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Nonlinear model predictive control of an industrial four-stage evaporator system via simulation

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Abstract

Issues related to applicability of model predictive control (MPC) to the nonlinear and integrating processes are addressed in this study. An industrial four-stage evaporator system is taken as an exemplary process, and two different models of this system are used as process and its prediction model in the controller. Unlike the past studies, where the necessity of stabilization is advocated prior to MPC implementation on an open-loop unstable process, nonlinear MPC without any pre-stabilization is successfully achieved by using process state variables for initialization, suitable prediction horizon and sampling period. However, steady state offset was observed. A useful offset removal technique is proposed and implemented successfully. Performance of NMPC is compared with that of decentralized controllers for the evaporator system, and the results show that both can provide comparable control.

Keywords: Model predictive control; Four-stage evaporator system; Open-loop unstable process; Nonlinear control

1. Introduction

Industry has widely accepted model predictive control (MPC) as a powerful feedback control strategy which is well suited for high performance control of constrained multivariable processes because explicit pairing of input and output variables is not required. Moreover, process constraints and time delays can be incorporated directly into the associated open-loop optimal control problem. Popular MPC techniques include dynamic matrix control (DMC) [6] model algorithmic control (MAC, also known as IDCOM) [33], generalized predictive control (GPC) [4,5], extended prediction self-adaptive control (EPSAC) [8], Peterka's [31] predictive control and multivariable optimal constrained control algorithm (MOCCA) [38]. Since their inception, MPC strategies have steadily gained industrial popularity. Shell oil company employed MPC algorithms in their fluid catalytic cracker unit [23,32]. Lebourgeois [21] described application of IDCOM identification and control algorithm to the running sections of a PVC plant at Rhone-Poulenc factory in Lavera, France. Engrand [9] implemented IDCOM as a standard control package for a crude distillation which is characterized by large dead times and high interaction of the controlled variables. Details and features of some of these industrial MPC controllers are available in the recent book by Camacho and Bordons [2]. Mehra et al.[27] reviewed a number of applications of MPC including superheater, steam generator, wind tunnel, boiler, distillation column, glass furnace etc. Other industrial applications include hydrocracker reactor [7,23]. Ohshima et al. [28] applied a multirate, multivariable MPC to a semi-commercial polymerization reactor.

In all the above studies and applications of MPC, process model is assumed to be linear, which restricted use of MPC to linear and mildly nonlinear processes. Since systems with moderate to strongly nonlinear dynamics are often encountered in chemical process industry, there is a need for nonlinear model-based control to achieve tighter control of these processes. Recognizing this need, a number of MPC algorithms incorporating nonlinear prediction models (hence called as nonlinear MPC or NMPC) have appeared in the literature in the last decade, e.g., [1,24,30]. A comprehensive review of NMPC including its applications to simulated examples, experimental processes and a

Abbreviations: BPE, boiling point elevation; CW, cooling water; D, underflow; DMC, dynamic matrix control; F, liquor feed; FT, flash tank; HD, heater discharge; HF, heater feed; HT, heater; HW, hot water; *K*, adaptation vector; NMPC, nonlinear model predictive control; P, product flow; S, steam flow; V, vapour flow

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Nomenclature

c	specific heat capacity
h	flash tank level
$\dot{m}$	mass flow
M	control horizon
P	prediction horizon
Q	volumetric flow
T	liquor temperature, sampling period
u, U	manipulated input variable
x, X	state variable
y	controlled output variable

Greek letters

ρ	liquor density
Φ	objective function

Subscripts

F	feed
p	process
P	liquor product
r	setpoint
S	steam
V	vapour
W	water

few industrial processes, is available in [11]. This review shows that reported simulation and experimental studies on NMPC are for small size problems, often for single-input single-output or two-input two-output reactor applications. A significant exception is the study of Ricker and Lee [34], who studied NMPC of Tennessee Eastman plant. However, the nonlinear process model was linearized at each sampling instant for prediction and control. A similar strategy was recently employed by Wang et al. [39] for control of optimal grade transition of polymerization reactors.

The broad objective of the present study is to apply and evaluate NMPC for an industrial four-stage evaporator system. A continuous evaporator process is important in several chemical and mineral processing industries. Recently, Kam and Tadé [15] presented two mechanistic models (referred to as M1 and M2) of a multieffect evaporator system in an alumina refinery. Model M1 has more complex dynamics and is control nonaffine in nature, whereas model M2 is developed with a few additional assumptions and is control-affine. In the control study of the evaporator system using feedback linearization [16,17], model M1 was used as the "real" process and model M2 as the "model" of the process in the controller design. This implementation introduces both structural and parameter mismatch between the process and the model. Comprising of numerous state, input and output variables, and having severe nonlinearity, these evaporator models provide a rigorous base for MPC studies on moderate size systems.

An interesting characteristic of models M1 and M2 is that they are open-loop unstable in nature [17], and is mainly due to integrating characteristics of liquid level in the evaporator tanks. This along with the mismatch between models M1 and M2 poses a challenge in the application of NMPC. In conventional MPC, effect of process/model mismatch is reduced by adding the difference between the model prediction and the latest plant measurement to the value predicted by the model. This can result in slow control and limit applicability of conventional MPC to open loop stable plants only. However, possibility of employing MPC for unstable systems is not completely ruled out as can be seen from the studies of several researchers, e.g., [10,26,29,37,40]. Zheng and Morari [40] derived stability conditions for MPC with hard constraints on inputs and soft constraints on the outputs for an infinitely long prediction horizon. They showed that MPC is "globally" asymptotically stabilizing if and only if all the eigen values of the open-loop linear system are strictly inside the unit circle. However, similar proof for a nonlinear system is not available in the literature. Gobin et al. [10] studied linear MPC (DMC) through simulation for driving two industrial polymerization reactors in series from a stable to an unstable operating point. Although the authors stated that they were successful in implementing MPC around an unstable operating point without making any modification of control loop structure (such as stabilizing the process in a cascade arrangement), complete details of implementation are not reported.

Özkan and Çamurdan [29] argued that the control of the process around an unstable point using a MPC is not possible since the internal stability condition for implementing these controllers, is not fulfilled. Some compensation is, therefore, necessary before the MPC algorithm can be implemented. They implemented DMC for a CSTR in a cascade arrangement. In the inner loop, the process is stabilized around the unstable point using a proportional controller, and the stabilized process is controlled by DMC in the outer loop. Similar approach was reported by Sriniwas and Arkun [37]. They presented a case study where MPC is applied to control a nonlinear open-loop unstable process, viz. the Tennessee Eastman Process. Control of this process by NMPC was studied by Ricker and Lee [34] too; however, feedback stabilization and cascade loops were necessary for this. Thus, MPC in these applications acts as a supervisory controller that dictates the setpoint of the system for a lower level PID loop, and MPC is applied to a stable closed loop process.

Meadows and Rawlings [26] employed NMPC for a fluidised bed reactor for controlling the system at an unstable steady state. However, their manipulated variable is not a physical quantity, rather an expression which ensures stabilization of the original unstable system through proportional controller gain. This arrangement is similar to the linear MPC application for CSTR by Özkan and Çamurdan [29] and Tennessee Eastman problem by Sriniwas and Arkun [36]. Camacho and Bordons [2] stated that MPC strategy can be applied to unstable systems as well. Nevertheless, they remarked that the key to success in such cases lies with the apposite modelling of the system to be controlled.

Very recently, Mayne et al. [25] surveyed stability and optimality for constrained MPC (both linear and nonlinear). From an extensive literature, they distilled essential principles that ensure stability, however, the discussion is limited to open-loop stable processes.

Hence, the potential and efficacy of NMPC is studied extensively in this paper for moderate size, nonlinear, open loop unstable evaporator system without using feedback linearization or stabilization and retaining the integrating characteristic of the process while solving the optimal control problem. In order to simulate practical situations and as was done earlier [16,17], the simpler model M2 is used for controller design in the present study too and its efficacy is tested by implementing on the more detailed model M1. A simple adaptation strategy is proposed and tested for eliminating the offset. Control performance of the resulting NMPC is studied for several disturbances expected in the plant, and compared with that of decentralized proportional-integral (PI) controllers.

Industrial implementations of MPC are generally for large systems with many units, inputs, outputs and constraints. They are often based on linear models and are part of a multilevel hierarchy of control functions such as lower-level PID loops, upper-level optimizer. Recently, Lee et al. (2000) [22] discussed the relative merits of two options for interfacing MPC with low-level loops: MPC manipulates control valves directly (option A) and MPC manipulates setpoints of lower-level loops (option B), and suggested modifications to overcome the deficiencies of each option. Simulation results in Lee et al. (2000) show that modified option A is comparable to or better than others. Further, valve constraints can be incorporated directly in modified option A; but implementing MPC directly may be difficult for fast loops. Hence, in this study, NMPC is implemented on the simulated evaporator system for all controlled variables directly (without lower-level PID loops) to gain the maximum benefit of NMPC and to check the viability of NMPC even for relatively faster level loops.

2. Multistage evaporator system

The selected evaporator system is the first step in the liquor burning process associated with the Bayer process for alumina production at the Wagerup alumina refinery in western Australia. It consists of one falling film, three forced-circulation and a super-concentration evaporators in series. The main components of each stage are a flash tank (FT), a flash pot and a heater (HT). A simplified schematic of the evaporator system is depicted in Fig. 1. Flash pots are not shown in this figure for simplicity of the schematic. Spent liquor, which is recovered after precipitation of the alumina from its solution, is fed to the falling film stage (FT #1). The volatile component, water in this case, is removed

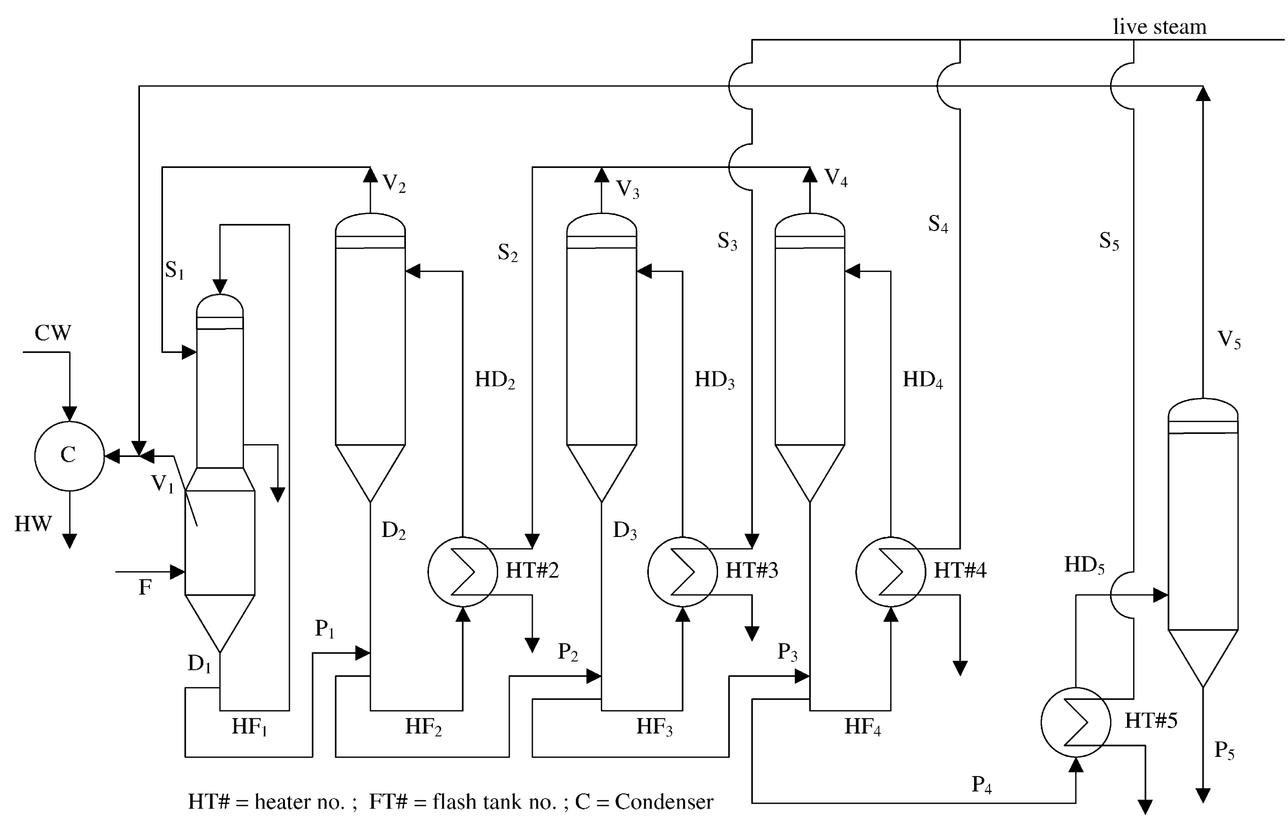

Fig. 1. A simplified schematic of the evaporator system.

under high recycle rate and the product is further concentrated through the three forced-circulation stages (FT #2–4). The super-concentration stage (FT #5) is used to remove the residual 'flashing' of the concentrated liquor without recycle.

In each of the forced-circulation and super-concentration stages, the spent liquor is heated through a shell and tube heat exchanger (heater) and water is removed as vapour at lower pressure in the FT. The vapour given off is used as the heating medium in the heaters upstream. The flashed vapour from FT #3 and 4 are combined and used in HT #2 while the vapour from FT #2 is used in HT #1. The flashed vapour from FT #5 is sent directly to the condenser, C in Fig. 1. The steam condensates from the heaters are collected in the flash pots. Live steam is used as the heating medium for HT #3, 4 and 5. Live steam to HT #3 is set in ratio to the amount of live steam entering HT #4, while the amount of live steam to HT #5 is set depending on the amount of residual 'flashing' to be removed. The cooling water flow to the contact condenser, C is set such that all remaining flashed vapour is condensed. The evaporator system is crucial in the aluminium refinery operation and is difficult to control due to recycle streams, strong process interactions and nonlinearities.

2.1. Models for the evaporator system

Kam and Tadé [15] have developed two mathematical models, M1 and M2 for the evaporator system using unsteady state mass and energy balances around the units in Fig. 1. The differences between M1 and M2 are due to different assumptions that were used in their development. As was done by Kam and Tadé [16], the models for and control of the first four stages only are considered in the present study too. Each of the two models for the first four stages consists of 12 ordinary differential equations with five input and five output variables. The state, input and output variables for the two models are summarized in Table 1. Due to proprietary reasons, the actual values of these variables are multiplied with an arbitrary factor. However, this change does not alter the basic characteristics of the models. Note that the values of the variables in Table 1 are only approximate steady state values; exact values depend on the model selected, and will have to be obtained in each case. The controlled and manipulated variables (y's and u's, respectively) were selected according to the actual plant configuration. In the plant, all these manipulated inputs and the controlled outputs are measured online. Additionally, on-line measurements of the product liquor temperatures of the first four stages (T_1, T_2, T_3, T_4) are available.

Table 1
State, input and output variables and their nominal values for the evaporator system

State	Value	Input	Value	Output	Value
x_1, h_1	1.5 m	u_1, Q_{P1}	32.736 m^3/h	y_1, h_1	1.5 m
x_2, h_2	2.25 m	u_2, Q_{P2}	27.713 m^3/h	y_2, h_2	2.25 m
x_3, h_3	2.25 m	u_3, Q_{P3}	23.850 m^3/h	y_3, h_3	2.25 m
x_4, h_4	2.25 m	u_4, Q_{P4}	21.642 m^3/h	y_4, h_4	2.25 m
x_5, ρ_4	1.54 g/cm^3	u_5, $\dot{m}_{S4}$	2.3814 m^3/h	y_5, ρ_4	1.54 g/cm^3
x_6, T_1	66.0 °C				
x_7, T_2	90.6 °C				
x_8, T_3	129 °C				
x_9, T_4	135 °C				
x_{10}, ρ_1	1.357 g/cm^3				
x_{11}, ρ_2	1.422 g/cm^3				
x_{12}, ρ_3	1.49 g/cm^3				

2.2. Model M1

Development and complete details of the model M1 are available in [15]. Hence, only the equations for the second stage of the evaporator system are presented here.

$$\frac{\mathrm{d}h_2}{\mathrm{d}t} = \frac{1}{A_2}\left[Q_{P1} - Q_{P2} - \frac{E_2}{\rho_W}\right] \tag{1}$$

$$\frac{\mathrm{d}\rho_2}{\mathrm{d}t} = \frac{1}{h_2 A_2}\left[E_2\left(\frac{\rho_2}{\rho_W} - 1\right) - Q_{P1}\rho_1\left(\frac{\rho_2}{\rho_1} - 1\right)\right] \tag{2}$$

$$\begin{aligned}\frac{\mathrm{d}T_2}{\mathrm{d}t} = \frac{1}{\mathrm{CoT}_2}\Bigg[&\frac{1}{(V_2 - h_2 A_2)} \times \left(E_2 - \dot{m}_{V2} + \rho_{V2}\left(Q_{P1} - Q_{P2} - \frac{E_2}{\rho_W}\right)\right)\Bigg] \\ &- \frac{1}{\mathrm{CoT}_2}\left[\mathrm{CoRho}_2\left(\frac{1}{h_2 A_2}\left(E_2\left(\frac{\rho_2}{\rho_W} - 1\right) - Q_{P1}\rho_1\left(\frac{\rho_2}{\rho_1} - 1\right)\right)\right)\right]\end{aligned} \tag{3}$$

where

$$E_2 = \frac{Q_{P1}\rho_1 c_1 T_1 - Q_{P2}\rho_2 c_2 T_2 + \dot{m}_{S2}\lambda_{S2}}{\lambda_{V2}} \tag{4}$$

$$\mathrm{BPE}_2 = 102.69\rho_2 - 128.82 \tag{5}$$

$$\rho_{V2} = \frac{MP_2}{R(273.1 + T_2 - \mathrm{BPE}_2)} \tag{6}$$

$$P_2 = 0.133\exp\left(A - \frac{B}{C + 273.1 + T_2 - \mathrm{BPE}_2}\right) \tag{7}$$

$$\mathrm{CoT}_2 = \rho_{V2}\left(\frac{B}{(C + 273.1 + T_2 - \mathrm{BPE}_2)^2} - \frac{1}{(273.1 + T_2 - \mathrm{BPE}_2)}\right) \tag{8}$$

$$\mathrm{CoRho}_2 = -102.69\rho_{V2}\left(\frac{B}{(C + 273.1 + T_2 - \mathrm{BPE}_2)^2} - \frac{1}{(273.1 + T_2 - \mathrm{BPE}_2)}\right) \tag{9}$$

The constants M and R are the molecular mass of water and the gas constant, respectively, and A, B and C are constants in the Antoine equation for the vapour pressure–temperature relation of water vapour.

The flashed vapour from FT #2 is used in HT #1. As such, the amount of vapour that is drawn from FT #2 (i.e. $\dot{m}_{V2}$) depends on the amount of condensation due to heat exchange with the liquor in HT #1. The rate of vapour withdrawal from FT #2 is given as

$$\dot{m}_{V2} = \frac{Q_{HF1}\rho_{HF1}c_{HF1}(T_{S1} - (T_{S1} - T_{HF1}) \times \exp(-UA_1/Q_{HF1}\rho_{HF1}c_{HF1}) - T_{HF1})}{\lambda_{S1}} \quad (10)$$

where the subscript HF and S refer to heater feed and steam, respectively. The steam temperature in HT #1 (i.e. T_{S1}) is the same as the saturation temperature of the flashed vapour from FT #2,

$$T_{S1} = T_2 - \mathrm{BPE}_2 \quad (11)$$

The liquor density (ρ_{HF1}) and temperature (T_{HF1}) in FT #1 are obtained from mass and energy balances at the mixing point as follows:

$$T_{HF1} = \frac{R_1 c_1 T_1 + Q_F \rho_F c_F T_F}{Q_{HF1}\rho_{HF1}c_{HF1}} \quad (12)$$

$$\rho_{HF1} = \frac{R_1 + Q_F\rho_F}{Q_{HF1}} \quad (13)$$

The recycle rate R_1 is set to a constant.

Evaporation rate E_2 in Eq. (4) depends on the amount of steam condensing in HT #2, which is equal to the amount of flashed vapour from FT #3 and FT #4 (i.e., $\dot{m}_{S2} = \dot{m}_{V3} + \dot{m}_{V4}$), and is also governed by the rate of heat transfer in HT #2 given by

$$\dot{m}_{S2} = \frac{Q_{HF2}\rho_{HF2}c_{HF2}(T_{S2} - (T_{S2} - T_{HF2}) \times \exp(-UA_2/Q_{HF2}\rho_{HF2}c_{HF2}) - T_{HF2})}{\lambda_{S2}} \quad (14)$$

where

$$T_{S2} = T_3 - \mathrm{BPE}_3 \quad (15)$$

$$T_{HF2} = \frac{R_2 c_2 T_2 + Q_{P1}\rho_1 c_1 T_1}{Q_{HF2}\rho_{HF2}c_{HF2}} \quad (16)$$

$$\rho_{HF2} = \frac{R_2 + Q_{P1}\rho_1}{Q_{HF2}} \quad (17)$$

2.3. Model M2

Additional assumptions are used to simplify model M1 to model M2, and equations for all the five stages are available in [15]. Several equations of model M2 are the same as that of model M1. For example, model equations for the second stage are Eqs. (1) and (2), and the following.

$$\frac{dT_2}{dt} = \frac{1}{\mathrm{CoT}_2}\left(E_2 - \dot{m}_{V2} + \rho_{V2}\left(Q_{P1} - Q_{P2} - \frac{E_2}{\rho_W}\right)\right) \quad (18)$$

The quantities in these equations are the same as given along with model M1 except Eqs. (7), (8), (12) and (14), which for model M2 are:

$$\mathrm{CoT}_2 = (V_2 - A_2 h_2)\left(\frac{1.58M}{R(273.1 + T_2 - \mathrm{BPE}_2)} - \frac{\rho_{V2}}{(273.1 + T_2 - \mathrm{BPE}_2)}\right) \quad (19)$$

$$\dot{m}_{S2} = \dot{m}_{V3} + \dot{m}_{V4} \quad (20)$$

$$\dot{m}_{V2} = E_2 \quad (21)$$

$$P_2 = 1.58T_2 - 105.77 \quad (22)$$

The value of BPE_2 is constant (=16) for model M2. The model equations for the liquor temperature of model M2 in Eqs. (18) and (19) are considerably simpler than Eqs. (3) and (8) of model M1. The simplification is due to the additional assumptions that the boiling point elevation (BPE) is independent of the liquor density and that the vapour pressure–temperature relation of the flashed vapour is linear (Eq. (22)), which was obtained by local linearization of Eq. (7) at the nominal liquor temperature. Another noticeable difference between the model equations of the two models is the steam flow to HT #2 and the vapour withdrawal rate from FT #2. Note that the vapour withdrawal rate in model M2 is equal to the rate of evaporation in the FT (i.e. Eq. (21)), and hence it does not depend on the heat transfer rate in the heater.

Inspection of level dynamics (Eq. (1)) shows that both models M1 and M2 will have integrating characteristics. Furthermore, Kam and Tadé [15] showed that the local linear model of M2 at the nominal steady state, has some poles in the right half plane. Thus models M1 and M2 of the evaporator system have unstable open-loop behaviour. These results and all equations of models M1 and M2 are also available in [18], who discuss the use of both models for education and research in process control. Open-loop responses of model M1 and M2 for a step change in steam flow rate to stage 4 (i.e., m_{S4}), presented in [18] show that the two models differ significantly in the transient response of some state variables, model gains, etc. Model mismatch between M1 and M2 was also shown using closed-loop simulation [18].

3. Control of the evaporator system by NMPC

In general, NMPC refers to a control problem where the model, performance or objective function (Φ) and the constraints (H and Q in Eqs. (26) and (27)) are nonlinear functions of state, input and output variables of the system. The general predictive control problem can be represented as

$$\min \Phi[X(k+i), U(k+i-1), Y(k+i), Y_r(k+i)] \quad (23)$$

with respect to $U(k+j)$ for $j = 1, 2, \ldots, M$ subject to

$$X(k+i+1) = F[X(k+i), U(k+i)], \quad i = 1, 2, \ldots, P \tag{24}$$

$$Y(k+i) = G[X(k+i), U(k+i), Y_p(k)], \quad i = 1, 2, \ldots, P \tag{25}$$

$$H[Y(k+i), U(k+i)] \leq \underline{0}, \quad i = 1, 2, \ldots, P \tag{26}$$

$$Q[Y(k+i), U(k+i)] = \underline{0}, \quad i = 1, 2, \ldots, P \tag{27}$$

where k denotes the current sampling instant, $k+i$ denotes the ith sampling instant in the future starting from instant k, P and M are, respectively, the prediction and control horizons (both in terms of number of sampling instants) and $U(k+i-1) = U(k+M)$ if $i > M$. Here, vectors $X \in R^n$, $Y \in R^m$, $Y_p \in R^m$, $Y_r \in R^m$ and $U \in R^m$ represent model states, model outputs, measured outputs, setpoints and manipulated inputs, respectively. The control problem is posed in the discrete form and the manipulated inputs are assumed to be piece-wise constant. Eqs. (24) and (25) represent the dynamic model of the process, which in the present application is model M2. The other possible constraints are of two types, viz. equality and inequality algebraic constraints (Eqs. (26) and (27)) arising from the limits on the manipulated inputs, product quality specifications or safety requirements. The controller is implemented in a moving horizon framework, i.e., only the first input (at $k+1$ instant) from the future input vector obtained through optimization is used and the whole procedure is repeated at the next sampling instant.

The objective function, used in this work, is

$$\Phi = \sum_{i=1}^{P} (Y_r(i) - Y(i))^2 \tag{28}$$

There are quite a few methods of solving the optimal control problem (Eqs. (23)–(27)) through nonlinear programming [11]: sequential approach, simultaneous method and successive linearization. In this work, sequential approach has been chosen for its easy implementation. In this approach, manipulated variables (*U*) are the only decision variables in the optimization. Within a sampling period, the prediction model is simulated again and again over the prediction horizon to calculate *Y*(*i*) for $i = 1, 2, \ldots, P$ until the minimum value of Φ is obtained; and the corresponding set of decision variables are rendered as manipulated inputs for the system in the next sampling instant.

3.1. Implementation of NMPC

The simulation programs are developed using MATLAB 5.3 and its associated ODE solver and optimization toolboxes. Nelder–Mead optimization technique (fminsearch.m) is used for unconstrained optimization. Initially, constraints in the form of upper and lower bounds on the manipulated inputs (Eq. (26)) were considered while performing optimization. These trials were carried out with constr.m program. However, this was found to be unnecessary because all the manipulated inputs were generally within their upper and lower limits and never touched the constraint boundaries. Moreover, constr.m program needs the gradient of the objective function which is calculated numerically by the program itself. The accuracy of gradients calculated in this way is questionable and hence usually avoided. The ode45.m program in the ODE solver toolbox uses 4th order Runge–Kutta method. Windows-NT workstation with dual Pentiun III Xeon processors each of 550 MHz was used for simulations.

The main difficulty associated with M1–M2 combination is that model M2 is not capable of replicating the transient behaviour of model M1 for a long period of time. And there could be substantial differences in the responses predicted by the two models at larger times. This leads to a major problem in the application of NMPC to the evaporator system because the output predicted by model M2, while solving the optimal control problem (Eqs. (23)–(27)), should be within an acceptable limit, i.e., large process/model mismatch is not desirable in this stage of the calculation. In the MPC applications, this process/model mismatch is generally taken care of by adding the difference between the measured process and model outputs at the latest time to the predicted outputs in the optimization step. This strategy was not successful in the application of NMPC to the evaporator system. The reason was found to be the significant differences between the state variables of models M1 (process) and M2 (used in the control) after some time. To tackle this problem, an unconventional technique is used in the present application of NMPC. State variables of the process are used to initialise the model M2 calculations in the optimal control problem at every sampling time. In the actual plant, all state variables in Table 1 except ρ_1, ρ_2 and ρ_3, are measured. If necessary, these densities can be measured by installing suitable instruments. In the present application, therefore, state variables of process (model M1) are assumed to be available. Estimation of ρ_1, ρ_2 and ρ_3 via state observer is possible, e.g., [16], and will be considered in our future study. Furthermore, a small prediction horizon is used in the NMPC in order to avoid extremely large process/model mismatch.

3.2. Load disturbances and setpoint changes

Several measured and/or unmeasured load disturbances may occur during the operation of the industrial evaporator system. Common disturbances are due to changes in the feed (such as flow rate, density and temperature in *F* in Fig. 1) to the evaporator system and/or changes in the heat transfer coefficient of the heaters. Setpoint changes in ρ_4 are also possible. Hence, the following regulatory and/or servo cases are considered in the present study.

Case 1 : Change in flow rate of feed (Q_F) from the nominal value of 37.7 to 39.7 m^3/h.
Case 2 : Change in flow rate of feed (Q_F) from the nominal value of 37.7 to 35.7 m^3/h.
Case 3 : Simultaneous change in flow rate of feed (Q_F) from the nominal value of 37.7 to 39.7 m^3/h and a 15% decrease in the heat transfer coefficient, UA in heaters 1 and 2.
Case 4 : Change in density of feed (ρ_F) from the nominal value of 1.310 to 1.376 g/cm^3.
Case 5 : Change in density of feed (ρ_F) from the nominal value of 1.310 to 1.245 g/cm^3.
Case 6 : Change in temperature of feed (T_F) from the nominal value of 60 to 66 °C.
Case 7 : Change in temperature of feed (T_F) from the nominal value of 60 to 54 °C.

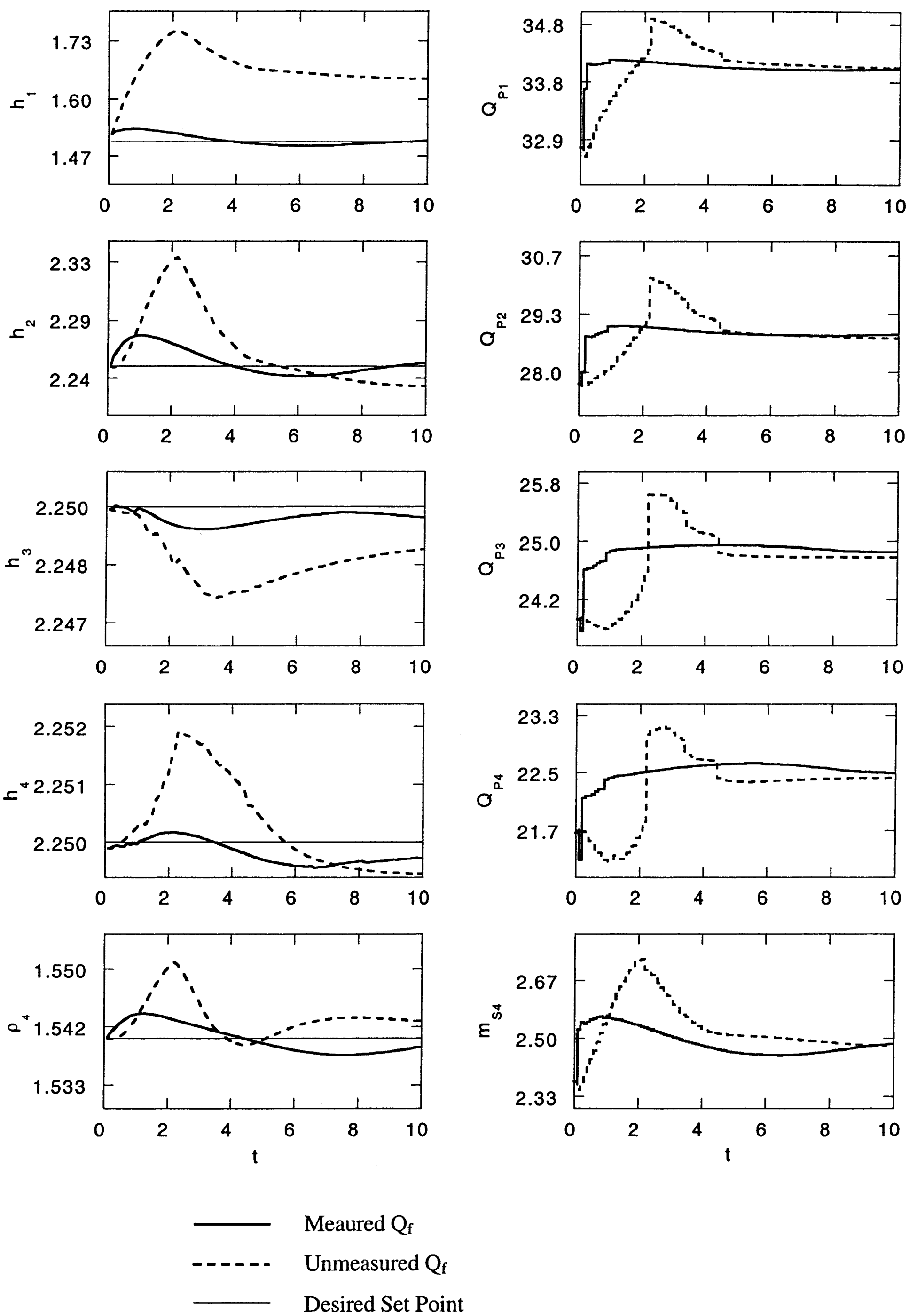

Fig. 2. Control performance of NMPC for a measured and unmeasured step change in feed flow rate, Q_F.

Case 8 : Change in the setpoint of product liquor density from FT #4 (ρ_4) from the nominal value of 1.54 to 1.62 g/cm^3.

Case 9 : Change in the setpoint of product liquor density from FT #4 (ρ_4) from the nominal value of 1.54 to 1.46 g/cm^3.

Case 10 : Simultaneous change in the setpoint of ρ_4 from 1.54 to 1.46 g/cm^3 and in the setpoint of h_1 from 1.5 to 1.8 m.

3.3. Tuning of NMPC and offset removal

The most crucial part in any controller design is to tune the controller parameters to ensure good control performance. Parameters in NMPC are sampling period (T), prediction horizon (P) and control horizon (M). Some initial trials were conducted for selecting suitable values for these parameters. A load disturbance of change in flow rate of feed (Q_F) from the nominal value of 37.7 to 39.7 (Case 1), was introduced in

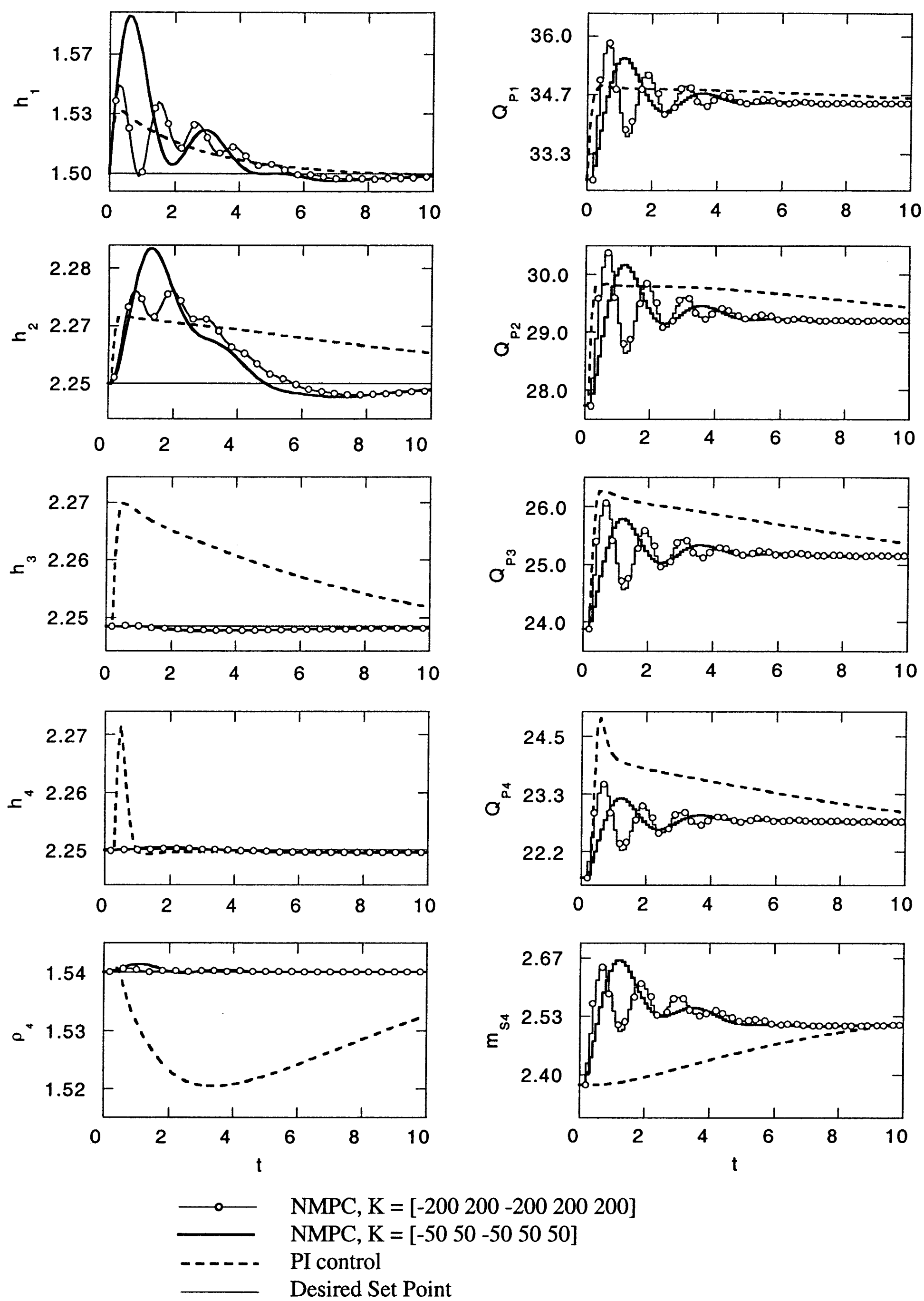

Fig. 3. Control performance of NMPC (with two different settings) and PI for a step change in feed flow rate (Case 1).

all these initial trials. Two values of T (namely, 0.1 and 0.01) were considered for selection. It is of prime importance (as discussed earlier) to keep the prediction horizon within a certain limit so that the prediction capability of M2 remains reliable. It is observed through open-loop studies that the prediction capability of model M2 is extremely poor beyond 1 h of simulation. Hence, suitable combinations of T and P were selected so that the prediction time of 1 h is not exceeded. In the literature on MPC, $M = 1$ is a standard choice. Thus, $M = 1$, $T = 0.1$ or 0.01, and $P = 10$–40 were tried for the evaporator control by NMPC. It is observed from these trials that control performance with $T = 0.01$ is not acceptable because computational time increases a lot as P increases and small value of P together with $T = 0.01$ constitutes very small prediction horizon in terms of time which is not enough for MPC calculations. However, computational time with $T = 0.1$ and $P = 10$ is acceptable. Control with $T = 0.1$, $P = 10$, $M = 1$ is shown as dashed lines in Fig. 2. Although $M = 1$ is the usual choice, it can be any integer within $1 \leq M \leq P$. Hence, $M = 2$, 5 and 10 were tried. Resulting control was no better than that with $M = 1$ (shown in Fig. 2) except that the computational time increased with higher value of M. Thus, $T = 0.1$, $P = 10$ and $M = 1$ were considered to be reasonable and selected for the NMPC of the evaporator system.

Regulatory performance of NMPC shown in Fig. 2 is far from satisfactory. The main problem is the offset in h_1, h_2 and ρ_4. Note that offset is observed in h_3 and h_4 too, but their magnitude is negligible. Offset could be caused by process/model mismatch and/or finite prediction horizon. The common approach to eliminate this offset is by adding the difference between the measured process and model outputs at the latest time to the predicted outputs in the optimization step. However, as noted before, this was not successful for the evaporator system, and process state variables are used to initialise the model M2 calculations in the optimal control problem. As reported by Meadows and Rawlings [26], this does not guarantee an offset-free performance in the presence of modelling errors. Results in Fig. 2 are consistent with this. For cases without modelling error, the updating of state variables may provide offset-free control by NMPC. To verify this and to understand the offset problem, several additional tests were conducted assuming that the load disturbances are known (i.e., Q_F is measured and hence it can be used in the NMPC controller) thus reducing process/model mismatch. The results (Fig. 2) show that offset is practically removed if the disturbance in Q_F is measured and used in the controller calculations. Since disturbances in practice are unmeasured and unknown, a better technique to eliminate the offset is necessary.

Kurtz and Henson [19] proposed a novel disturbance modelling technique that ensures offset-free setpoint tracking for nonlinear processes. They incorporated a linear MPC algorithm with conventional input–output linearizing (IOL) controller to exploit the constraint handling capability of the former. The MPC controller generates a proportional state feedback which produces offset in the presence of process/model mismatch. Offset is eliminated by augmenting a disturbance vector with the state observer vector, that shifts the target values of the desired states (through some observer gain matrices) into the IOL block. Similar theory on disturbance model has been proposed for linear MPC, independently by Campbell and Rawlings [3], who categorised the disturbance models into three types, viz. generic disturbance

Table 2
Integral squared error (ISE) values of closed loop performances for cases 1–10

Case	Control	ISE for					Total ISE
		h_1	h_2	h_3	h_4	ρ_4	
1	NMPC	0.0067	0.0021	0.44E−5	0.11E−5	0.20E−5	0.0088
	PI	0.0018	0.0026	0.0019	0.80E−4	0.0022	0.0085
2	NMPC	0.0063	0.0018	0.17E−5	0.49E−6	0.15E−5	0.0082
	PI	0.0018	0.0025	0.0018	0.76E−4	0.0026	0.0088
3	NMPC	0.035	0.026	0.63E−4	0.10E−4	0.71E−5	0.0616
	PI	0.0026	0.0036	0.0031	0.17E−3	0.0055	0.015
4	NMPC	0.018	0.017	0.48E−3	0.16E−3	0.62E−3	0.0364
	PI	0.0017	0.0093	0.0087	0.11E−3	0.0028	0.0226
5	NMPC	0.024	0.023	0.23E−3	0.42E−4	0.13E−3	0.0465
	PI	0.0017	0.0093	0.0088.	0.12E−3	0.0050	0.0249
6	NMPC	0.24E−3	0.93E−4	0.16E−5	0.47E−6	0.87E−6	0.337E−3
	PI	0.39E−4	0.28E−4	0.20E−4	0.68E−6	0.15E−3	0.235E−3
7	NMPC	0.24E−3	0.97E−4	0.61E−6	0.56E−7	0.72E−6	0.339E−3
	PI	0.40E−4	0.28E−4	0.21E−4	0.69E−6	0.15E−3	0.237E−3
8	NMPC	0.081	0.094	0.26E−4	0.27E−4	0.0026	0.178
	PI	0.16E−3	0.0026	0.0031	0.62E−5	0.0245	0.030
9	NMPC	0.121	0.138	0.99E−4	0.22E−4	0.0030	0.261
	PI	0.24E−3	0.0044	0.0048	0.73E−4	0.0261	0.035
10	NMPC	0.085	0.092	0.56E−4	0.96E−5	0.0020	0.179
	PI	0.011	0.0083	0.0099	0.0048	0.0227	0.057

model, output disturbance model and measured input disturbance model. They used integrating disturbance models to achieve offset-free control. In another paper, Meadows and Rawlings [26] discussed the steady state performance of NMPC. They opined that steady state target optimization technique provides a general framework to handle a larger variety of process models than can be addressed with the conventional NMPC feedback. However, it is not always possible to have the correct knowledge of future steady state conditions in the presence of process/model mismatch.

In the context of linearizable systems, Sastry and Isidori [35] discussed parameter adaptation approach for improving control of nonlinear processes. This adaptation approach was used by Iyer and Farell [14] to improve the performance of IOL control of a reactor. In a parallel study, Huberman and Lumer [13] introduced a simple adaptive control mechanism into nonlinear systems where a parameter in the system is updated using the difference between setpoint and output, and its derivative. This approach is similar to the parameter adaptation of Sastry and Isidori [35], and was used in

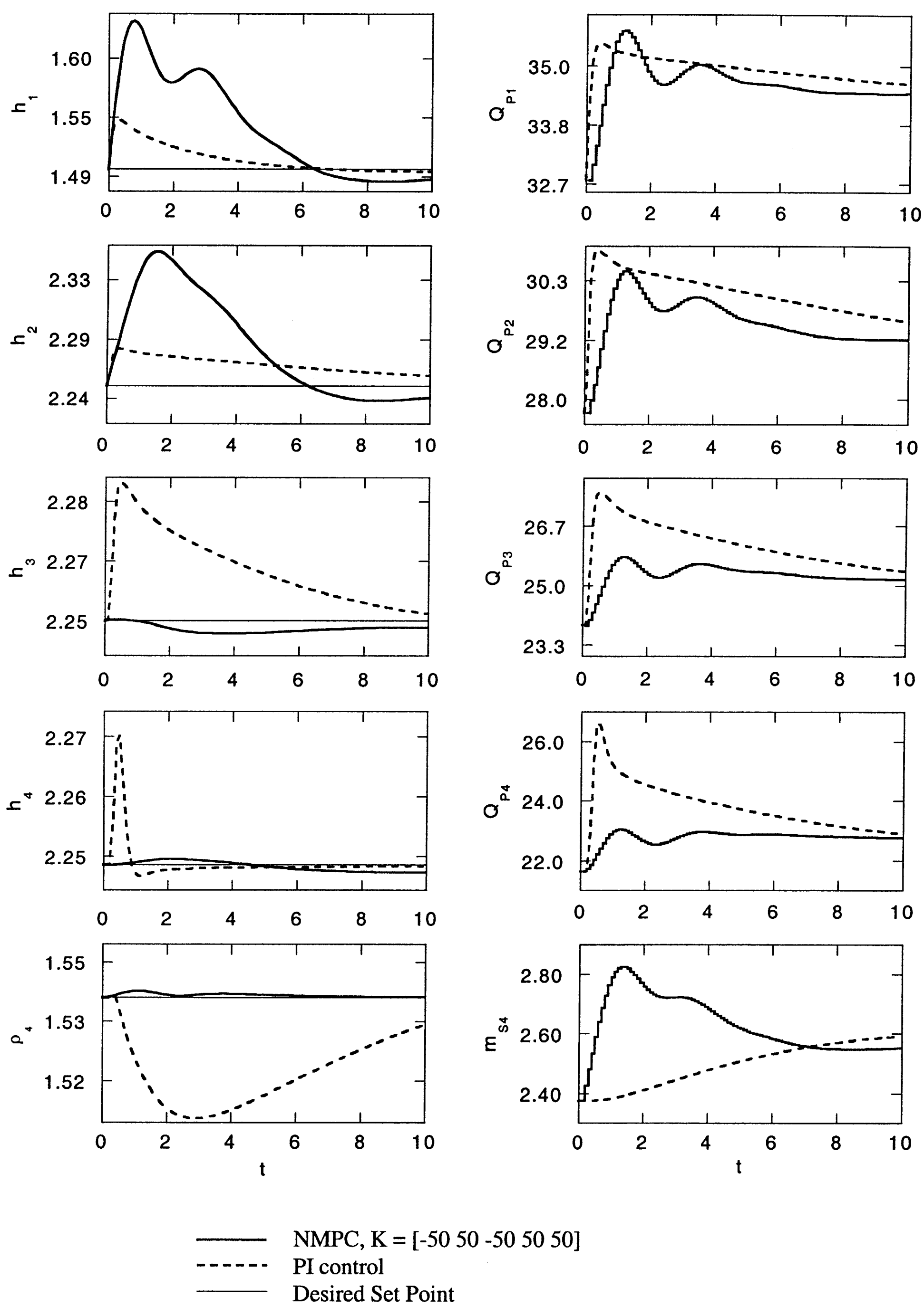

Fig. 4. Control performance of NMPC and PI for a simultaneous change in feed flow rate and a decrease in UA (Case 3).

the internal model control of nonlinear systems by Lakshmi Narayanan et al. and Shukla et al. [20,36]. Hu and Rangaiah [12] proposed a parameter adaptation law for internal model control of nonlinear processes and studied its performance theoretically as well as via simulation on typical processes.

3.4. Proposed adaptation

Motivated by the success of the parameter adaptation approach in the above studies, we propose a simple parameter adaptation technique for eliminating the offset in NMPC. Considering that frequent disturbances are mainly in Q_F, this quantity has been chosen as the model parameter to be updated irrespective of the actual disturbance in the real process. The simple adaptation law is given as

$$\frac{dQ_{F_m}}{dt} = K(Y_r - Y_p) \tag{29}$$

where Y_r and Y_p are the vectors representing setpoint and (process) output variables. Eq. (29) provides updated Q_{F_m}

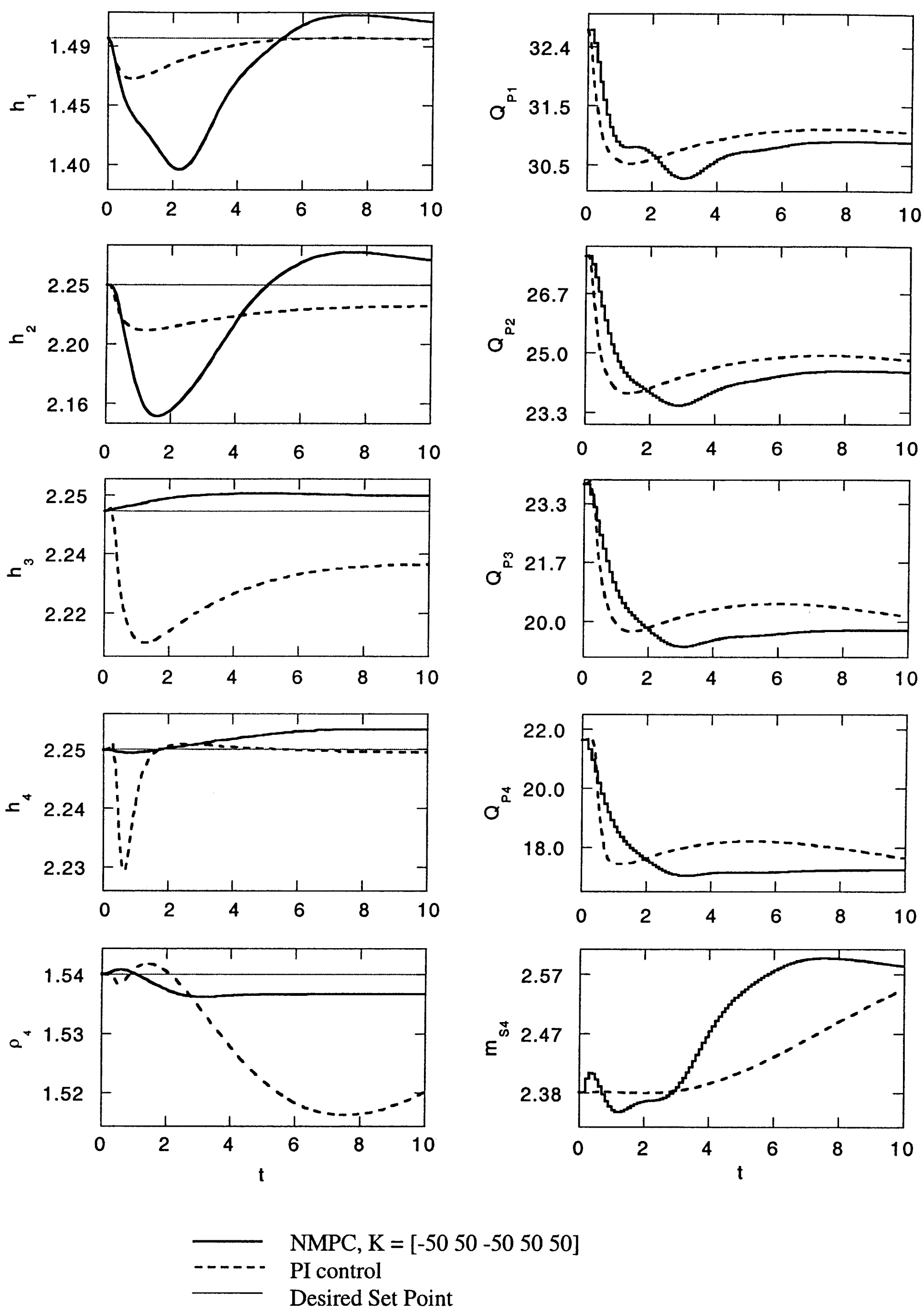

Fig. 5. Control performance of NMPC and PI for a step change in feed density (Case 5).

for use in the model M2 for predicting outputs, Y in the control objective, Φ (Eq. (28)). The main purpose of parameter adaptation here is to improve the performance of NMPC. As such, the simple adaptation law may not estimate the disturbance. The effectiveness of the proposed adaptation will be evaluated for the 10 cases listed above, which includes disturbances in quantities other than Q_F as well as setpoint changes.

Although K could be a 5×5 gain matrix, in the present study it is assumed to be a diagonal matrix to simplify the task to choosing only five values. Since 1 h simulation of the evaporator control by NMPC takes nearly 1 h of computational time on the workstation, it is difficult to perform rigorous tuning of K, e.g., by minimizing a suitable integral error criterion. Hence, K is selected to eliminate offset by a combination of physical insight and heuristics. First, sign of each diagonal element is chosen by considering the response of model M2 to step changes in Q_F (through a few open-loop simulations) and the sign of the gain in the industrial PI controller (which indicates the effect

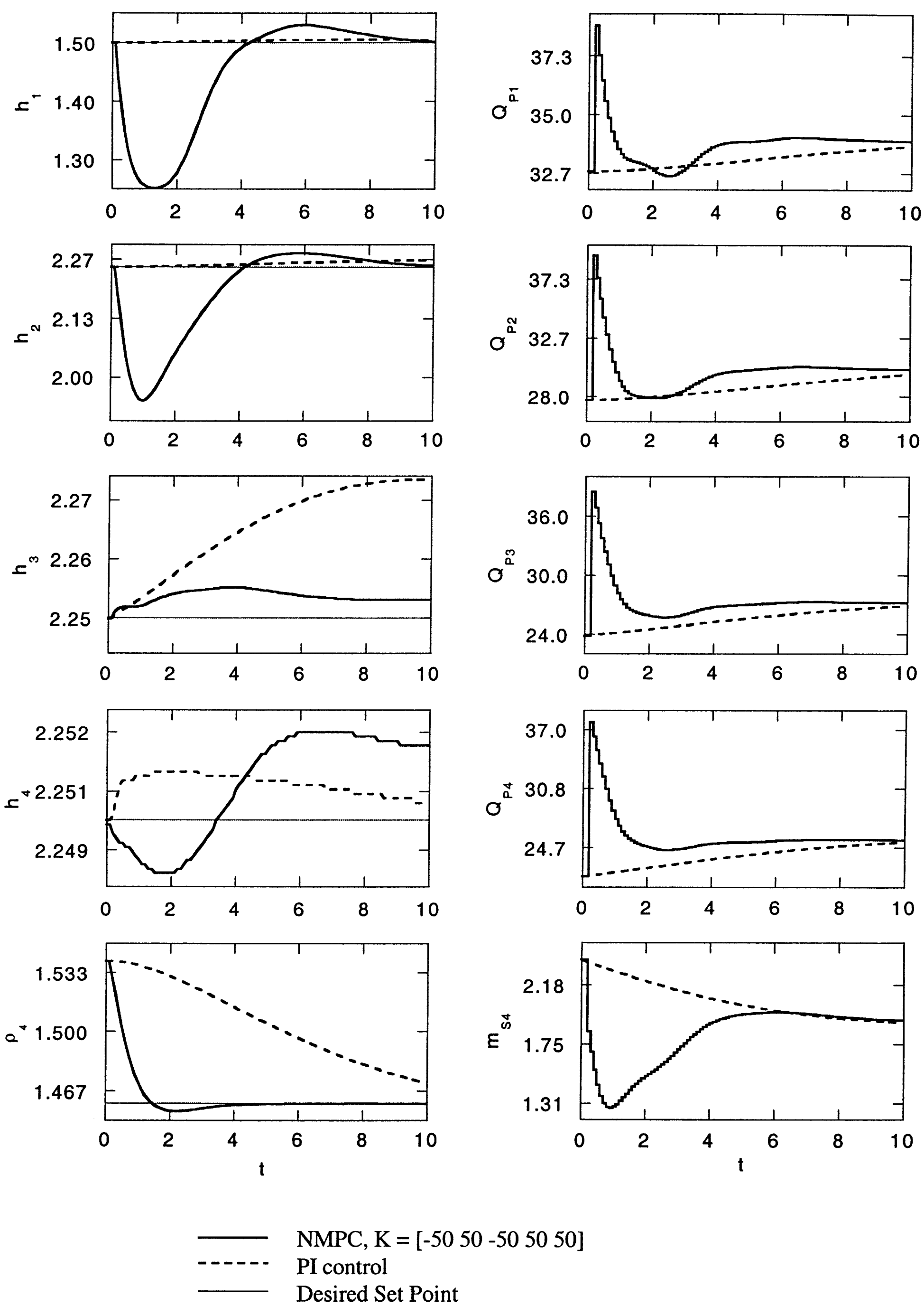

Fig. 6. Control performance of NMPC and PI for a step change in the setpoint of product liquor density from FT #4 (Case 9).

of each manipulated variable on the corresponding output variable). Next, a few closed-loop simulations are carried out with different values for K and introducing a change in Q_F. Fig. 3 shows the closed-loop responses for two sets: $K = \text{diag}[-50 + 50 - 50 + 50 + 50]$ and $\text{diag}[-200 + 200 - 200 + 200 + 200]$. (Different absolute value for each element is possible but closed-loop responses in our trials did not show significantly better performance.) Although control with the second K is better, the conservative setting of $K = \text{diag}[-50 + 50 - 50 + 50 + 50]$ is selected for further tests.

3.5. Performance of NMPC with adaptation

With the K reasonably tuned for one disturbance, simulations are then carried out to examine control performance of NMPC for other disturbances as well as set-point changes (viz. cases 1–10). The results are compared

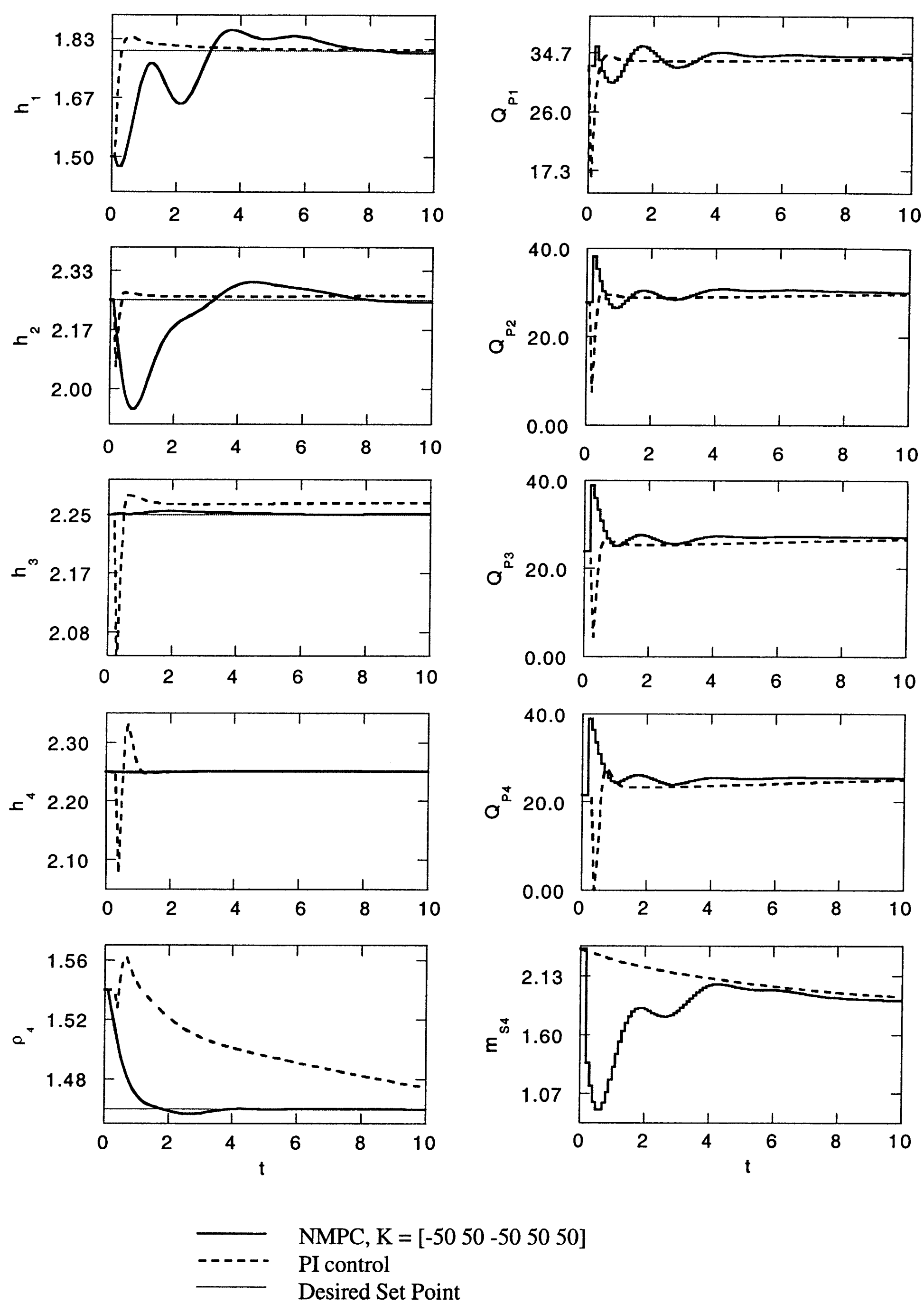

Fig. 7. Control performance of NMPC and PI for a step change in the setpoint of liquid level in FT #1 and of product liquor density from FT #4 (Case 10).

with decentralized PI controllers, which are currently used in the plant with controller gain, $K_c = [-10, -10, -10, -10, 0.6]$ and integral time, $\tau_i = [20, 20, 20, 20, 3]$. Since these may not be the optimal settings, PI controllers are tuned by minimizing the sum of integral of squared errors (ISE) of all the five output variables to change in the feed flow rate (Q_F) from the nominal value of 37.7 to 39.7 (Case 1). Comparison of control by NMPC and PI controllers to be discussed later, is based on ISE. For tuning PI controllers, the simpler model M2 (and not M1) is used as the "process" (since extensive tests on the real plant simulated by model M1 in this study, are not possible), and minimization of ISE is performed using Nelder–Mead technique (i.e., fminsearch.m). Detailed results from the minimization showed that reduction in ISE can be achieved but at the expense of aggressive control action, which may not be acceptable in practice. Hence, PI controllers are tuned to give total ISE (i.e., sum of ISEs for all output variables when the controllers are implemented on the more detailed model M1 as the "process") comparable to that of NMPC for the change in the feed flow rate (Case 1). These selected settings are: $K_c = [-53.28, -106.45, -93.62, -93.15, 0.05]$ and $\tau_i = [2.528, 19.53, 10.13, 0.2112, 0.0501]$, which are then implemented on the more detailed model M1. Transient responses of the output and manipulated variables with these PI controllers, are also shown in Fig. 3.

Control performance of NMPC and decentralized controllers for all the 10 cases is summarized in Table 2, which shows ISE for each output variable as well as total ISE for both NMPC and PI control in each case. As can be seen from ISE values, changes in feed flow rate and density have greater effect on control (cases 1–5) compared to changes in feed temperature (cases 6 and 7). For all 10 cases, PI control seems to be comparable to or better than NMPC in terms of total ISE. However, NMPC consistently provides smaller ISE in ρ_4 than PI. This is of practical significance since variation in ρ_4 affects subsequent processing operations and hence is more important than that in levels (h_i). Note that PI controllers may be tuned differently in order to achieve better control of ρ_4; but this may be at the expense of higher ISE in other outputs.

Transient responses of output and manipulated variables by NMPC and PI control for selected cases are compared in Figs. 3–7. From the responses for load disturbances (Figs. 3–5 for cases 1, 3 and 5, respectively), it can be seen that settling time and propagation of disturbance for PI control are more than those for NMPC. The small offset of less than 0.5% present in ρ_4 for control by NMPC (see Fig. 5) persisted even after a long time, which may be due to numerical errors and/or tolerances used in the optimization. On the other hand, response of ρ_4 by PI shows a large deviation from the setpoint for more than 10 h although there was no offset eventually (not shown in Fig. 5). For setpoint changes (Figs. 6 and 7 for cases 9 and 10 respectively), NMPC provides faster action and thus faster response compared to PI. Movement of some manipulated variables for case 10 under PI control, is significantly large. Thus PI controllers may have to be tuned differently for setpoint changes.

The major disadvantage of using NMPC is large computation time. Because of the necessity of solving optimal control problem on-line, the algorithm simulates model M2 again and again until optimality in manipulated variable is reached. It is observed that around 10–12 h of real-time is needed to execute 40 h of simulation on the Pentium III workstation, whereas PI controller takes only a few minutes of real-time for the same simulation run. However, this implies that the NMPC can be employed to control a real-time plant since chemical plants tend to have slow dynamics.

4. Conclusions

The feasibility and potential of NMPC for open-loop unstable MIMO systems without stabilization is studied by considering a multistage industrial evaporator system. Initially, stable control by NMPC was obtained but steady state offset was observed. A simple parameter adaptation technique is proposed and successfully applied to obtain offset-free control. The performance of NMPC for the evaporator system is compared with that of well-tuned decentralized PI controllers. The results show that NMPC is better than PI controllers in terms of reduced propagation of disturbance and faster response. However, total ISE of all output variables is generally smaller in the case of PI controllers. Since both NMPC and PI controllers can be tuned to achieve the desired objective, these two controllers seem to be comparable for the evaporator system studied. Further studies are required to improve NMPC for industrial processes, particularly for open-loop unstable systems.

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