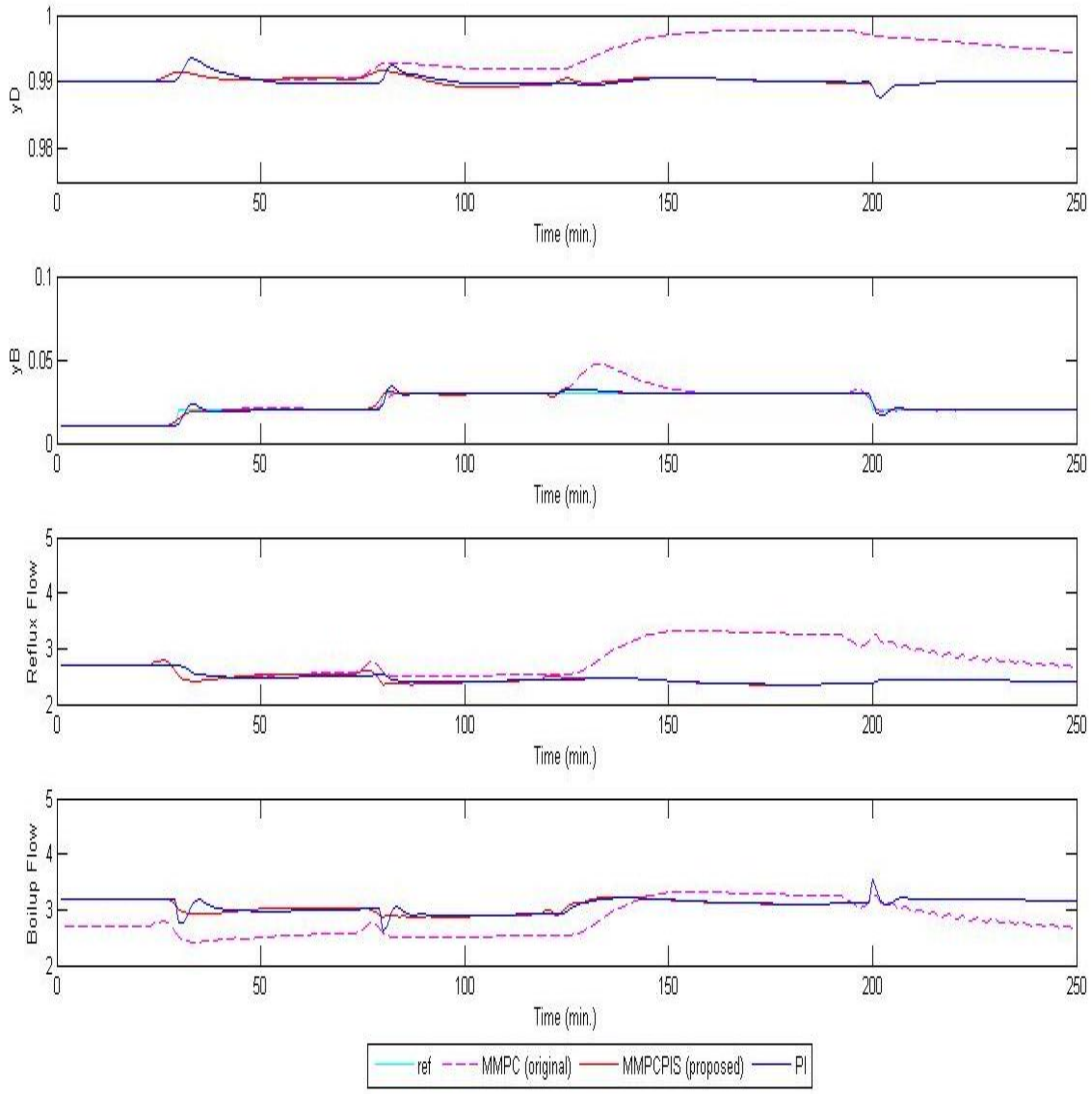

Figure 8 Controller performance of MMPCPIS and PI (Δz_F = +50%)

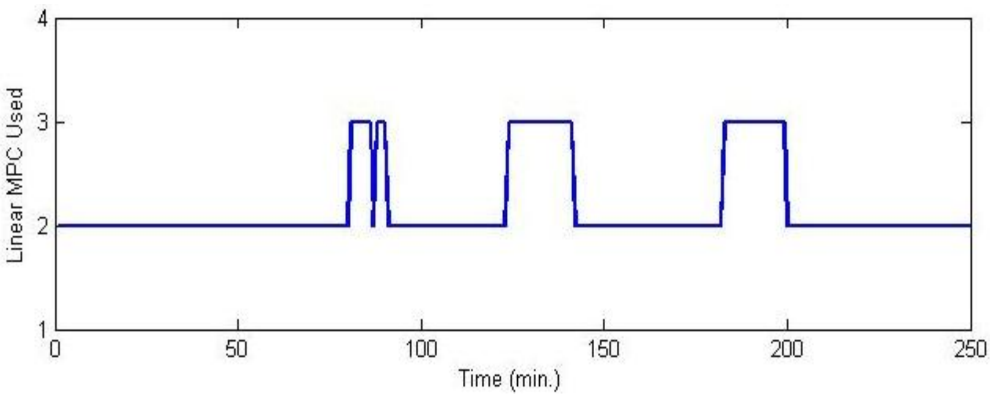

Figure 9 Switching of MMPCPIS (Δz_F = +50%)

5. CONCLUSION

MMPCPIS can improve the control performance of the previous strategy to improve MMPC when dealing with very large disturbance changes, which is a hybrid controller (HC), and also can improve the control performance of the PI controller, significantly. MMPCPIS provided improvements by 27% and 31% of the ISE for feed flow rate disturbance change and feed composition, respectively, compared with the PI controller, and 24% and 54% of the ISE for feed composition disturbance change and feed composition, respectively, compared with HC.

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