Identification and Control of Non-Linear System Using Model Predictive controller

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Abstract-

The modeling of level and temperature process is the most common problems in the process industry. In this paper system identification is performed for a hybrid tank system. Hybrid tank is an example for highly non-linear system. This system has two inputs heater current and flow and the outputs are level and temperature. The Main aim of this paper is to maintain level and temperature at a desired value. Input flow is measured using turbine flow meter. The output temperature is measured using RTD. The level is measured using differential pressure transmitter (DPT). The simulation is performed in MATLAB environment using system identification algorithm. Model Predictive controller is implemented for this identified model.

Keywords- *System identification, MIMO, Model Predictive controller.*

I. INTRODUCTION

In control engineering, the system identification uses statistical methods to build mathematical models of dynamical systems from measured data. Constructing models from observed data. System identification is the process for finding out the model of the hybrid tank process. Generally the hybrid tank process is a nonlinear process including much nonlinearity and other models like delay, valves, transmitters, etc. System identification enables us to acquire the model of this nonlinear process by using the inputs and outputs of the hybrid tank process.

Using a predictive strategy based on a fuzzy model, the problems of the mixed discrete and continuous variables and nonlinearity is solved together [1]. The time-optimal control for set point changes and an adaptive control for process parameter variations using neural network for a non-linear conical tank level process [2].

The boiler is a non-linear, time varying multi-input multi-output (MIMO) system, Mamdani's fuzzy model improves the final outcome and controls multi-dimensional dynamic system with ease [3]. Fuzzy Based Function Expansion -based MRAC is proposed for controlling the plant with unknown parameters [4].

The measured disturbances it is assumed that the future values will be equal to the current values. The performance of MPC depends largely on the used process model. The model must be able to accurately predict the future process outputs, and at the same time be computationally attractive to meet real-time Demands [5].

The error function is reduced due to online tuning of the membership functions and control rules of fuzzy controller. The outlet temperature of shell and tube heat exchanger and for the control of level and temperature of a nonlinear coupled tank system is obtained by using SA-FLC algorithm [6].

The mathematical models of the process are obtained by the application of System Identification techniques. The version of MPC known as Dynamic Matrix Control (DMC) is applied in order to regulate the contents of C02 in an ethane output stream from the absorber tower using amine as a treating agent [7].

II. PROCESS DESCRIPTION

A HYBRID TANK PROCESS

The continuous-flow, well-stirred Hybrid tank process finds wide application in the chemical industry. The basic arrangement, sketched below, comprises a tank at surrounding temperature T_a. Here motor driven stirrer is used. The contents in the tank are stirred and then uniform heat is applied for whole tank. The flow of the liquid, level of the liquid temperature of the liquid and heater voltage are important parameters.

Fig1

Fig1 represents the simple diagram of Hybrid Tank Process. The water in reservoir is transferred to tank using pumps. The height of the tank is 60 centimeter.

B. LEVEL PROCESS IN HYBRID TANK

The level of the hybrid tank is measured using level transmitter. By measure the level DPT (Differential Pressure Transmitter) is used. Differential Pressure is obtained by finding the difference in pressure between the atmosphere and tank.

C. FLOW PROCESS IN HYBRID TANK

The flow of the hybrid tank is measured using flow transmitter. Flow transmitter used here is Turbine type Flow transmitter. The total number of revolutions made by the inner turbine wheel is directly proportional to the inflow of the hybrid tank. Output signal from flow transmitter is (4 to 20mA) which is converted into (0 to 5V) when acquired in the DAC.

D. TEMPERATURE PROCESS IN HYBRID TANK

The temperature of the hybrid tank is measured using RTD's. The RTD's are produce a current value according to the temperature in the tank. The tank temperature is increased using two heating coils which are powered by a SCR. SCR is a silicon controlled rectifier. The current output (4 to 20mA) of the RTD's are converted into corresponding (0 to 5V) when acquired in the DAC.

III. SYSTEM IDENTIFICATION

The models are in form of differential equations developed from physical principles or from transfer function models. The parameters of the model can have unknown or uncertain value in the process. It can be regarded as "black-box"-models which express the input-output property of the system. It can try to estimate such parameters from measurements taken during experiments on the system. Mathematical models of dynamical systems are of rapidly increasing importance in engineering and today all designs are more or less based on mathematical models. Leading Physical laws governing the behavior of the system are known as *white-box models* of the system. In a white-box model, all parameters and variables can be interpreted in terms of physical entities and all constants are known a priori. At the other end of the modeling scale we have so called *black-box modeling* or *identification*. Black-box models are constructed from data using no physical insight and the model parameters are simply knobs that can be turned to optimize the model set.

VI. System identification for MIMO system

The System Identification is performed for MIMO (Multi Input Multi Output) system. The Input is Flow and Heater voltage. The Flow is represented as LPH (Liter per Hour) and the Heater Voltage is representing as volts. The Output is Level and Temperature of the Liquid. The Level is representing as cm (centimeter) and Temperature in terms of degree Celsius.

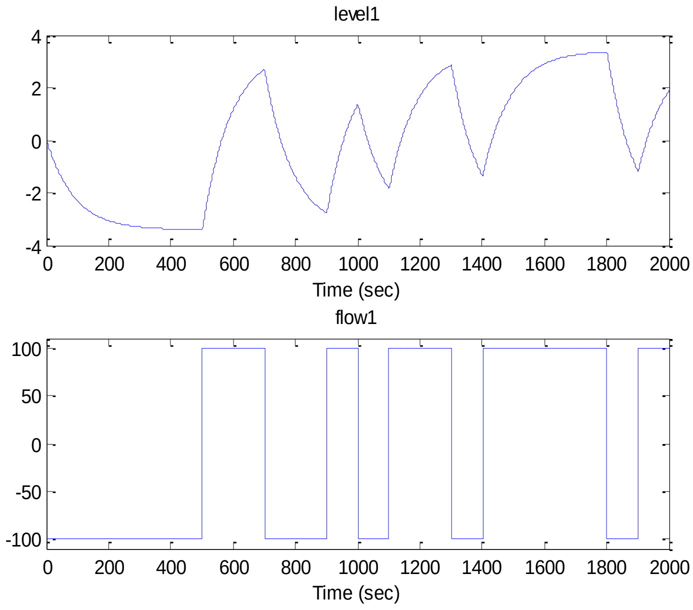

Fig 1

Fig 1 represents Flow and level. The input PRBS (pseudo random binary signal) signal is applied for level steady state change.

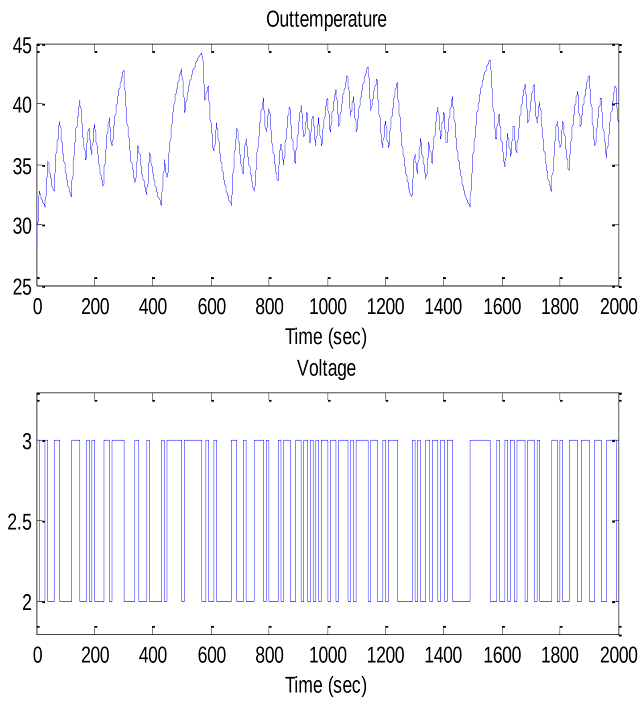

Fig 2

Input PRBS in the range of -100 to 100. The 2000 samples are taken. Fig 1 represents the Flow. Flow varies from -100 to 100 LPH. X axis represents Time in seconds. Y axis represents Flow and Level. Fig 2 represents Temperature and corresponding voltage. The X axis represents Time in seconds and Y axis represents Temperature and Voltage.

A. Estimation

The first 1400 samples are taken for Estimation. The Linear Parametric Estimation cannot be used for MIMO System. The ARMAX, BJ, ARX, models are not applicable for MIMO System.

The State Space model Estimation is only suitable for MIMO System. The diffferent state model estimation is available for MIMO system in MATLAB. PEM method called as Prediction Error Minimization. It automatically computes the orders of the system.

N4SID means Estimate State space model using subspace method. In this method user can specify the orders of the method. The both input Heater voltage and Flow taken as input for estimation and the Level and temperature are taken for output. The multi input and multi output taken at a time for system identification. The prediction Error method of estimation is used. The m1 represents PEM method. Mp represents N4SID method.

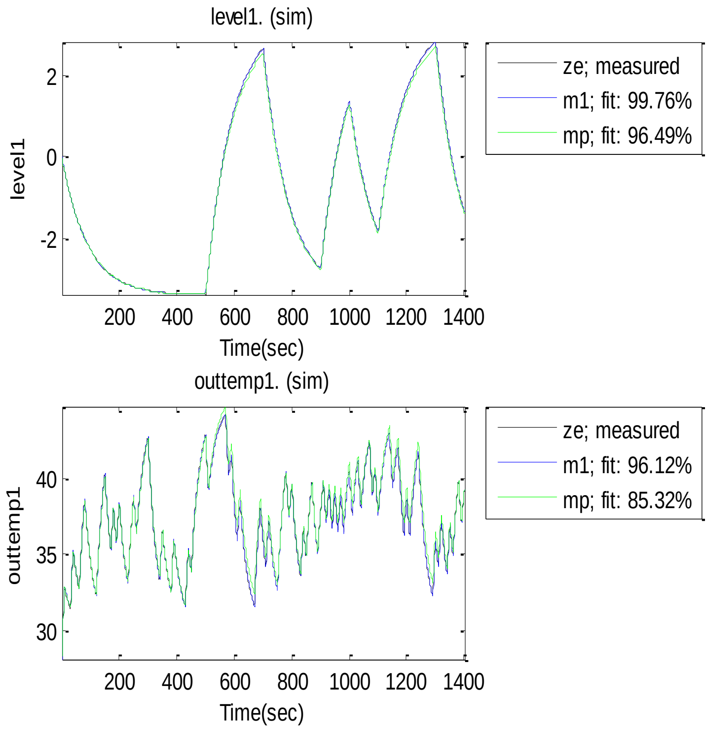

Fig 3

Fig 3 represents Estimation for MIMO system. The PEM and N4SID methods are used for MIMO System identification. The fit obtained for N4SID method for Level as 99.76% and Temperature fit 96.12%. The fit obtained from PEM method for level as 96.49% and Temperature fit as 85.32%.

C. *Validation*

The remaining 600 samples are taken for validation for level and temperature.

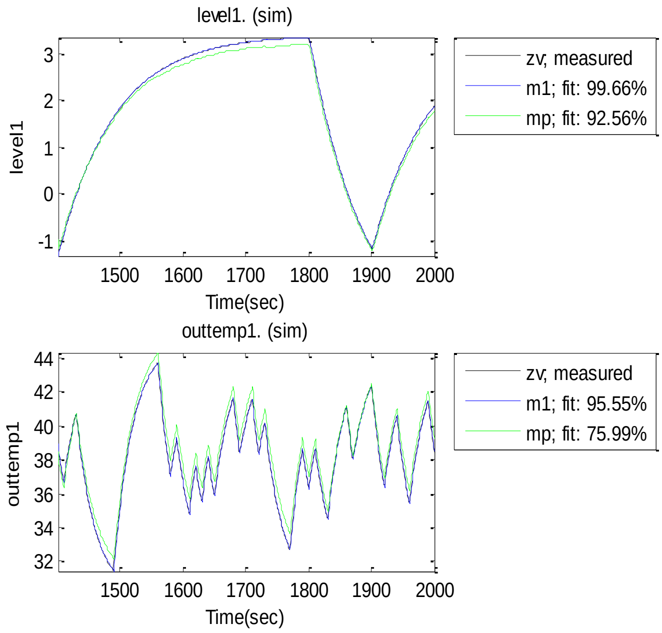

Fig 4

The Level and temperature are taken for output. The multi input and multi output taken at a time for system identification. The level is representing as LPH and Temperature represent as degree Celsius. Fig 4 represents Validation for MIMO system. The X axis represents as Time in seconds and Y axis represent as Level and temperature. Usually 70% data's are taken for Estimation, and remaining 30% data's are taken for validation.

The fit obtained for N4SID method for Level as 99.66% and Temperature fit 95.55%. The fit obtained from PEM method for level as 92.56% and Temperature fit as 75.99%.

TABLE: 3 COMPARISION

Model	**Level Estimation Fit**	**Level Validation Fit**	**Temperature Estimation Fit**	**Temperature Validation Fit**
PEM	96.49	92.56	85.32	75.99
N4SID	99.76	99.66	96.12	95.15

The Estimation fit is obtained for N4SID method for Level as 99.14% and Temperature fit 98.81% and fit obtained from PEM method for level as 97.36% and Temperature fit as 97.65%. The Validation fit is obtained for N4SID method for Level as 98.87% and Temperature fit 98.11%. The fit obtained from PEM method for level as 97.26% and Temperature fit as 97.65%. The best fit obtained at N4sid method.

VII MPC Controller

The models used in MPC are generally intended to represent the behavior of complex dynamical systems.MPC ControllerMPC models predict the change in the dependent variables of the modeled system that will be caused by changes in the independent variables. Chemical process, independent variables that can be adjusted by the controller are often either the set points of regulatory PID controllers (flow, pressure, temperature, etc.) or the final control element (valves, dampers, etc.). The Independent variables that cannot be adjusted by the controller are used as disturbances. Dependent variables in this process are other measurements that represent either control objectives or process constraints.

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

For many real processes are not linear, it 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. Model predictive controllers that consist only of linear models, the Superposition principles of linear algebra enables the effect of changes in multiple independent variables to be added together to predict the response of the dependent variables. It simplifies the control problem to a series of direct matrix algebra calculations that are fast and robust.

For the linear models are not sufficiently accurate to represent the real process nonlinearities, several approaches can be used. The process variables can be transformed before and/or after the linear MPC model to reduce the nonlinearity. The process is controlled with nonlinear MPC that uses a nonlinear model directly in the control application. The nonlinear model 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 models are linearized for specify a model for linear MPC.

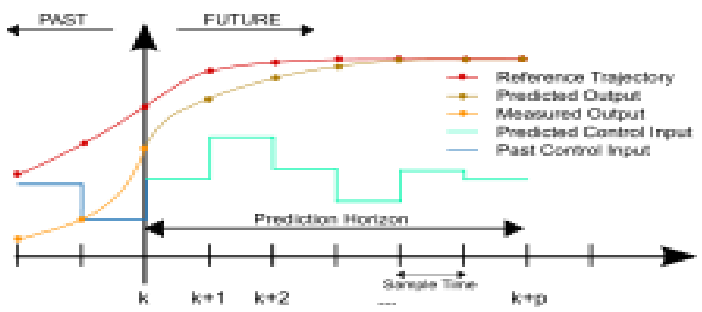

Fig 1

Fig 1 represents a discrete MPC scheme. MPC is based on iterative and finite horizon optimization of a plant model. The time t is the current plant state is sampled and a cost minimizing control strategy is computed (via a numerical minimization algorithm) for a relatively short time horizon in the future (t, t+T). Specifically, an online calculation is used to explore state trajectories that emanate from the current state and find (via the solution of Euler-Lagrange equations) a cost-minimizing control strategy until time (t+T).

The first step of the control strategy is implemented, plant state is sampled again and the calculations are repeated starting from the now current state, a new control and new predicted state path. The prediction horizon shifted forward and for this reason MPC is also called **receding horizon control**.

In this approach is not optimal, but it gives very good results. More academic research has been done to find fast methods of solution of Euler-Lagrange equations, to understand the global stability properties of MPC's local optimization, used to improve the MPC method.

A. *Results*

The initial level set point as 30 and the temperature set point as 60. After 500 seconds Level is increased from 30 to 50 and temperature increased from 60 to 80.

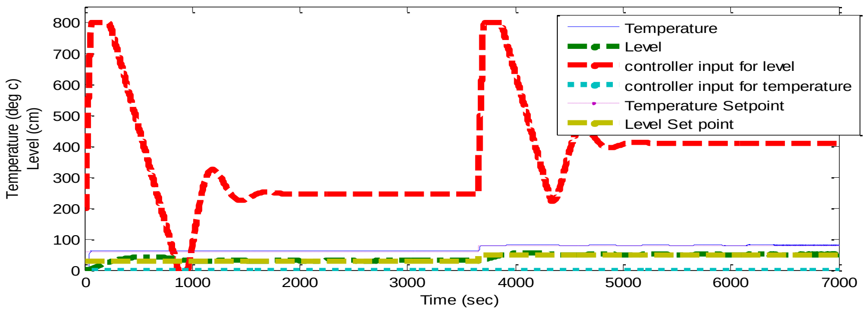

Fig2

Fig 2 represents the Output response with controller variable flow and Heater voltage. Flow varies from 0 to 800 LPH. Heater voltage varies from 0 to5volts.

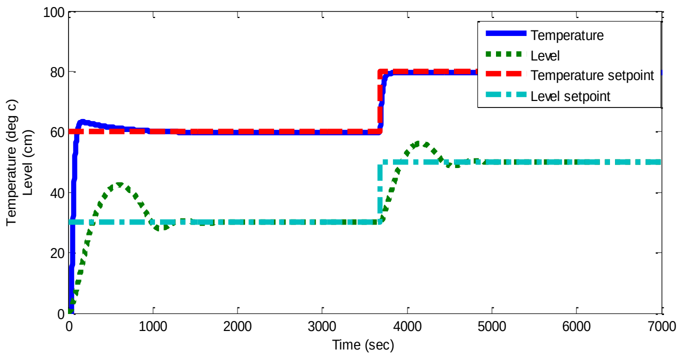

Fig3

The Model Predictive controller takes controller action to reach the set point as desired one. The MPC controller parameters are control horizon, Predictive horizon and control intervals. Control intervals are specifying in time units. The control interval is 1.0, Control horizon is 2 and Predictive horizon is 10. The control horizon is always less than predictive horizon. In the constraints block specify the range of input and output signals. Fig 2 represents the controller tuning performed for corresponding Level and Temperature change without controller variable. The X axis represents Time in seconds; Y axis represents Level in centimeter and Temperature in degree Celsius. The Level initial set point is 30 and after 500 sec it changeover to 50. The Temperature set point is 60 after 500 sec it changeover to 80.

Conclusion

The system identification is performed for nonlinear hybrid tank process. The MIMO system identification is performed using N4SID and PEM Method. The best fit is obtained by N4SID method. For that Obtained model, Model predictive controller is implemented. By using Model Predictive controller, the better performance is obtained.

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