IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727,
PP 10-16
www.iosrjournals.org

Design of Model Predictive Controller for Level Process

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Abstract : *The objective of this study is to investigate the Model predictive control (MPC) strategy, analyze and compare the control effects with Proportional-Integral-Derivative (PID) control strategy in maintaining a water level system. An advanced control method, MPC has been widely used and well received in a wide variety of applications in process control, it utilizes an explicit process model to predict the future response of a process and solve an optimal control problem with a finite horizon at each sampling instant. In this project, we first designed and built up a closed-loop water level system. Next, we modeled the system and linerized the model for simplification in the analysis and design. Then, we implemented the model in a simulation environment based on MATLAB. We tried both MPC and PID control methods to design the controller for the water level system, and compared the results in terms of peak time, settling time, overshoot, and steady-state error under various operational conditions including time delays. The results showed the advantage of MPC for dealing with the system dynamic over PID and could be designed for more complex and fast system dynamics even in presence of constraints.*

Keywords: *Model Predictive Control (MPC), FOPDT (First Order Plus Delay Time), Proportional Integral Derivative (PID), SOPDT (Second Order Plus Delay Time).*

I. Introduction

Due to the fast development of process industry, the requirements of higher product quality, better product function, and quicker adjustments to the market change have become much stronger, which lead to a demand of a very successful controller design strategy, both in theory and practice . As a closed loop optimal control method based on the explicit use of a process model, model predictive control has proven to be a very effective controller design strategy over the last twenty five years and has been widely used in Process industry such as oil refining, chemical engineering and metallurgy.The purpose of this work is to study the theory of model predictive control method, analyze and indentify the characteristics and the performance of model predictive controller compared with PID controller when being implemented in the water level control system.
PID controller is relatively simple in structure which can be easily implemented in practice. Therefore, it is widely used in process control industry. In this report, simple methods proposed by Ziegler-Nichols [1], Astrom Hagglund [8] is implemented for the real time measurement of laboratory Level control system. System model for laboratory level control system using system identification toolbox of MATLAB 7.1 version is determined and this level loop is configured with SCADA. Controller performance is determined on the basis of time domain specification. Existing control loop uses PID controller more than 90%. Since 1940's many methods are proposed to tune PID controller but every method have some limitations. As a result, the design of PID controller still remains a challenge before researchers and engineers.

II. Proportional – Integral – Derivative (Pid) Control

A proportional–integral–derivative controller (PID controller) is a controller which is popularly used in industrial control systems . It is fed with the error signal, that is, the difference between the reference, or the desired output and the actual output (which is obtained as a feedback). The controller then attempts to bring the actual output to track the reference. The structure of PID controller is showed in fig 1 [2]

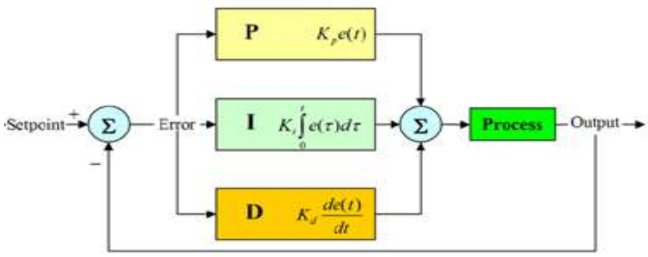

Fig. 1 Structure of PID Control

The PID controller algorithm involves three separate constant parameters (proportional, integral and

derivative, denoted by P, I and D respectively) and is thus, also called three- term control. P depends on the present error, I on the accumulation of past errors, and D is a prediction of future errors, based on current rate of change. The weighted sum of these three actions is given as input to the process through a control element. By tuning the three parameters, the controller provides the required control action.
If C(t) represents the controller output, which is the manipulated variable (MV(t)), that is, the process input, then:

$$C(t) = MV(t) = Kpe(t) + KI\int_0^t e(t)\,dt + Kd\frac{d}{dt}e(t) + Pout \quad \textbf{(1)}$$

Effect of proportional gain: If the proportional gain is too small, it results in a small output response for a large input error. This, results in a large steady-state error. Effect of integral gain: The integral gain removes the residual steady state error that occurs with a pure proportional controller. However, a very high integral gain results in overshoot. Effect of derivative gain: The derivative gain is used to reduce the overshoot caused by the integral gain and improve the combined controller-process stability. But, it slows down the transient response of the system as well as, increases sensitivity of the system to noise. So, a lead-compensator is used as an approximation of the differentiator.

In order to calculate the output of the PID controller, the three terms are summed together, which can be expressed as formula (1) [5] [8]:

For the control process, better performance can be achieved by tuning the control loop, which is adjusting the control parameters to satisfy the desired control response.

Therefore, tuning PID control parameters is a complicated process that we have to find an optimal way to arrange the values of the parameters for the control response. In this thesis, we used Ziegler-Nichols oscillation method, which is introduced in [1] and Astrom Hagglund method, which is introduced in [2] [8].

III. Model Predictive Control (Mpc)

The general design objective of model predictive control is to optimize, based on the computed trajectory of future manipulated variable u, predict the future behavior of the plant output y. The optimization is performed within a limited time window by giving plant information at the start of the time window. Model Predictive Control, or MPC, is an advanced method of process controls that has been in use in the process industries such as chemical plants and oil refineries since the 1980s [7]. Model predictive controllers rely on dynamic models of the process, most often linear empirical models obtained by system identification. Hence the models are used to predict the behavior of dependent variables (i.e. outputs) of the modeled dynamical system with respect to changes in the process independent variables (i.e. inputs). In chemical processes, independent variables are most often set points of regulatory controllers that govern valve movement (e.g. valve positioners with or without flow, temperature or pressure controller cascades), while dependent variables are most often constraints in the process (e.g. product purity, equipment safe operating limits). The model predictive controller uses the models and current plant measurements to calculate future moves in the independent variables that will result in operation that honors' all independent and dependent variable constraints. The MPC then sends this set of independent variable moves to the corresponding regulatory controller set points to be implemented in the process [12]. Despite the fact that most real processes are approximately linear within only a limited operating window, 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 [11] [12].

Model Predictive Control Strategy

Model predictive control (MPC) includes a class of control algorithms that utilize an explicit process model to predict the future response of a plant. At each control interval an MPC algorithm attempts to optimize future plant behavior by computing a sequence of future manipulated variable adjustments. The first input in the optimal sequence is then sent into the plant, and the entire calculation is repeated at subsequent control intervals. The following is a figure2 shows the basic idea of predictive control based on a single-input, single output plant.

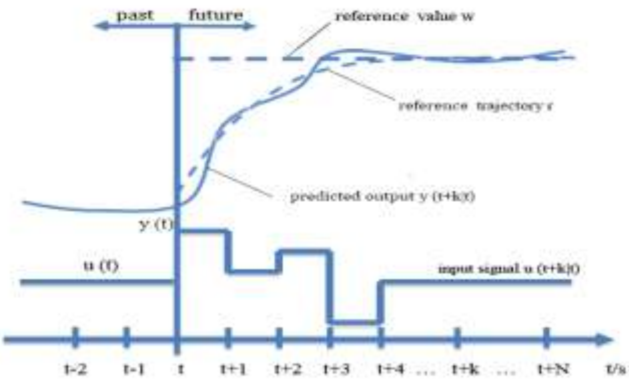

Fig. 2 Model Predictive Control Strategy

We marked the current time as ‘t’, with the plant output y(t). The figure also shows reference value *w*, reference trajectory ‘r’ and control signal u(t+k│t).The period from ‘t’ to ‘t+N’ is called the prediction horizon, which determines the predicted output y(t+k│t) and dictates how ‘far’ we wish the future to be predicted for. The objective of model predictive control law is to drive future plant outputs y(t+k│t) as close as *w* as shown in figure 2.

Objective Function Optimization Problem

The term optimization implies a best value for some type of performance criterion. This performance criterion is Known as an objective function. Here, we first discuss possible objective functions, then possible process models that can be used for MPC.

Here, there are several different choices for objectives functions. The first one that comes to mind is a standard least-squares or “quadratic “objective function. The objective function is a “sum of squares “ of the predicted errors (differences between the set points and model-predicted outputs) and the control moves (changes in control action from step to step)

A quadratic objective function for a prediction horizon of 3 and a control horizon of 2 can be written

$$\Phi = (Rk + 1 - \hat{y}k + 1)^2 + ((Rk + 2 - \hat{y}k + 2)^2 + ((Rk + 3 - \hat{y}k + 3)^2 + w\Delta U\,k^2 + w\Delta\,Uk + 1^2 \qquad (2)$$

Where $\hat{y}$ represents the model predicted output, r is the set point, ΔU is the change in manipulated input from one sample to the next, w is a weight for the changes in the manipulated input, and the subscripts indicate the sample time (k is the current sample time). For a prediction horizon of P and a control horizon of M, the least Squares objective function is written

$$\Phi = \sum(Rk + 1 - \hat{y}k + 1)^2 + w\sum\Delta Uk + 1^2 \qquad \ldots\ldots\ldots\ldots \qquad (3)$$

Another possible objective function is to simply take a sum of the absolute values of the predicted errors and control moves. For a prediction horizon of 3 and a control horizon of 2, the absolute value objective function is

$$\Phi = |Rk + 1 - \hat{y}k + 1| + |Rk + 2 - \hat{y}k + 2| + |Rk + 3 - \hat{y}k + 3| + w\,|\Delta U\,k| + w|\Delta\,Uk + 1| \qquad (4)$$

Which has the following general form for a prediction horizon of P and a control horizon of M :

$$\Phi = \sum|(Rk + 1 - \hat{y}k + 1)| + |\Delta Uk + 1| \qquad (5)$$

The optimization problem solved stated as a minimization of the objective function, obtained by adjusting the M control moves, subject to modeling equations (equality constraints), and constraints on the inputs and outputs.

$$Min\ \Phi$$

Least-squares formulations are by far the most common objective functions in MPC. Least squares yields analytical solutions for unconstrained problems and penalizes larger errors (relatively) more than smaller errors. The absolute value objective function has been used in a few algorithms because linear programming (LP) problem results. LPs are routinely solved in large-scale scheduling and allocation problems. For example, an oil company often uses an LP to decide how to distribute oil to various refineries and to decide how much and what product to produce at each plant .The LP approach is not useful for model predictive control, because the manipulated variable moves often " hop" from one extreme constraint to another.

IV. Description Of Level Control Process

Level control process is designed for understanding the basic principles of level control. The process setup consists of supply water tank fitted with pump for water circulation. The level transmitter used for level sensing is fitted on transparent process tank. The process parameter (level) is controlled by microprocessor based digital indicating controller which manipulates pneumatic control valve through I/P converter. A pneumatic control valve adjusts the water flow in to the tank. These units along with necessary piping are fitted on support housing designed for tabletop mounting. The controller can be connected to computer through USB port for monitoring the process in SCADA mode. Fig. 3 explores the system schematic arrangement of Level Control System

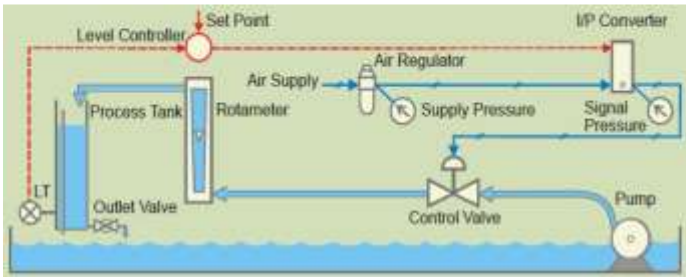

Figure. 3.System schematic arrangement of level control system

Determination of Process Model

A process model is a system of mathematical equations and constants that are usually solved on a computer to make quantitative predictions about some aspect(s) of a real process. The specific variables required as input data and generated as output predictions are important features of the model. The equations often stem from a numerical solution to one or more differential equations and their boundary conditions.
In the design of model based controller, system model is an important element. White box model requires complete and correct physical data of the system under consideration. But this data is not available for the system described. Hence, system model is determined through system identification. We used time domain step test data from the system for determination of model. We considered FOPDT model [4] [8].
This step response locates the system parameters like steady state gain, time delay and the time constant of the process from which model obtained is of general form as,

$$G_s = \frac{K_p e^{-t_d s}}{1+\tau s} \tag{6}$$

Where, K_p is steady state gain of system , τ is time constant of system , t_d is dead time of system.

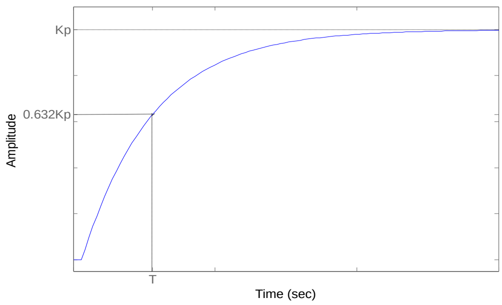

Fig. 4 A typical step response of FOPDT system

Figure 5 shows a typical step response of SOPTD system. This step response locates the system parameters like peak overshoot, settling time, dead time of the system from which the model can be obtained as,

$$G(s) = \frac{\omega_n^2 e^{-t_d s}}{s^2 + 2\xi\omega_n s + \omega_n^2} \tag{7}$$

Where, ω_n is natural frequency of system, ξ is damping ration of system, t_d is dead time of system.

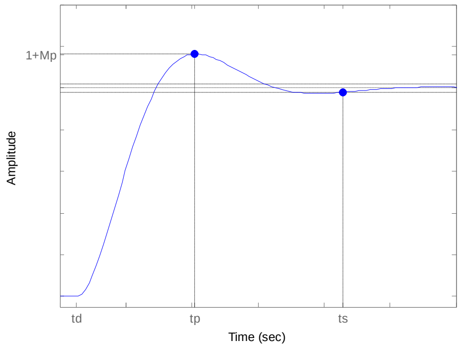

Fig.5 A typical step response of SOPDT system

The system parameters ω_n and ξ are calculated from peak overshoot M_p and settling time (2% criterion) t_s by solving (3) and (4) given by,

\

$$M_P = e^{\frac{\pi\xi}{\sqrt{1-\xi^2}}} \tag{8}$$

$$t_s = \frac{4}{\xi\omega_n} \tag{9}$$

In the given case, from the open loop response of the Level Control System, it is seen that by measuring input –output data we can create the mathematical models of dynamic systems from measured input-output data by using system Identification Toolbox in MATLAB. The following estimate of the plant is obtained by using system Identification Toolbox:

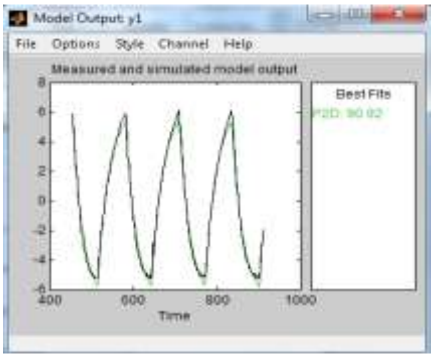

Fig. 6 Measured and simulated output using system identification toolbox of MATLAB

Hence, For the best fit of 90.92% shown above in figure 4 we get FOPDT model as,

$$G_p(s) = -0.22 \times \frac{e^{-1.69s}}{(1+26.43s)} \tag{10}$$

V. Simulation Results & Discussion

The simulation results for PID controller tuning by Ziegler-Nichols & Astrom Hagglund methods for FOPDT model (10) obtained for Level control system is shown in figure 7

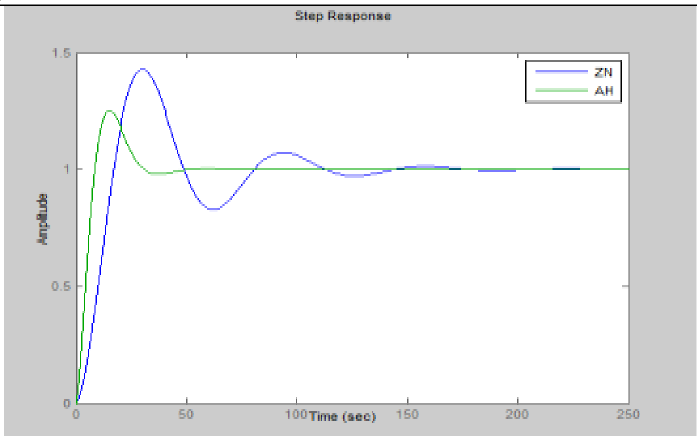

Fig.7 Unit step response of Ziegler Nichols & Astrom Hagglund PID Controller for Level control system model (10)

The step response of the proposed MPC controller with the control horizon M=2, prediction horizon, P =10 without manipulated variable constraint and output variable constraint is shown in Fig.8

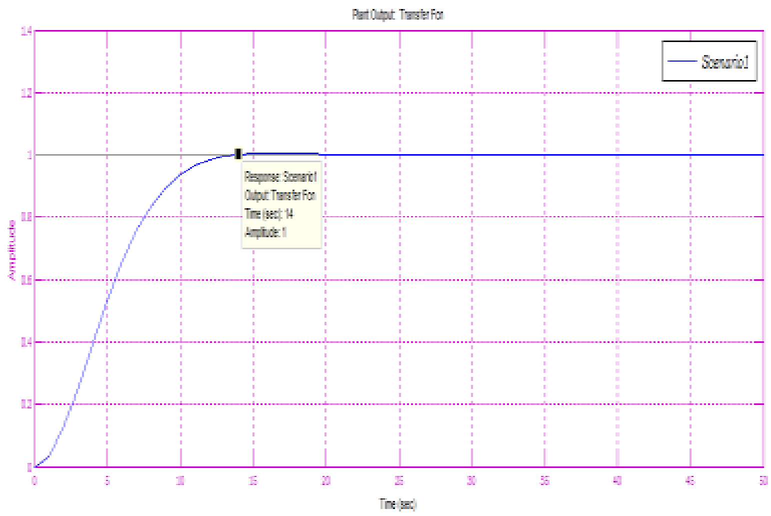

Fig. 8 Unit step response of Model Predictive Controller for Level control system model (10)

Table 1 shows the performance comparison results of Model Predictive control method with the conventional PID Controllers methods on the basis of time domain specifications for Level control system (10).

Table 1 Comparison of controller performance on the basis of time domain specifications

Controllers / Parameters	PID Controller (Zeigler-Nichols Method)	PID Controller (Astrom Hagglund Method)	MPC Controller
Peak Time (t_p) sec.	30.51	14.97	0
Settling Time (t_s) *sec.*	208.4	52.96	14
Maximum Overshoot(M_p)	1.428	1.252	0
Steady State Error(e_{ss})	0	0	0

Table 1 shows the result of response of controller we have taken for analysis, using simulation process. These controllers have different responses for the input taken as Step. After simulation we have find that these entire controller have different value of parameters such as peak time t_p settling time t_s, maximum overshoot (M_p), and steady state error e_{ss}. In the analysis we have seen that more accurate result came using Astrom Hagglund PID Controller over Ziegler-Nichols PID controller, further better result got in case of MPC Controller. Table 1 show that MPC controller gives better time domain specifications than PID Controller.

VI. Conclusion

A high performance Model based Predictive Control algorithm is proposed for the level Control process. The MPC control algorithm is compared with conventional PID control in terms of time domain specifications like settling time, overshoot, Peak time, steady state error. The Model Predictive Controller gives better performance than PID Controller for the level control system. MPC controller can adjust the control action before a change in the output set point actually occurs. Hence from the results we conclude that MPC is better than PID controller

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