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A General Application of a Direct Method for Multivariable MPC Control Strategy in Chemical Processes

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Abstract – **A general application of a direct method for model predictive control strategy is proposed for multivariable nonlinear control problem in chemical processes. The aim is to provide a solution to nonlinear control problem that is favorable in terms of industrial implementation. The scheme utilizes multiple linear models to cover wider range of operating conditions. Depending on the operating conditions, suitable models of 2x2, 3x3, and 4x4 processes are used in control computations. Servo and regulatory controls of the system are examined on constrained and unconstrained conditions. Comparisons are made to conventional controllers. The results confirmed the potentials of the proposed strategy.**

Keywords – Tuning, model predictive control, multivariable, nonlinear control, chemical process

I. INTRODUCTION

The cornerstone of MPC is the model [1]. It cause MPC is called MBPC (model-based predictive control). MPC uses models in 2 ways: using a reliable model to predict effect of past control moves on P future outputs, assuming no future moves, and using the same model to compute the optimal M controller moves. Implement first move and repeat procedure.

Predictive control is now one of the most widely used advanced control methods in industry, especially in the control of processes that are constrained, multivariable and uncertain. A large number of implementation algorithms, included industrial predictive control applications [2] have a appeared in the literature.

II. TUNING THE MPC CONTROLLER

Dynamic matrix control (DMC) [3] is the most popular MPC algorithm used in the chemical process industry today. Over the past decade, DMC has been implemented on a wide range of process applications. A major part of DMC's appeal in industry stems from the use of a linear finite step response model of the process and a simple quadratic performance objective function. The objective function is minimized over a prediction horizon to compute the optimal controller output moves as a least-squares problem.

Tuning in conventional control strategy (P, PI, and PID) is related to obtain an optimum setting of controller parameters (K_c, T_i *and* T_d). Ziegler-Nichols, Lopez, Ciancone, etc. [4] are some examples of single-loop tuning in P, PI, and PID controllers. Huang, et. al. [5] has proposed a direct method for multi-loop PI/PID controller design based on FOPDT/SOPDT model of each loop.

MPC controller has certain parameters setting to achieve its optimum performance. During the time, trial-and-error efforts have been done to reach this goal until Shridhar & Cooper [6, 7] proposed a tuning strategy for unconstraint SISO and multivariable MPC. Dougherty 8and Cooper [8] proposed a non-adaptive DMC tuning strategy (see Table 1) based on all of FOPDT models in systems.

The principles of the multivariable DMC tuning strategy [8] are:

1) T – Sampling time. While a large T refers to a low computation load, a small T refers to a properly track the evolving dynamic behavior. Too slow of a sampling rate will lead to information losses, and too fast of a sampling rate could lead to numerically sensitive procedures. Nevertheless, this method allows values of T other than the recommended value given in Table 1.
2) P (prediction horizon) and N (model horizon). Both P and N have the same setting and are related to the settling time of the *slowest* (the largest time constant) sub-process in the multivariable system. A large P improves the nominal stability of the closed loop. Meanwhile, a large N makes controller has long enough time to avoid the instabilities that can otherwise result since truncation of the model horizon misrepresents the effect of controller output moves in the predicted process variable profile.
3) M – Control horizon. M equals to 63.2% of the settling time of the slowest sub-process in the multivariable system. This ensures M to be long

enough such that the results of the control actions are clearly evidenced in the response of the measured process variable.

4) γ_s^2 - Controlled variable weights. The setting of those parameter are free. However, in the most case, they are set equal to one.

5) γ_s^2 – Move suppression coefficients. Its primary role in DMC is to suppress aggressive controller actions. When the control horizon is 1 (M = 1), no move suppression coefficient is needed (λ = 0). If the control horizon is greater than 1 (M > 1), then the analytical equation given in Table 1 is used.

Table 1 Non-adaptive DMC tuning strategy [8]

Approximate the process dynamics of all controller output to measured process variable pairs with FOPDT models:

$$\frac{y_r(s)}{u_s(s)} = \frac{K_{rs}e^{-\theta_{rs}s}}{\tau_{rs}+1} \quad (r = 1,2,\dots,R; s = 1,2,\dots,S)$$

1. Select the sample time as close as possible to:
$$T_{rs} = Max(0.1\tau_{rs}, 0.5\theta_{rs}) \quad (r = 1,2,\dots,R; s = 1,2,\dots,S)$$
$$T = Min(T_{rs})$$
2. Compute the prediction horizon, P; and the model horizon, N:
$$P = N = Max\left(\frac{5\tau_{rs}}{T} + k_{rs}\right) \text{ where } k_{rs} = \left(\frac{\theta_{rs}}{T} + 1\right) \quad (r = 1,2,\dots,R; s = 1,2,\dots,S)$$
3. Compute a control horizon, M:
$$M = Max\left(\frac{\tau_{rs}}{T} + k_{rs}\right) \quad (r = 1,2,\dots,R; s = 1,2,\dots,S)$$
4. Select the controlled variable weights, γ_r^2, to scale process variable units to be the same.
5. Compute the move suppression coefficients, λ_r^2:
$$\lambda_r^2 = \frac{M}{10}\sum_{r=1}^{R}\left[\gamma_r^2 K_{rs}^2\left\{P - k_{rs} - \frac{3}{2}\frac{\tau_{rs}}{T} + 2 - \frac{(M-1)}{2}\right\}\right] \quad (s = 1,2,\dots,S)$$
6. Implement DMC using the traditional step response matrix of the actual process and the initial values of the parameters computed in steps 1–6.

III. APPLICATION IN GENERAL PROCESSES

Dougherty and Cooper [8] have proved the non-adaptive DMC tuning strategy in the three 2x2 processes (general transfer function, multi-tank, and distillation column). Here, we shall illustrate comparisons between PI/PID and MPC controller strategy using Table 1 in the same and more complex processes: 2x2 process, 3x3 process and 4x4 process [5].

3.1 Wood and Berry distillation column (2x2 process)

Wood and Berry distillation column model [5] is the most popular model of 2x2 process system. This model consists of two matrixes: manipulated variable matrix (2x2) and disturbance matrix (2x1). Nevertheless, the first matrix (manipulated variable matrix) is commonly used by researchers [5, 9].

Table 2 shows results of PID and MPC tuning in Wood & Berry model. Responses of Wood & Berry model using these settings are shown by Figure 1. Although, MPC controller is not set in the optimum setting, MPC controller performances are better than PID controller performance. MPC controller tuning has improved its performance by decreasing the overshoot significantly. In unit step change test of y1, the y2's overshoot sharply falls from 0.342 to 0.056, or going down 84%.

Table 2 PID and DMC parameters setting in WB model (2x2 process)

Wood & Berry model (2x2 process)	PID controller tuning (Proposed 2 method)	DMC controller tuning
$\begin{bmatrix} Y_D(s) \\ Y_B(s) \end{bmatrix} = \begin{bmatrix} \frac{12.8e^{-s}}{16.7s+1} & \frac{-18.9e^{-3s}}{21s+1} \\ \frac{6.6e^{-7s}}{10.9s+1} & \frac{-19.4e^{-3s}}{14.4s+1} \end{bmatrix} \begin{bmatrix} R(s) \\ V(s) \end{bmatrix} + \begin{bmatrix} \frac{3.8e^{-8s}}{14.9s+1} \\ \frac{4.9e^{-3s}}{13.2s+1} \end{bmatrix} F(s)$	$g_c(s) = k'_c\left(1 + \frac{1}{\tau'_R s}\right)\left(\frac{1 + \tau'_D s}{1 + \tau_f s}\right)$ • Loop 1: $k'_c = 0.694$, $\tau'_R = 7.44$, $\tau'_D = 0.4$, $\tau'_f = 0.02$ • Loop 2: $k'_c = -0.074$, $\tau'_R = 4.68$, $\tau'_D = 1.59$, $\tau'_f = 0.08$	Ts = 1.5 P = 153 M = 35

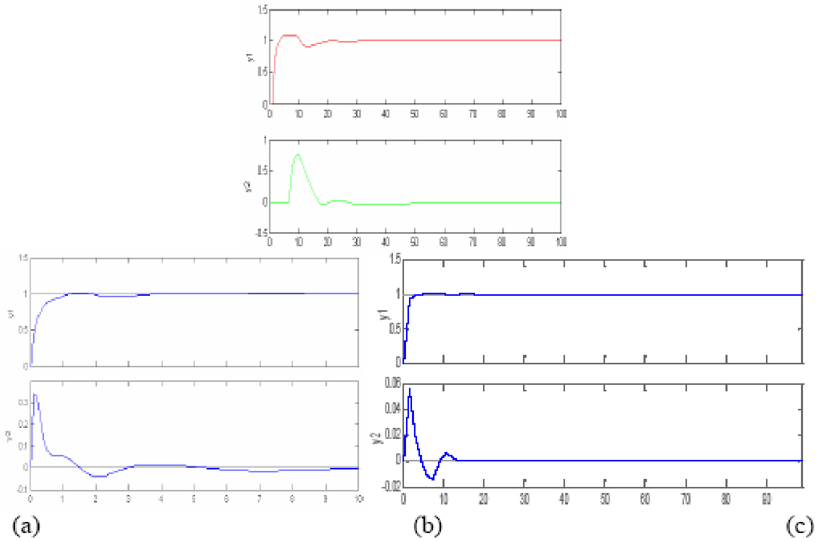


Figure 1 Response of multi-loop control for WB process (step change in y1): (a) PID controller performance using Proposed 2 tuning, (b) MPC controller performance using Ts=0.1, P=10, M=2 (default setting), (c) MPC controller performance using Ts=1.5, P=153, M=35 (tuning setting)

3.2 OR (3x3) process

The Ogunnaike and Ray (OR 3x3) process [5] as follows is considered (see Table 3). PID controller tuning uses BLT-4 method instead of proposed method by Huang et. al. [5]. In this case, responses of OR (3x3) process are unstable using their proposed method, though they are good using BLT-4.

As shown by Table 1, the tuning strategy uses FOPDT (first-order plus dead-time) model to calculate Ts, P, and M. Because of OR (3x3) model has one SOPDT (second-order plus dead-time), this transfer function has to be changed into FOPDT. By using PRC (process reaction curve) from step change testing of the SOPDT and applying a method that is developed by Cecil L. Smith [4], the FOPDT is obtained.

Figure 2 shows responses of multi-loop control for OR (3x3) process: (a), (b), and (c) PID controller performance using BLT-4 tuning (unit step change in y1, y2, y3 respectively). They have very poor performances. This disadvantage is improved by MPC controller.

Next, we are going to compare between responses using default setting and tuning setting. The results are shown by Figure 3 and Table 4. Almost performances by tuning setting are better than by the default setting. Only two point where the default setting is better than the tuning setting, they are overshoot of y2 in y1's step change, and settling time of y2 in y2's step change.

Table 3 PID and DMC parameters setting in OR model (3x3 process)

OR model (3x3 process)	PID controller tuning (BLT-4 method)	DMC controller tuning
$G_p(s) = \begin{bmatrix} \frac{0.66e^{-2.6s}}{6.7s+1} & \frac{-0.61e^{-3.5s}}{8.64s+1} & \frac{-0.0049e^{-s}}{9.06s+1} \\ \frac{1.11e^{-6.5s}}{3.25s+1} & \frac{-2.36e^{-3s}}{5s+1} & \frac{-0.01e^{-1.2s}}{7.09s+1} \\ \frac{-34.68e^{-9.2s}}{8.15s+1} & \frac{46.2e^{-9.4s}}{10.9s+1} & \frac{0.87(11.61s+1)e^{-s}}{(3.89s+1)(18.8s+1)} \end{bmatrix}$	$g_c(s) = k'_c\left(1+\frac{1}{\tau'_R s}\right)\left(\frac{1+\tau'_D s}{1+\tau_f s}\right)$ Loop 1: $k'_c = 1.214$, $\tau'_R = 20.35$, $\tau'_D = 0.32$, $\tau'_f = 0.016$ Loop 2: $k'_c = -0.77$, $\tau'_R = 11.04$, $\tau'_D = 0.71$, $\tau'_f = 0.36$ Loop 3: $k'_c = 4.879$, $\tau'_R = 3.57$, $\tau'_D = 0.3$, $\tau'_f = 0.015$	Ts = 0.71 P = 91 M = 30

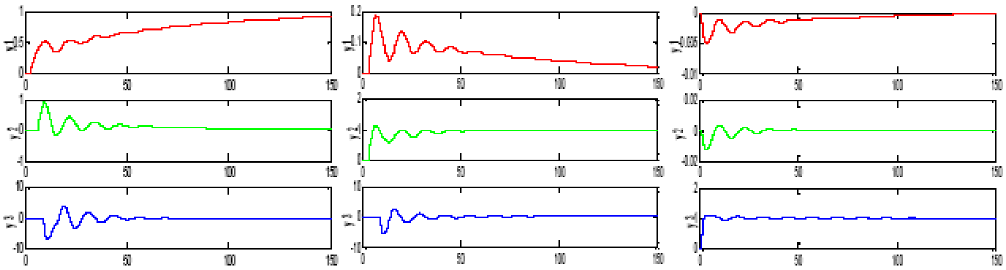
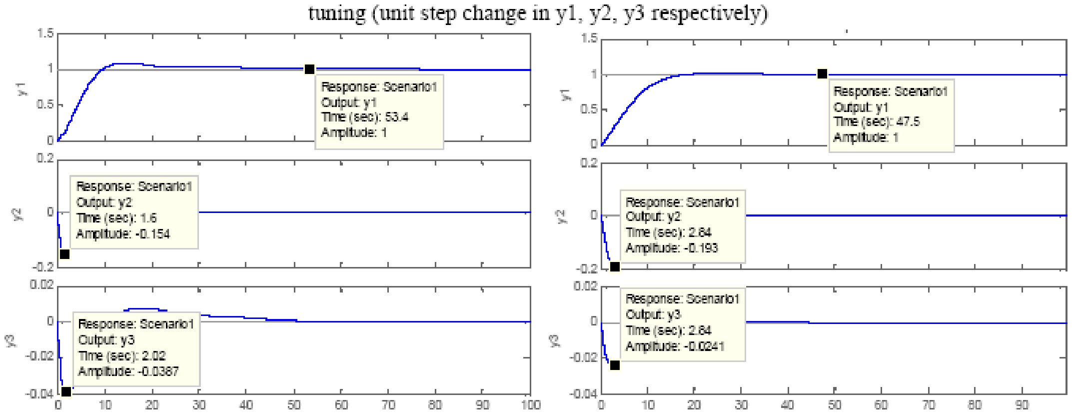

(a) (b) (c)

Figure 2 Responses of multi-loop control for OR (3x3) process: (a), (b), and (c) PID controller performance using BLT-4 tuning (unit step change in y1, y2, y3 respectively)



(a) (b)

Figure 3 Responses of multi-loop control for OR (3x3) process (step change in y1): (a) MPC controller performance using Ts=0.1, P=10, M=2 (default setting); (b) MPC controller performance using Ts=0.71, P=91, M=30 (tuning setting)

Table 4 Performance of MPC controller of OR (3x3 process) model

Step Change	Controlled Variable	Default Setting		Tuning Setting	
		Settling time	Overshoot	Settling time	Overshoot
y1	y1	53.4	0.08	47.5	0.02
	y2		-0.153		***-0.193***
	y3		-0.0386		-0.0241
y2	y1		-0.156		-0.138
	y2	21.7	0.01	***31***	0.01
	y3		-0.151		-0.0552
y3	y1		-0.0303		-0.0273
	y2		-0.0852		-0.0614
	y3	6.52	0	3.18	0

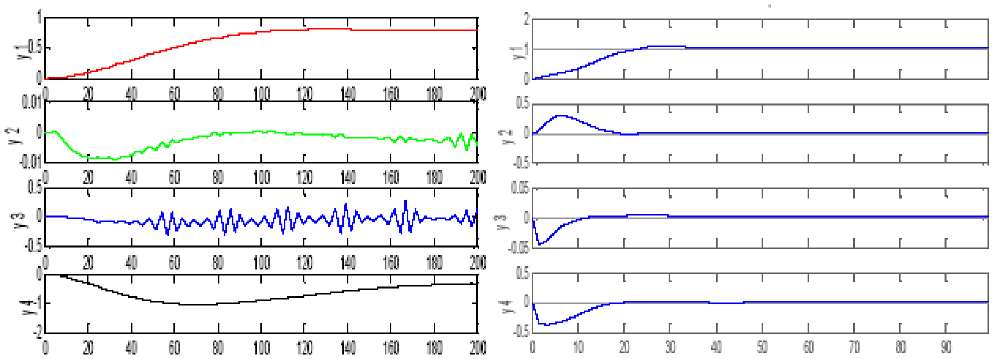
3.3 Alatiqi case 1 (4x4) process

Consider alatiqi case 1 (A1 4x4) process (see column 1 in Table 5). Alatiqi process has 16 empirical models that consist of three FOPDT models, two models having zeros, and eleven SOPDT models. All of empirical models have to be changed in FOPDT model to calculate MPC controller tuning. We use some PRCs (process reaction curves) from step change testing of the SOPDTs and the models having zeros, and apply a method that is developed by Cecil L. Smith [3] btain the FOPDT.

PI controller shows the poor performance (see Figure 4). Also, the controller performance as shown by Figure 5 is extremely poor, because the responses are unstable. So, in this case, the default setting can not be used in MPC controller. Inevitable, we have to use the tuning setting in this case.

Table 5 PID and DMC parameters setting in Alatiqi case 1 model (A1 4x4 process)

Alatiqi case 1 model (A1 4x4 process)	PI controller tuning (Lee et al. method)	DMC controller tuning
$G_p(s) = \begin{bmatrix} \frac{2.22e^{-2.5s}}{(36s+1)(25s+1)} & \frac{-2.94(7.9s+1)e^{-0.05s}}{(23.7s+1)^2} & \frac{0.017e^{-0.2s}}{(31.6s+1)(7s+1)} & \frac{-0.64e^{-20s}}{(29s+1)^2} \\ \frac{-2.33e^{-5s}}{(35s+1)^2} & \frac{3.46e^{-1.01s}}{32s+1} & \frac{-0.51e^{-7.5s}}{(32s+1)^2} & \frac{1.68e^{-2s}}{(28s+1)^2} \\ \frac{-1.06e^{-22s}}{(17s+1)^2} & \frac{3.511e^{-13s}}{(12s+1)^2} & \frac{4.41e^{-1.01s}}{16.2s+1} & \frac{-5.38e^{-0.5s}}{17s+1} \\ \frac{-5.73e^{-2.5s}}{(8s+1)(50s+1)} & \frac{4.32(25s+1)e^{-0.01s}}{(50s+1)(5s+1)} & \frac{-1.25e^{-2.8s}}{(43.6s+1)(9s+1)} & \frac{4.78e^{-1.15s}}{(48s+1)(5s+1)} \end{bmatrix}$	$g_c(s) = k_c'\left(1 + \frac{1}{\tau_R' s}\right)$ Loop 1: $k_c' = 0.385$, $\tau_R' = 34.72$ Loop 2: $k_c' = 6.19$, $\tau_R' = 21.8$ Loop 3: $k_c' = 2.836$, $\tau_R' = 19.22$ Loop 4: $k_c' = 0.732$, $\tau_R' = 36.93$	Ts = 1.62 P = 191 M = 52



(a) (b)

Figure 4 Responses of multi-loop control for alatiqi case 1 (A1 4x4) process: (a) PI controller performance using Lee et. al. tuning (unit step change in y1); (b) MPC controller performance using tuning setting Ts=1.62, P=191, M=52 (unit step change in y1)

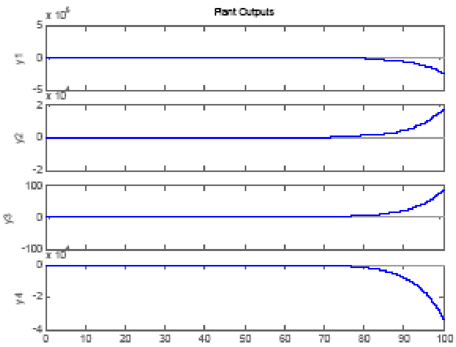


Figure 5 Alatiqi's Responses of MPC controller using default setting

IV. CONCLUSSIONS

MPC controller offers better control performances than PI/PID controller, especially in multivariable processes. Application of MPC controller in the three more complex models produces the fantastic performance. To achieve an optimum performance of MPC controller, non-adaptive DMC controller tuning can be used. This method has proved that the tuning setting has the optimum performance. In the complex processes like WB model (2x2 process) and OR model (3x3 process), the default setting can be used in MPC controller. But, in more complex process likes Alatiqi case 1 model (A1 4x4 process), the default setting produces very poor performance. So, we must use the tuning setting.

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