Study of Model Predictive Control in Chemical Plant

Babeeta Rathore[*1] Manju Khare[*2]
[1]Honouring M-Tech in Control System., [2]Assoc Prof, Electrical & Electronics Engg Dept.
[1,2]Lakshmi Narain College of Technology, Bhopal,India
Email: [1]babeetarathore@gmail.com ,[2]kharemanju@gmail.com

Abstract— **Controlling a system and state constraints is one of the most important problems in control theory, but also one of the most challenging. Another important but just as demanding topic is robustness against uncertainties in a controlled system. One of the most successful approaches, both in theory and practice, to control constrained systems is model predictive control (MPC). The basic idea in MPC is to repeatedly solve optimization problems on-line to find an optimal input to the controlled system. In recent years, much effort has been spent to incorporate the robustness problem into this framework.**

Keywords— Model predictive control (MPC); proportional-integral-derivative controller (PID)

I. INTRODUCTION

The models used in MPC are generally intended to represent the behaviour of complex dynamical systems. The additional complexity of the MPC control algorithm is not generally needed to provide adequate control of simple systems, which are often controlled well by generic PID controllers. Common dynamic characteristics that are difficult for PID controllers include large time delays and high-order dynamics.

MPC models predict the change in the dependent variables of the modelled system that will be caused by changes in the independent variables. In a chemical process, independent variables that can be adjusted by the controller are often either the set points of regulatory PID controllers (pressure, flow, temperature, etc.) or the final control element (valves, dampers, etc.). Independent variables that cannot be adjusted by the controller are used as disturbances. Dependent variables in these processes are other measurements that represent either control objectives or process constraints.

MPC uses the current plant measurements, the current dynamic state of the process, the MPC models, and the process variable targets and limits to calculate future changes in the dependent variables. These changes are calculated to hold the dependent variables close to target while honouring constraints on both independent and dependent variables. The MPC typically sends out only the first change in each independent variable to be implemented, and repeats the calculation when the next change is required.

While many real processes are not linear, they can often be considered to be approximately linear over a small operating range. Linear MPC approaches are used in the majority of applications with the feedback mechanism of the MPC compensating for prediction errors due to structural mismatch between the model and the process. In model predictive controllers that consist only of linear models, the superposition principle of linear algebra enables the effect of changes in multiple independent variables to be added together to predict the response of the dependent variables. This simplifies the control problem to a series of direct matrix algebra calculations that are fast and robust.

When linear models are not sufficiently accurate to represent the real process nonlinearities, several approaches can be used. In some cases, the process variables can be transformed before and/or after the linear MPC model to reduce the nonlinearity. The process can be controlled with nonlinear MPC that uses a nonlinear model directly in the control application. The nonlinear model may be in the form of an empirical data fit (e.g. artificial neural networks) or a high-fidelity dynamic model based on fundamental mass and energy balances. The nonlinear model may be linearized to derive a Kalman filter or specify a model for linear MPC.

II. MODEL PREDICTIVE CONTROL

Model Predictive Control is the only advanced control technique, which has been very successful in particular applications. Model predictive control (MPC) refers to a class of computer control algorithms that control the future behaviour of a plant through the use of an explicit process model. At each control interval the MPC algorithm computes an open-loop sequence of manipulated variable adjustments in order to optimize future plant behaviour. The Model Predictive Control problem is formulated as solving on-line a finite horizon open loop optimal control problem subject to system dynamics and constraints involving states and controls. Fig 1 shows the basic principle of model predictive control. Based on measurements obtained at time t, the controller predicts the future dynamic behaviour of the system over a prediction horizon T and determines (over a control horizon) the input such that a predetermined open-loop performance object function is optimized.

Model predictive control (MPC) is a very attractive concept for the development and tuning of nonlinear controllers in the presence of input, output or state constraint. The first input in the optimal sequence is injected into the plant, and the entire optimization is repeated at subsequent control intervals. MPC technology was originally developed for power plant and petroleum refinery applications, but can now be found in a wide variety of manufacturing environments including chemicals, food processing, automotive, aerospace, metallurgy and pulp and paper. The application of MPC controllers based on linear dynamic models cover a wide range of applications, and linear MPC theory can be considered quite mature. Nevertheless, many manufacturing processes are inherently nonlinear and there are cases where nonlinear effects are significant and can-not be ignored. These include at least two broad categories of applications:

1. Regulator control problems where the process is highly nonlinear and subject to large frequent disturbances (pH control, etc.).
2. Servo control problems where the operating points change frequently and span a wide range of nonlinear process dynamics (polymer manufacturing, ammonia synthesis, etc.).

Model based predictive control, MBPC, strategy has received particular attention in the areas of process control, is based on the use of a model for predicting the future behaviours of the system over a finite future horizon. The control signal to be applied to the plant at the current sampling time is obtained by solving a finite dimension optimization problem over the prediction horizon. "MPC is the family of controllers in which there is a direct use of an explicit and separately identifiable model" The advantages of MPC compared with many other control techniques can be listed as follows:

It can use step and impulse response data which can easily be obtained,

- It can handle input/output constraints directly,
- It gives satisfactory performance even with time delays and high nonlinearities,
- It can be used in multivariable format,
- It is robust in most cases,
- Implementation of the technique is simple,
- It can optimize over a trajectory,
- It can be used to control various processes, whether simple or complex ones.

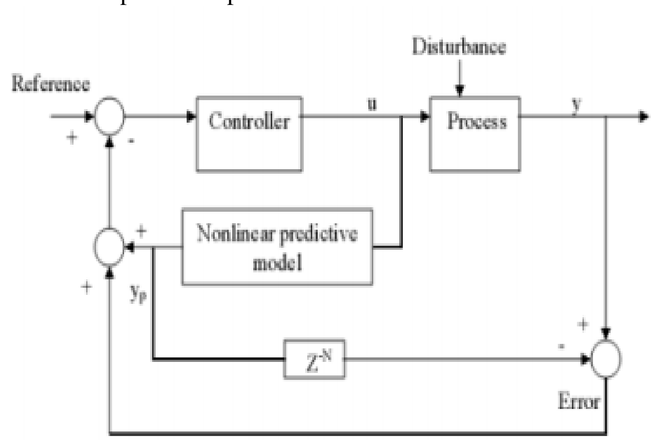

Fig 1: Block Diagram of the MPC controller.

The sum of squared difference between the predicted outputs and their set points over the future prediction horizon and the sum of squares of the control moves over the control horizon. The control of a process, quantitative formulation of the control objective is to minimize the cost

$$\min J(N_1, N_2, U) = \lambda_y \sum_{i=N1}^{N2} [r(t+i) - y_p(t+i)]^2 + \lambda_U \sum_{i=1}^{NU} [\Delta u(t+i-1)]^2$$

Subject to the constraints

NU ⩽ N1,2

| Δu(t) | ⩽ Δumax

umin ⩽ u(t) ⩽ umax

ypmin ⩽ yp ⩽ ypmax

where r is the reference, yp is the predicted output, u is the control variable, λy and λU are the output and the input weighting parameter: N1, N2 represents minimum and maximum prediction horizon and NU is the controller moves horizon. Here U is the NU future inputs vector defined as,

$$U = [u(t), u(t+1), \dots\dots\dots u(t+N_U-1)]^T$$

III. RESULTS AND DISCUSSION

A comparative analysis of the performance of the chemical plant by both MPC and PID controller is obtained by undergoing simulations in Matlab. This system gave the better performance over PID system in both the linear and nonlinear form.

MPC controllers is probably the best assumption that can be used for stable plants in the total absence of disturbance and measurement information, but better feedback is possible if the distribution of disturbances can be characterized more carefully.

The setup and performance of the PID system shown below in fig. 2 to 6:

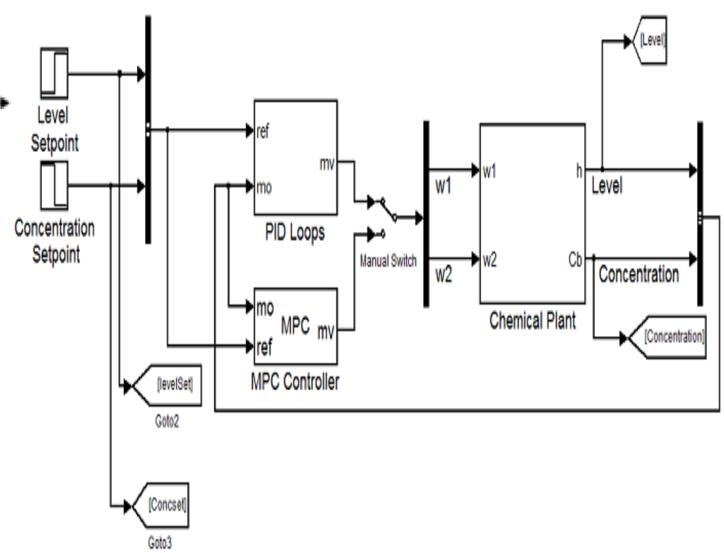

Fig 2: Simulation diagram of PID Controller for chemical plant.

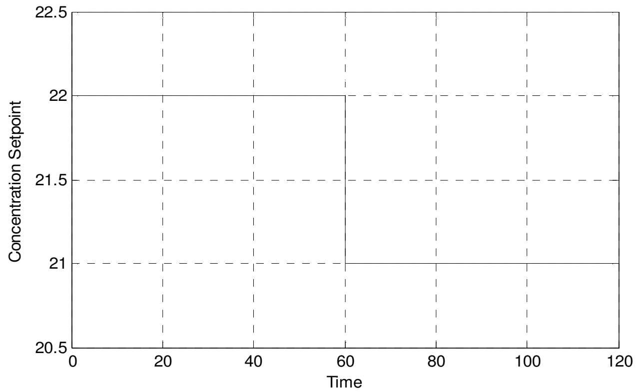

Fig 3: Concentration Setpoint input of PID Controller.

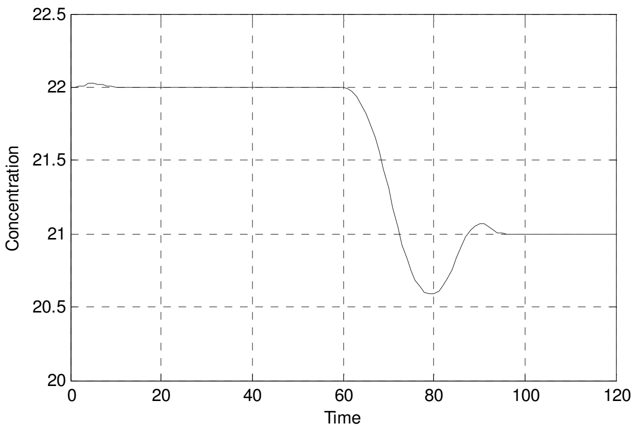

Fig 4: Concentration output of PID Controller.

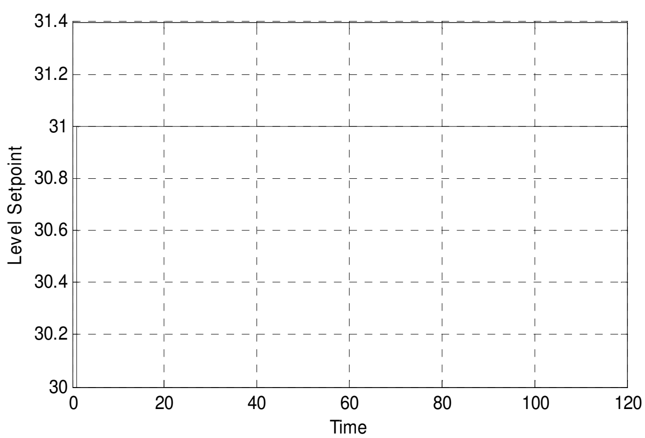

Fig 5: Level Setpoint input of PID Controller.

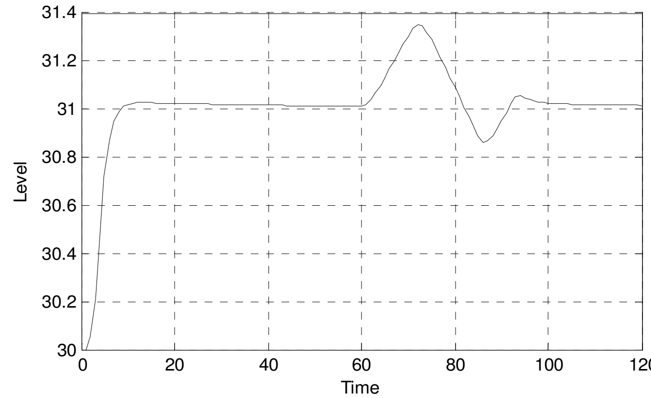

Fig 6: Level output of PID Controller.

The Setup and performance of the MPC system shown below in fig 7 to 11:

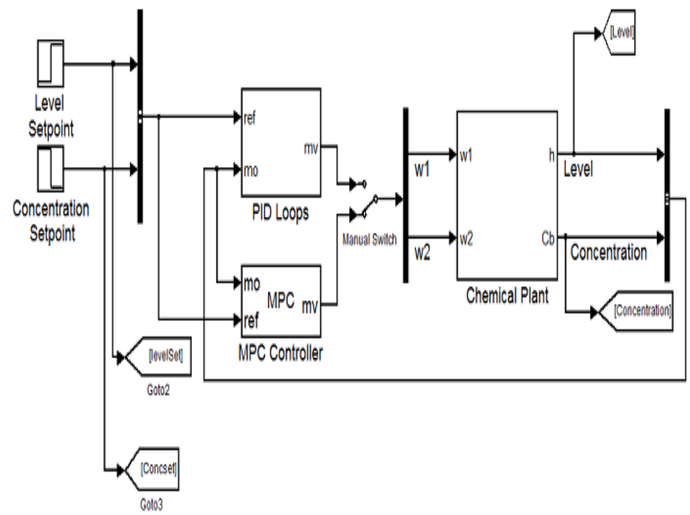

Fig 7: Simulation diagram of MPC Controller for chemical plant.

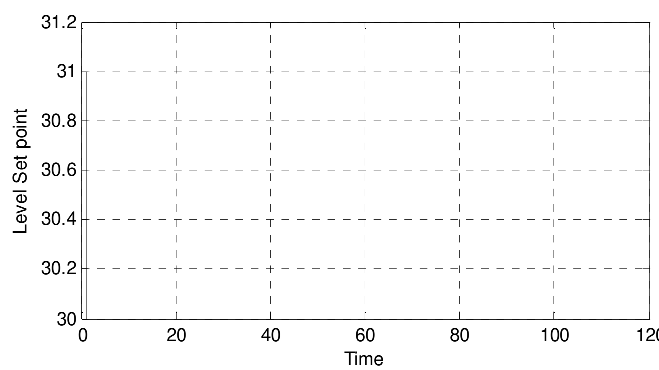

Fig 8: Level Setpoint input of MPC Controller.

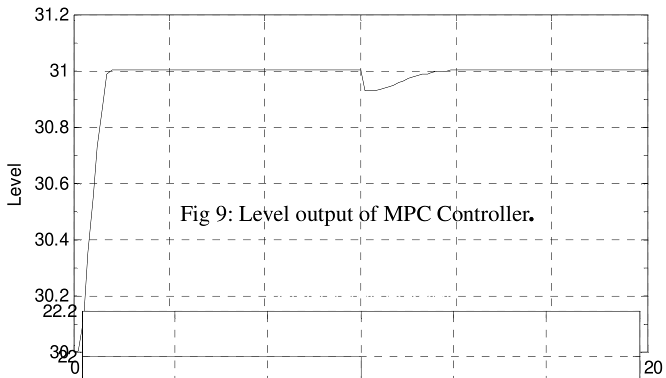

Fig 9: Level output of MPC Controller.

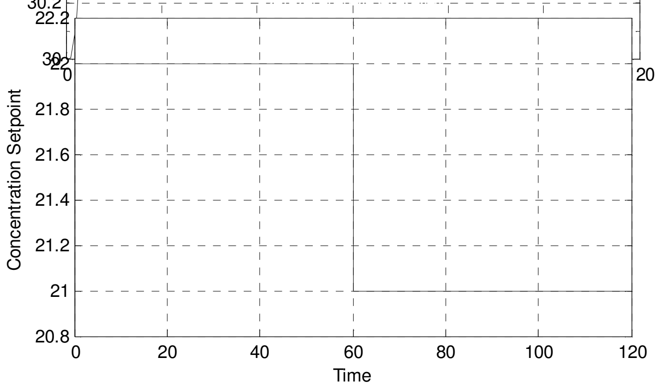

Fig 10: Concentration Setpoint input of MPC Controller.

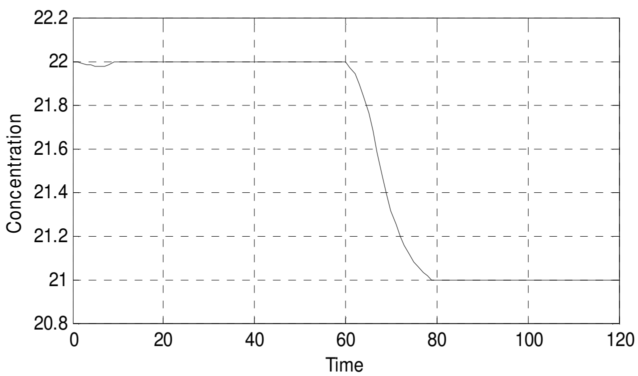

Fig 11: Concentration output of MPC Controller.

IV. CONCLUSION

We have used the MPC controller and output compared with PID for chemical plant. This system gave the better performance over PID system in both the linear and nonlinear form. This simulation results prove our concept and this allow us to use MPC for more complex systems.

REFERENCES

[1] Allgower, F., & Zheng, A., (Eds.). (2000). Nonlinear model predictive control, progress in systems and control theory. Vol. 26. Basel, Boston, Berlin: Birkhauser Verlag.
[2] Bartusiak, R. D., & Fontaine, R. W. (1997). Feedback method for controlling non-linear processes. US Patent 5682309.
[3] Kouvaritakis, B., & Cannon, M. (Eds.) (2001). Nonlinear predictive control, theory and practice. London: The IEE.
[4] Maciejowski, J. M. (2002). Predictive control with constraints. Englewood Cliffs, NJ: Prentice Hall.
[5] Martin, G., & Johnston, D. (1998). Continuous model-based optimization. In Hydrocarbon processing's process optimization conference, Houston, TX.
[6] Young, R. E., Bartusiak, R. B., & Fontaine, R. B. (2001). Evolution of an industrial nonlinear model predictive controller. In Preprints: Chemical process control—CPC VI, Tucson, Arizona
[7] Mayne, D. Q., Rawlings, J. B., Rao, C. V., & Scokaert, P. O. M. (2000). Constrained model predictive control: Stability and optimality.
[8] MATLAB, Optimization and Control Toolbox, www.mathworks.com