Evaporation Process Control using MIMO MPC

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ABSTRACT

In the processing industry, controllers play a crucial role in keeping our plants running—virtually everything from simply filling up a storage tank to complex separation processes, and to chemical reactors. There are some important issues when we design a control system. In the first place, we need to identify the role of various variables. We need to determine what we need to control, what we need to manipulate, what are the sources of disturbances, and so forth. However, chemical processes are highly non-linear in nature, especially when they have multiple inputs – multiple outputs (MIMO) variables with complex interactions. Evaporators usually operate before a major drying process, which require more energy and is difficult to control. It is therefore important to achieve good control in the evaporation stage so that the drying process is operating with steady inputs. In this paper three of main evaporated process variables such as Liquid level in separator, operation pressure, and the product concentration are first controlled using PI controller in the presence of a variables step changes and a load disturbance. Advanced controllers such as model predictive control that is used for a wide range of application in the process industry. The potential utilization of such advanced predictive controllers is to design control systems that give effective control in this multivariable environment. Model predictive control is applied to the evaporated process with same mentioned conditions for variable step changes and load applied in case of PI controller. The objective of this paper is to present and illustrates in a comparatively study to the results obtained by PI controller, the use of MPC in providing an effective control for a MIMO evaporator plant in the presence of step and load disturbances change. The sum of the integral of absolute error (IAE) is used as a criterion for evaluating the controller's performance.

Keywords: Chemical process Control, Proportional-Integral Controller, Model Predictive Control, MATLAB / Simulink

1 Introduction

The principle in the evaporation process is separation by evaporation from a liquid mixture where at least one component is not volatile. The physical process of evaporation requires the input of energy in the form of heat to convert a liquid into vapour. Since all evaporators use the process of evaporation to remove water, every evaporator requires a source of heat to operate [1]. The heat source for almost all evaporators is water vapour, either in the form of boiler steam or waste vapour from another process. Evaporators come in many different shapes and sizes. Selecting the best evaporator for a given application can sometimes be a confusing and even intimidating task. Technical terms like falling film, forced circulation, and multiple effect can add to the confusion [1,2]. In this article we will take a brief, not-too-technical look at the most common types of evaporators, how they work, and some of their applications. In this paper the study focuses on the forced circulation evaporation type.

2 Evaporation Process

Evaporation is an engineering operation that is usually used to remove a liquid from a solution, suspension or liquor by boiling some of the liquid. It is usually treated as a separation of liquid mixtures into concentrate and vapour. This operation is usually performed in a heating device called an evaporator. The evaporator is made of a heat exchanger for heating up a solution and a way to remove the vapour from the boiling solution [1]. The forced circulation evaporation process is of our interest case of study in this paper.

2.1 Forced Circulation Evaporation Process

The forced circulation evaporator was developed for processing liquors which are susceptible to scaling or crystallizing. Liquid is circulated at a high rate through the heat exchanger, As the liquid enters the separator where the absolute pressure is slightly less than in the tube bundle, the liquid flashes to form a vapour [2]. The forced-circulation evaporator is a common processing unit in milk, several types of food, sugar mills, alumina production and paper manufacture. This process is used to concentrate a dilute liquor by evaporating its solvent (usually water) as shown in the Figure 1.

A feed stream with solute of concentration C1 (mass percentage) is mixed with high volumetric recycle flow rate and fed into a vertical evaporator (heat exchanger). The mixture solution will pass through the tube. A saturated input steam is used to heat up the mixture by condensing on the outer surface of the tubes. The liquor which passes up inside the tube boils and then passes to a separator vessel. In the separator, the liquid and vapour are separated at constant temperature and pressure. The liquid is recycled with some being drawn off as product with solute concentration of C2. The vapour is usually condensed with water. Water is used as the coolant. The case study is the Newell and Lee forced circulation evaporator model [3].

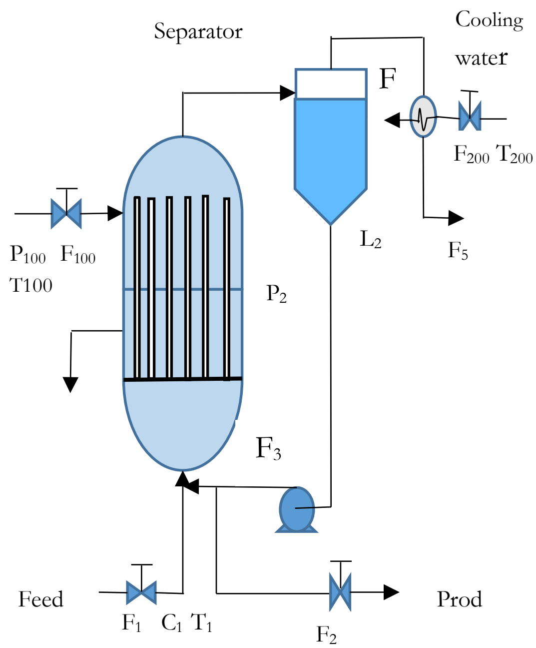

Figure 1: Forced Circulation Evaporator Process

2.2 Modelling the process

The process model can be divided to four parts as follow:

2.2.1 The separator:

$$\rho A\frac{dL_2}{dt} = F_1 - F_4 - F_5 \tag{1}$$

Where, ρ is the liquid density and A is the cross-sectional area of the separator and ρA is assumed to be 20 kg/m.

2.2.2 The evaporator: is represented by 5 equations

$$\mathrm{M}\frac{dC_2}{dt} = F_1C_1 - F_2C_2 \tag{2}$$

$$ß\frac{dP_2}{dt} = F_4 - F_5 \tag{3}$$

$$T_2 = 0.5616P_2 + 0.3126C_2 + 48.43 \tag{4}$$

$$T_3 = 0.507P_2 + 55.0 \tag{5}$$

where M is a constant liquid hold up in the evaporator of 20 kg. Cp and λ are the heat capacity and the latent heat of evaporation of the process liquid which is assumed constant at 0.07 kW/K(kg/min) and 38.5 kW/(kg/min) respectively. The constant ß = 4 kg/kPa is used to convert a mass of vapour into a pressure in the vessel.

2.2.3 The steam: The steam side of the evaporator is model with three algebraic equations as the dynamics are assumed to be very fast

$$T_{100} = 0.1538P_{100} + 90.0 \tag{6}$$

$$Q_{100} = 0.16(F_1 + F_3)(T_{100} - T_2) \tag{7}$$

$$F_{100} = \frac{Q_{100}}{\lambda s} \tag{8}$$

where λs = 36.6 kW/(kg/min) is the latent heat for steam. The term 0.16(F1 + F3) correlates the flow to the evaporator to the overall heat transfer coefficient times the area, UA1, at the given process conditions.

2.2.4 The condenser: The condenser is also modelled with the following set of algebraic equations:

$$Q_{200} = \frac{UA_2(T_3 - T_{200})}{1 + \frac{UA_2}{2CpF_{200}}} \tag{9}$$

$$T_{201} = T_{200} + \frac{Q_{200}}{F_{200}Cp} \tag{10}$$

$$F_5 = \frac{Q_{200}}{\lambda} \tag{11}$$

where UA_2 = 6.84 kW/K is the overall heat transfer coefficient times the area and the heat of evaporation, λ is 38.5 kW/(kg/min).

2.3 Pairing Variables

the layout of an evaporator has 8 degrees of freedom which can be categorised as manipulated variables, MV, and variables of disturbance D. The controlled variables CV are seen from the model's differential equations and all of these are evaluated. These three process variables are the system's desired control variable. This provides the following general overview of the model system. The relative gain array (RGA) can be used in order to get the best variable pairing that could achieve the best control performance [4]. The selected manipulated and controlled pairing variables are the product flow rate F_2 to control the product level L_2 in the separator, the cooling flow rate F_{200} to control operation pressure P_2, and feed flow rate F_1 to control the product concentration C_2. However, disturbances variables D, used are cooling water inlet temperature T_{200}, and the feed concentration C_1.

Table 1. *Nominal steady state parameters values for the evaporator system.*

Variable	Variable Description Value Unit	Value	Unit
F_1	Feed flowrate	10.0	kg/min
F_2	Product flowrate	2.0	kg/min
F_3	Circulating flowrate	50.0	kg/min
F_4	Vapour flowrate	8.0	kg/min
F_5	Condensate flowrate	8	kg/min
C_1	Feed concentration	5	%
C_2	Product concentration	25	%
T_1	Feed temperature	40.0	0C
T_2	Product temperature	84.6	0C
T_3	Circulating temperature	80.6	0C
L_2	Separator level	1.0	M
P_2	Operation pressure	50.5	kPa
F_{100}	Steam flowrate	9.3	kg/min
T_{100}	Steam temperature	119.9	0C
P_{100}	Steam pressure	194.7	kPa
Q_{100}	Heater duty	339.9	kW
F_{200}	Cooling flowrate	208.0	kg/min
T_{200}	Cooling water inlet temperature	25.0	0C
T_{201}	Cooling water outlet temperature	46.1	0C
Q_{200}	Condenser duty	307.9	kW

3 Controllers

There are many open loop and closed loop (feedback) controls strategies like, Proportional controller, Integral controller, Derivative controller, combination of these, PI, PD, PID, fuzzy logic controllers (FLC) etc which are available and proved its influence in process control.

3.1 PID Controllers

A PID controller represents the simplest form of controller that utilises Derivative and Integral operations on the system. PID controllers have several important functions: they have the ability to eliminate steady-state error through the integral action, and they can cope with actuator saturation, if used with anti-windup. These controllers are also effective for many control problems, particularly where there are benign process dynamics and modest performance requirements [5]. A PID controllers are also effective for particularly where there are benign processes dynamics and modest performance requirements [5]. The simplest form of PID controller can be represented by equation.

$$C(t) = K_c \left(e(t) + \frac{1}{\tau_i} \int_0^t e(t)dt + \tau_D \frac{de(t)}{dt} \right) \tag{12}$$

Where, $K_c =$ Proportional constant, $\tau_i =$ integral time constant, $\tau_D =$ Derivative time constant, $e(t) =$ error (controller input), $C(t) =$ Controller command (controller output).

3.2 Model Predictive Controller (MPC)

Model Predictive Control (MPC) has a long history in control engineering. It is one of the few fields that has attracted ongoing attention from researchers in both the industrial and academic communities. Four main aspects of model predictive control make the design approach appealing to both practitioners and academics. The first factor is the architecture, which uses a completely multivariable system structure, where the output parameters of the multivariable control system are related to the technical aspects of the system; thus, they can be understood and 'tuned' by engineers. The second factor is the potential of the system to manage both 'soft' constraints and hard constraints in a multivariate control setting. This is especially appealing to industry, where there are expected to be tight profit margins and limitations on the process activity. The third element is the ability to perform on-line optimization of the operation. The fourth element is the simplicity of the framework architecture [6,7,8].

Model Predictive Control Toolbox provides functions, an app, and Simulink® blocks for systematically analysing, designing, and simulating model predictive controllers. You can specify plant and disturbance models, horizons, constraints, and weights. The toolbox enables you to diagnose issues that could lead to run-time failures and provides advice on tuning weights to improve performance and robustness. By running different scenarios in linear and nonlinear simulations, you can evaluate controller performance [9]. The plant model is developed on a Simulink and connected to an MPC block as in Figure [2].

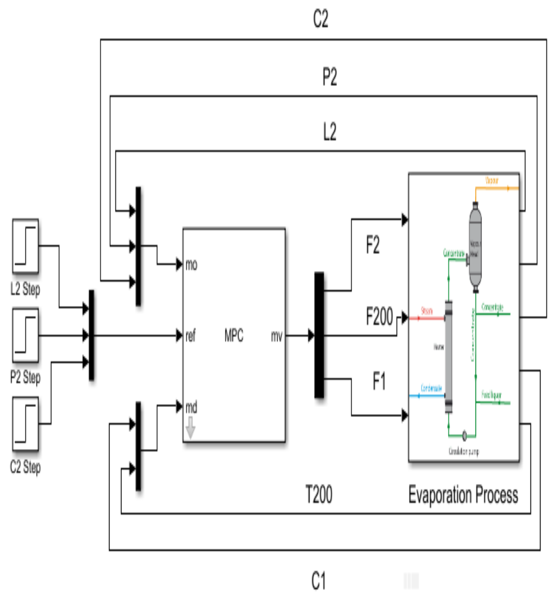

Figure 2. The Overall Control System

3.2.1- General formulation of MIMO MPC

The MPC controller performs all estimation and optimization calculations using a discrete-time, delay-free, state-space system with dimensionless input and output variables. Assume that the plant has m inputs and also denote to m^{th} future sampling discrete., q outputs and n_1 states. We also assume that the number of outputs is less than or equal to the number of inputs (i.e., $q \leq m$). In the general formulation of the predictive control problem, we also take the plant noise and disturbance into consideration. The multi-input multi-output (MIMO) model predictive control system is represented as follow [6].

$$x_m(k+1) = A_m x_m(k) + B_m u(k) + B_d \omega(k) \quad (13)$$

$$y(k) = C_m x_m(k) \quad (14)$$

where u is the manipulated variable or input variable, y is the process output, x_m is the state variable vector, and $\omega(k)$ is the input disturbance, assumed to be a sequence of integrated white noise. This means that the input disturbance $\omega(k)$ is related to a zero mean, white noise sequence $\epsilon(k)$ by the difference equation

$$\omega(k) - \omega(k-1) = \epsilon(k) \quad (15)$$

Note that from (13), the following difference equation is also true:

$$x_m(k) = A_m x_m(k-1) + B_m u(k-1) + B_d \omega(k-1) \tag{16}$$

By defining $\Delta x_m(k) = x_m(k) - x_m(k-1)$ and $\Delta u(k) = u(k) - u(k-1)$, then subtracting (16) from (13) leads to

$$\Delta x_m(k+1) = A_m \Delta x_m(k) + B_m \Delta u(k) + B_d\, \epsilon(k) \tag{17}$$

where $\Delta y(k+1) = y(k+1) - y(k)$
Choosing a new state variable vector $x(k)=[\Delta x_m(k)^T\ y(k)^T]^T$, we have:

$$\begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix} = \begin{bmatrix} A_m & o_m^T \\ C_m & I_{qxq} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} + \begin{bmatrix} B_m \\ C_m B_m \end{bmatrix} \Delta u(k) + \begin{bmatrix} B_d \\ C_m B_d \end{bmatrix} \epsilon(k)$$

$$y(k) = \begin{bmatrix} o_m & I_{qxq} \end{bmatrix} \begin{bmatrix} \Delta x_m(k) \\ y(k) \end{bmatrix} \tag{18}$$

where $I_{q\times q}$ is the identity matrix with dimensions $q \times q$, which is the number of outputs and o_m is a $q \times n_1$ zero matrix. In (18), Am, Bm and Cm have dimension $n_1 \times n_1$, $n_1 \times m$ and $q \times n_1$, respectively. For notational simplicity, we denote (18) by

$$x(k+1) = Ax(k) + B\Delta u(k) + B_\epsilon\, \epsilon(k)$$
$$y(k) = Cx(k) \tag{19}$$

where A, B and C are matrices corresponding to the forms given in (18).

3.2.2 Controllers Tuning

By default, MPC uses a static Kalman filter (KF) to update its controller states, which include the plant model states, disturbance model states, and measurement noise model states. This KF requires two gain matrices. By default, the MPC controller calculates them during initialization. They depend upon the plant, disturbance, and noise model parameters, and assumptions regarding the stochastic noise signals driving the disturbance and noise models. More details about state estimation in MPC are in [6, 9]. However, PID controller used is with a built – in tuning algorithm which by default, chooses a crossover frequency (loop bandwidth) based on the plant dynamics, and designs for a target phase margin to tune the PID gains.

4 Simulation Study

The performance of the Model predictive control (MPC) in controlling the evaporation process is examined, by applying a step response for the three controlled variables L_2 P_2 and

C_2 at t=100 t=200 t=300 respectively, and applying a disturbance step for C_1 and T_{200} at t=400 and t=500 respectively, the simulation is run for 600 min. Same operation conditions were applied using PI controllers. However, three PI controllers were needed to control the three parameters, therefore, the tuning process were not easy hence each loop is tuned with keeping the other two fixed and repeating this until an acceptable response is achieved. Figures 3 illustrates the performance obtained. Therefore, using a multi-input multi-output (MIMO) MPC is easier and reliable.

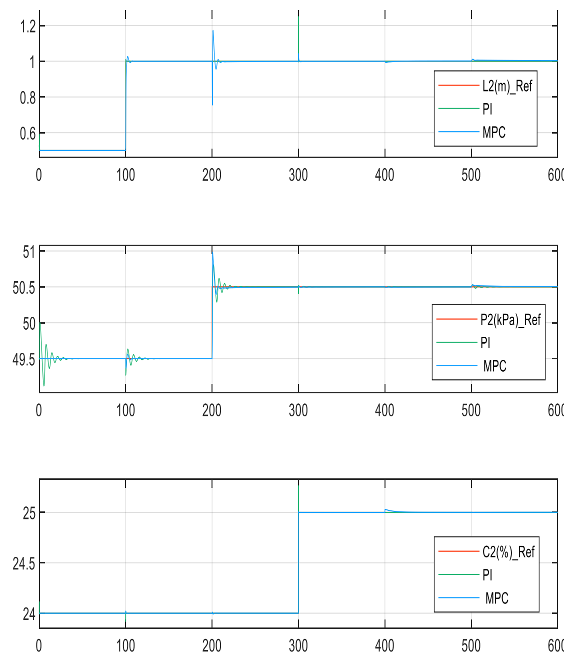

Figure 3: System response using both PI and MPC

4.1 Effect of step change

An Enlargements of the Figure 3, shows the comparison of the responses obtained by PI and MPC controllers. Moreover, examining the figure below, it is seen that using PI the L_2 response has a very small overshoot for the step change of L_2 and with no overshoot at P_2 step change while it has got a quite bigger for C_2 step change with settling time of 0.01 min. In contrast, of the MPC response which has a small overshoot at L_2 step at t=100 with a settling time of t=4 min, a bigger overshoot at the step of P_2 giving a settling of t=6 min, and a very small overshoot at C_2 step change showing a settling time of t=1 min. However, for the P_2 response, the performance of both controllers is quite similar, where, it has a small overshoot at the step change of L_2, but more oscillatory in PI response, with a settling time of t=17 min in case of PI and t=5 min in case of MPC. A bigger overshoot at the P_2 step change with settling time of t=22 and 10 min for PI and MPC respectively. A very small overshoot for C_2 step change with settling time of t=5, and 8 min for PI and MPC respectively. For the response of C_2 both controllers, show a quite negligible effect at the step changes of L_2, and P_2, while an obvious overshoot at the step change of C_2, with a settling time of t=0.1 and 0.2 min for PI and MPC.

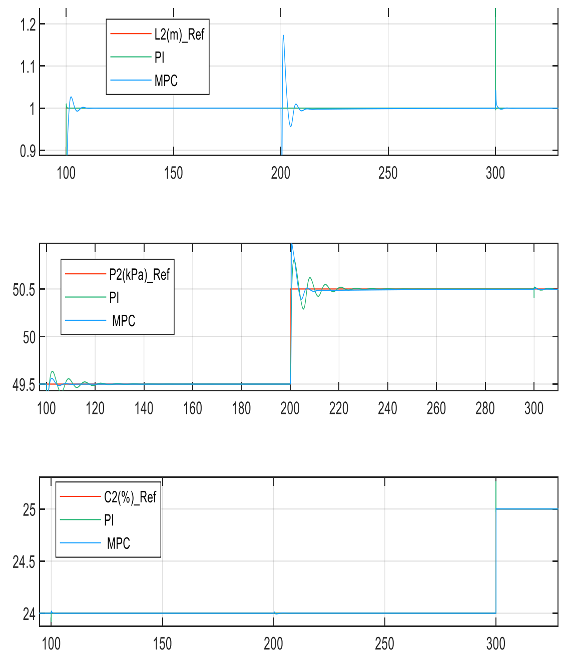

Figure 4: *enlargement of figure 3*

4.2 Effect of disturbances

Figure 5 shows the enlargement of Figure 3 from t=400 – 500 with the effect of disturbances C_1 and T_{200} respectively on the three responses. PI controller has a good effluence on rejecting the disturbances as can be seen on L_2 response, whereas a small downshoot and overshoot are apparent in the case of MPC in response to the two disturbances with a settling time of approximately t=11 min at C_1 and t=25 min at T_{200} disturbance. For P_2 response a very small overshoot for both controllers with a settling t= 6 min at C_1 disturbance for PI, and t=4 min for MPC respectively and t=18 min for PI and t=31 min for MPC at T_{200} disturbance. For C_2 response, the only obvious overshoot is that caused by MPC at C_1 with a settling time t=22 min. whereas the PI controller shows a good rejection for the two disturbances.

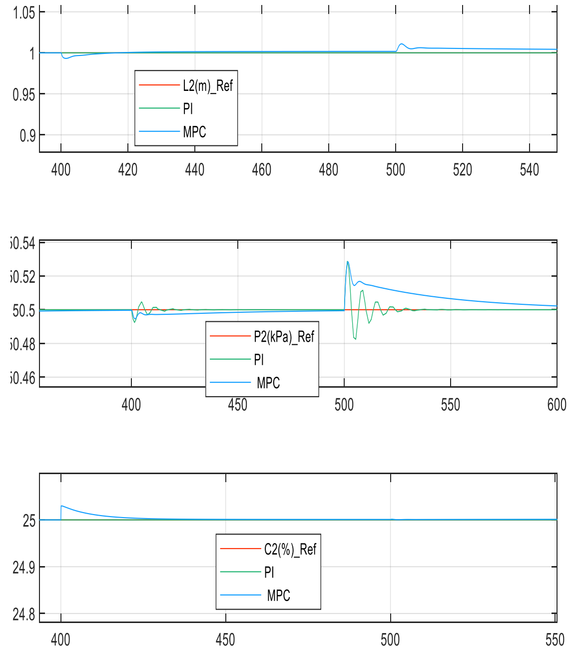

Figure 5: *2nd Enlargement of figure 3*

Table 2: *The values of Integral absolute error obtained (IAE)*

Controller	IAE			Total
	L_2	P_2	C_2	
PI	0.02	6.27	0.0005	6.2905
MPC	1.358	3.136	0.589	5.0830

5 Conclusion

Following the foregoing results obtained by both controller PI and MPC, it can be insured that the performances of both controllers were very good and they slightly differ in some points according to the structure of each of them. three PI controllers were needed to control the three variables which made it a time consuming as each PI control loop is dealt with by its own in tuning process. Hence, to tune each PI controller the other two will be fixed until a good response is obtained, then the same process is repeated with the next controller by fixing the other two, and keep repeating the tuning process for several times until a fairly good response is achieved by the three controllers. However, MPC are a multiple input multiple output controller, and all variables are controlled at once. Therefore, just one run might be sufficient after adjusting the MPC parameters (Control horizon, and prediction horizon). Moreover, the two controllers show a very good control tracking for the step changes applied at different time of the simulation for the three variables and a quite similar responses were obtained even when introducing the disturbances, despite a negligible difference. It is realised that the responses obtained using PI controller are more oscillatory than those obtained using MPC, whereas the responses obtained using MPC have less settling time in most cases compared to those obtained from PI controller. Therefore, the best comparison can be concluded from the values of the Integral absolute error (IAE) obtained for each controlled variable and the overall IAE. Hence L_2 and C_2 have very small values using PI, but a bigger value for P_2, while it is reduced up to its half value using MPC, but with a relative L_2 and C_2 values. However, as the optimisation process is based on the sum of IAE values at each iteration, then it is obvious that MPC has better performance on this respect.

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