Model Predictive Control Strategy for Industrial Process

V Balaji[1], E Maheswari[2]
[1] Principal, Lord Ayyappa Institute of Engineering and Technology, Kanchipuram
Mobile Ph.: 8098537791
[2] Asst. Professor, Sri Sairam Institute of Technology, Chennai
e-mail: balajieee79@gmail.com, maheseee25@rediffmail.com

Abstract

Model Predictive control (MPC) is shown as particularly effective for the self-tuning control of industrial processes. It makes use of a truncated step response of the process and provides a simple explicit solution in the absence of constraints. Here, we use Dynamic Matrix Control (DMC). DMC uses a set of basis functions to form the future control sequence. The industrial success of DMC has mainly come from its application to high dimension multivariable system without constraints. Here, main objective of DMC controller is to drive the output as close to the set point as possible in a least square sense with the possibility of the inclusion of a penalty term on the input moves. Therefore, the manipulated variables are selected to minimize a quadratic objective which can consider the minimization of future error. The implementation of internal model control is also shown here. The control strategy is to determine the best model for the current operating condition and to activate the corresponding controller. Internal model control (IMC) continues to be a powerful strategy in complex, industrial processes control application. This structure provides a practical tool to influence dynamic performance and robustness to modeling error transparently in the design. It is particularly appropriate for design and implementation of controllers for linear open loop stable system. A simulated example of the control of nonlinear chemical process is shown. The nonlinear chemical process study in this work is the exothermic stirred tank reactors system with the first order reaction. The reaction is assumed to be perfectly mixed and no heat loss occurs within the system. By using internal model control and dynamic matrix control has simulated control of the total process in CSTR. Simulation example provided to show the effectiveness of the proposed control strategy.

Keywords: MPC, DMC, IMC, CSTR

1. Introduction

Although the use of linear control method has been prevalent in the process industries, they have a limitation in especially when dealing with nonlinear plants in a wide operation region which has commonly found in most of the industries. Many economically important operations, such as reactors and high purity distillation columns, can be very nonlinear and very difficult to control adequately with linear controller. In fact, chemical reactors create some of the most challenging feedback control problems faced by process control engineers. Complex steady state and dynamic behavior, such as ignition or extinction behavior and parametric sensitivity create challenges which are though for traditional linear controller to handle. In recent years, the requirement of automatic control quality in the process industries increased significantly due to the increased complexity of the plants and sharper specifications of product quality. At the same time, available computing power increased to a very high level. As a result, computer models that are computationally expensive became applicable to complex problems. Model based control techniques were developed to obtained tighter control. Model predictive control was introduced successfully in several industrial plants. An important advantage of these control schemes is the ability to handle constrain of actuated variables and internal variables. In most application of model predictive technique, a linear model is used to predict the process behavior over the horizon of interest [1, 2]. As most real processes show a nonlinear behavior, some work was done to extend predictive control techniques to incorporate nonlinear models [3-5].

The most expensive part of the realization of a nonlinear predictive control scheme is the derivation of the mathematical model. In many cases, it is even impossible to obtain a

suitable physically founded process model due to the complexity of the underlying processes or the lack of knowledge of critical parameters (as, e.g., temperature and pressure dependent mass transfer coefficients or viscosities) of the models. DMC was developed at the end of the seventies by Culter and Rameker [1] of Shell Oil Co. and has been widely accepted in the industrial world, mainly by petrochemical industries [6]. Nowadays, DMC is something more than an algorithm and part of its success is due to the fact that the commercial product covers topic such as model identification or global plant optimization. In many practical cases, however, conventional controllers (P/PI/PID-controllers) are already in use at the plant, which stabilize the plant and provide some basics, sometime sluggish control.

The Internal model control (IMC) continues to be a powerful strategy in complex industrial processes control application. This structure provides a practical tool to influence dynamic performance and robustness to modeling error transparently in the design. It is particularly appropriate for the design and implementation of controllers for linear open loop stable system [2]. There are two ways to cope with nonlinear control design for plants subject to uncertainty and disturbances: robust and adaptive control, while neural adaptive controller being extensively developed [8-11]. The robust technique of internal model control is investigated here. A control system consists of the processes which to be controlled and a controlled device chosen by the designer which computes the controlled input as to convey the desired behavior to the controlled system. The controlled device consists of a controller and possibly other elements (observer, filter, internal model). Internal model control systems are characterized by a control device which consists of the controller and simulation model of the processes, the internal model.

This paper shows the simulink implementation of a tool, which was also extended for DMC. After the DMC has been trained, it can be used as an independent control strategy. By using simulink implementation of internal model control and dynamic matrix control, the characteristics of these approaches have been examined and some limitations from each of them have been pointed out. Continuous Stirred tank Reactor (CSTR) has been used as an example of the nonlinear system. The plant exhibits a strongly nonlinear behavior, so that a nonlinear prediction model has to be used.

2.   Model Predictive Control versus DMC

Model predictive control is a strategy which is based on the explicit use of some kind of processes model to predict the controlled variables over a certain time horizon, the prediction horizon. Dynamic matrix control (DMC) used here to predict future plant output, based on past and current values and on the proposed optimal future control action. These actions are calculated by the optimizer taking into account the cost function where future tracking error is considered as well as the constraints.

The control strategy consists of four parts:
1) At each sampling time, the value of the controlled variable y (t+k) is predicted over the prediction horizon k=1…NP.
   This prediction depends on the future values of the controlled variable u(t+k) within a control horizon k=1…NU, where NU<=NP. If NU<NP then u(t+k)=u (t+NU), k=NU+1….NP
2) A reference trajectory r (t+k), k=1…NP is defined which describes the desired process trajectory over the prediction horizon.
3) The vector of future control u (t+k) is computed that a cost of function depending on the predicted control error is minimized. The first element of the controlled variable is applied to the process.
4) The prediction error between the measured process output and the predicted output is used for disturbance estimation.

Step 1 to 4 is repeated at each sampling instant; this is called a receding horizontal strategy. We used the extended DMC algorithm to explicit the use of nonlinear model in the DMC scheme. In linear DMC, the prediction of the future values vector of the controlled variables y is performed using the dynamic matrix A, which consists of step response coefficients. At the core of MPC algorithm is a dynamic model, on recent, most industrial applications have relied on linear dynamic models. This dynamic model has been developed using empirical data obtained from plant testing. Linear models, rather than nonlinear models, have been used because of the

difficulty in developing a generic nonlinear model from empirical data and also because of the computational expense involved in using nonlinear models in MPC formulations.

The Model Predictive Controller is shown in the Figure1, which optimizer which uses to solve the control trajectory over a future time horizon based on dynamic model of the process. The Dynamic Matrix Controller is shown in the Figure 2.
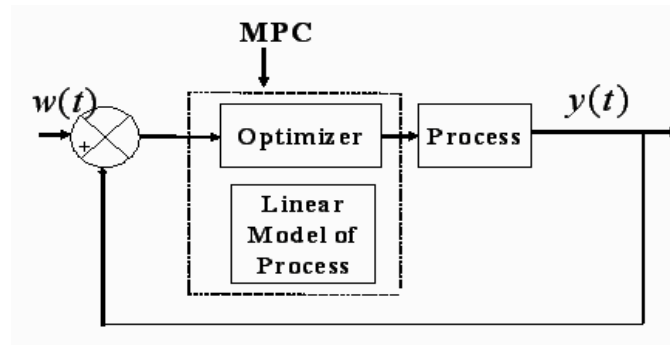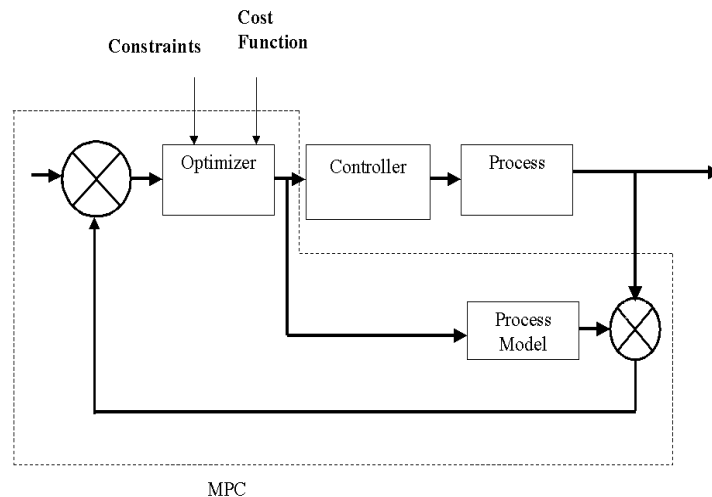

Figure 1. Block diagram of MPC

Figure 2. Block diagram of DMC

3. Internal Model Control (IMC)

The IMC design procedure is a two step approach although sub-optimal in a general norm sense provides a reasonable tradeoff between performance and robustness. The main benefit of the IMC approach is the ability to directly specify the complementary of sensitivity and sensitivity functions η and $\in$, directly specify the nature of the closed loop response. The IMC design procedure consists of two main steps. The first step will ensure that q is stable and casual. The second step will require q to be proper. An IMC model provides a practical tool to influence dynamic performance and robustness to modeling errors transparently in the design. IMC philosophy realizes on that control can be achieved only if the control system encapsulates, either implicitly or explicitly, some representation of the process to be controlled. If the controlled scheme has been developed based on an exact model of the process, then perfect control is possible. In IMC control law is easy to implement and requires little computation, its derivation is more complex. We consider a problem of tracking a set point sequence {r(k)},possibly in the presence of deterministic disturbances which might occur randomly, and those effect must be cancelled(regulation).The desired dynamical behavior of the control system is chosen to be given by a stable reference model. In this paper the reference model is selected for process with a, delay d, and order n. A suitable linear reference model is given by:

$$E(q^{-1})\, yr(k) = q^{-d} H(q^{-1})\, r(k) \tag{1}$$

where r denotes the set point and yr the output of the reference model, and where:

$$E(q^{-1}) = 1 + e_1 q^{-1} + \dots + e_n q^{-n} \tag{2}$$

$$H(q^{-1}) = h_0 + h_1 q^{-1} + \dots + h_n q^{-n} \tag{3}$$
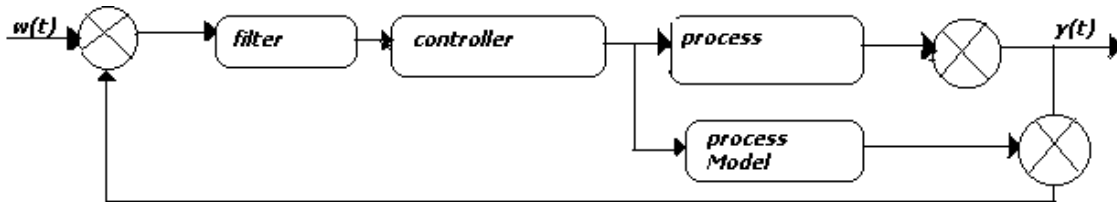
q^{-1} is the backward shift operator.

Figure 3. Block diagram of Internal Model Control (IMC)

4. Example

The aim of this simulation is to show the difference of the two controls strategy. The simulation is separated into two tasks. First, the Dynamic matrix control (DMC) strategy is used. During this period the model and controller parameters for the DMC and IMC are identified .A chemical system, known as a Continuous stirred tank reactor (CSTR), was utilized as an example to illustrate the use of proposed DMC and IMC tool. In the CSTR, two chemicals are mixed, and react to produce a product compound with concentration $C_A(t)$. The temperature of the mixer is $T(t)$. The reaction is exothermic, producing heat which acts to slow the reaction down. By introducing a coolant flow rate $qc(t)$, the temperature can be varied and hence the product concentration controlled .This system can be described by the following nonlinear simultaneous differential equations:

$$\acute{C}_A = q/v\,(C_{Af} - C_A) - k_0\, C_A \exp{- E/RT} \tag{4}$$

$$\check{T} = q/v\,(T_f - T) + (-\Delta H)\, k_0\, C_A\, /\, \rho C_p *\exp{- \underline{E}/RT} + (\rho_c\, C_{pc}/\rho C_p V)*q_{c^*}[1\text{-}\exp(-hA/q_c\rho_c C_{pc})]*(T_{cf}-T) \tag{5}$$
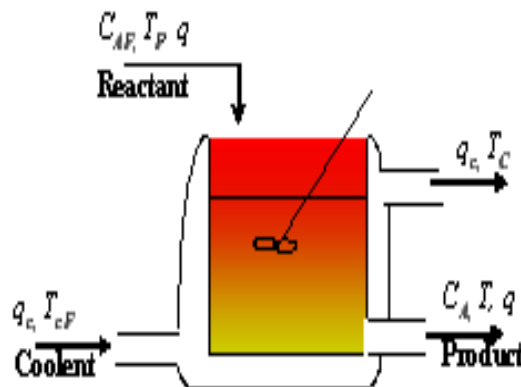

Figure. 4. Continuous stirred tank reactor (CSTR)

Ordinary Differential Equations describing
Rate of change of Concentration:

$$\frac{dC_A}{dt} = \frac{q}{V}(C_{Af} - C_A) - k_0 C_A e^{(-E/_{RT})}$$

Rate of change of Temperature:

$$\frac{dT}{dt} = \frac{q}{V}(T_f - T) + \frac{(-\Delta H)k_0 C_A}{\rho C_p} e^{(-E/_{RT})} + \frac{\rho_c C_{pc}}{\rho C_p V} q_c \left[1 - e^{\left(-hA/_{q_c \rho_c C_{pc}} \right)} \right] \cdot (T_{cf} - T)$$
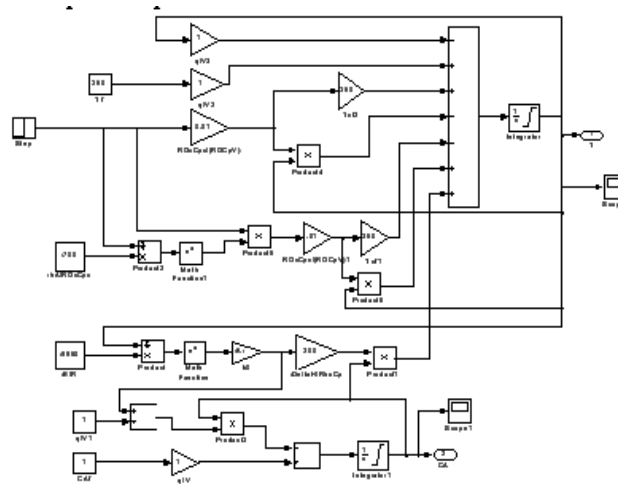
Figure 5. Open Loop Simulink Model of CSTR

5. Simulink Block Set Implementation

This section explains the application of the dynamic matrix control and internal model control strategies on the CSTR system for both set point tracking and actual output of the plant.
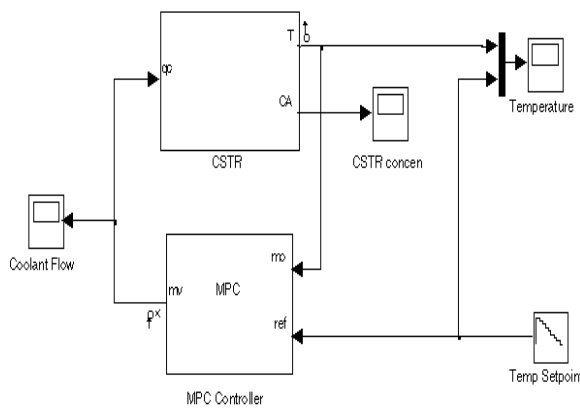

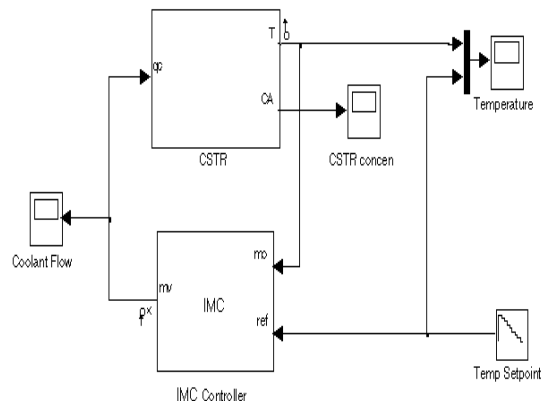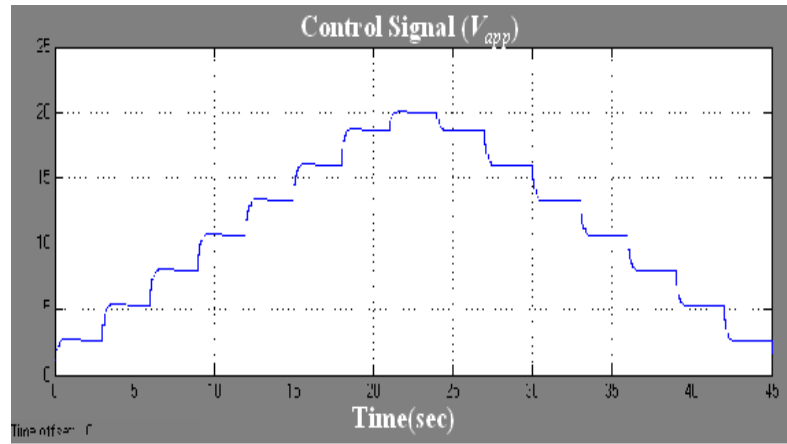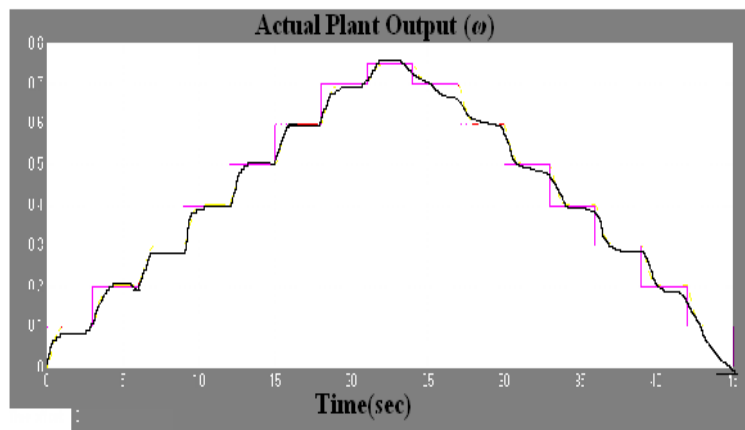Figure 6. Dynamic Matrix Control (DMC)

Figure 7. Internal Model Control (IMC)

(a)

(b)

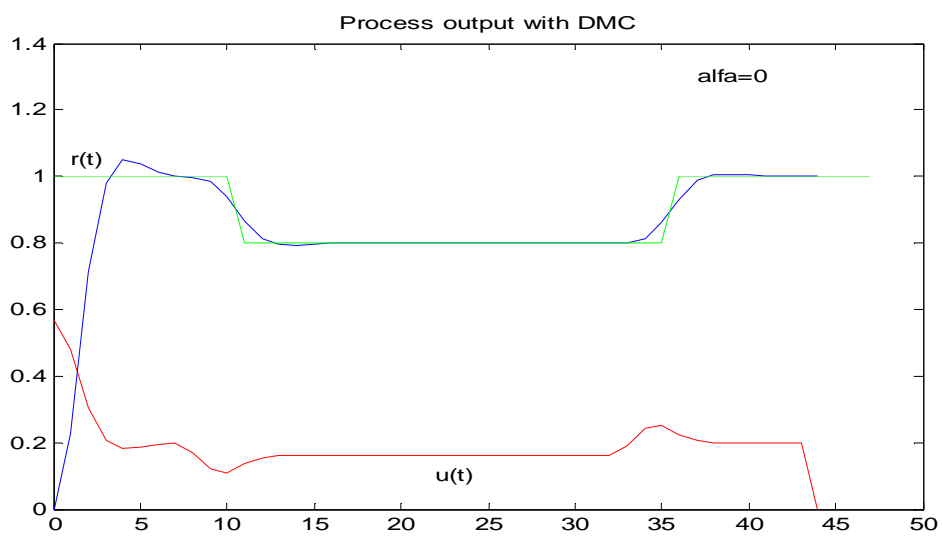Figure. 8. Control signal (a) and actual plant output (b)

Figure 9. DMC strategy, set point tracking
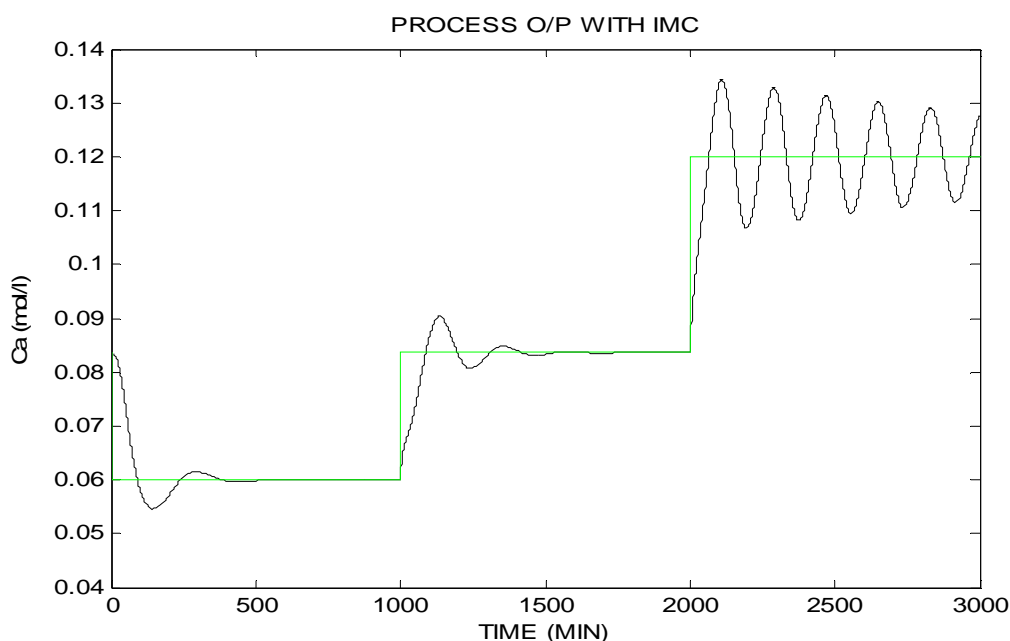
Figure 10. IMC strategy, set point tracking

6. Conclusion

The overall result shows the capability of employing these control strategies to control a non-linear system such as exothermic reactor (CSTR) which is use in this case study. Set point tracking behavior of the DMC and IMC is compared. At every change of operating condition linearization of nonlinear system is to be carried out. For nonlinear process i.e. Continues stirred tank reactor (CSTR), DMC has stable response around ingratiation point. As operating condition changes DMC became unstable. While for all set point changes, the IMC controller yields a fast response, but it introduced offset. The IMC requires slightly larger but acceptable control moves. If larger control moves are acceptable, faster set point tracking can be obtained by decreasing the pole of the set point filter. Proposed IMC strategy is potentially applicable to wide class of process control problem. Some oscillatory behavior of the control at the step changes can be seen in both cases which can be reduced by using Neural Network.

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