Nonlinear Process Identification and Model Predictive Control using Neural Network

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***Abstract*—In the domain of industry process control, the model identification and predictive control of nonlinear systems are always difficult problems .The main aim of this paper is to establish a reliable model for nonlinear process. In many applications, lack of process knowledge and/or a suitable dynamic simulator precludes the derivation of fundamental model. This necessitates the development of empirical nonlinear model from dynamic plant data. This process is known as 'Nonlinear System Identification'. Artificial neural networks are the most popular frame-work for empirical model development .The model is implemented by training a Multi-Layer Perceptron Artificial Neural network (MLP-ANN) with input-output experimental data. Satisfactory agreement between identified and experimental data is found and results shown that the neural model successfully predicts the evolution of the product composition. Trained data available from nonlinear system using Model Predictive Control (MPC) algorithm. The Simulation result illustrates the validity and feasibility of the MPC algorithm.**

Keyword- ***Neural Networks, NARX model identification, Nonlinear model predictive control***

I. INTRODUCTION

This topic presents the application of Artificial Neural Networks (ANN) based Model Predictive Control (MPC) scheme to control a nonlinear system. Neural networks have been successfully applied to broad spectrum of data-intensive application, such as: Process Modelling and Control, Character Recognition, Machine Diagnostics, Target Recognition, Medical Diagnosis, Credit Rating and Voice Recognition. In recent year, the requirement for the quality of automatic control in the process industries increased significantly due to the increased complexity of the plants and sharper specification of product quality. At the same time, the available computing power is increased to a very high level. Intelligent and model based control techniques are developed to obtain tighter control for such applications. Such as Model Predictive Control (MPC), Internal Model Control (IMC), global linearization and generic model control [1].

Model Predictive Control refers to class of algorithms in which dynamic process model is used to predict and optimize process performance.MPC is well suited for high performance control of constrained multivariable processes because constraints can be incorporated directly into the associated open-loop optimal control problem. The critically important issue is to generate a more accurate nonlinear model for process prediction and optimization problem. In many applications, lack of process knowledge and/or a suitable dynamic simulator precludes the derivation of fundamental model. This process is known as nonlinear system identification. A fundamental difficulty associated with the empirical modelling approach is the selection of a suitable model form. Discrete-time models are most appropriate because plant data is available at discrete time instants and NMPC is most naturally formulated in discrete time. Artificial neural networks are the most popular frame-work for empirical model development [8].

II. NONLINEAR PROCESS IDENTIFICATION

An easy way to comply with the conference paper formatting requirements is to use this document as a template and simply type your text into it. The use of neural networks offers some useful properties and capabilities such as: Nonlinearity, Input-Output mapping, Adaptivity, Fault tolerance. There are large numbers of neural network algorithms available. These algorithms include: multilayer perceptron (Back propagation Networks), Radial Basis Functions (RBF) networks, Hopfield networks and adaptive resonance networks. Of all these networks, the backpropagation and Radial Basis Function networks have been applied in most process control applications. Multilayer perceptrons have been applied successfully to solve some difficult and diverse problems by training them in a supervised manner with a highly popular algorithm known as the error backpropagation algorithm. This algorithm is based on error correction learning rule [3],[6],[7].

In general, parameters in a dynamic model, regardless of the form of its mathematical representation, can be estimated by two different approaches: a serial-parallel and a parallel identification method. In most of the neural network applications, a multilayer feedforward network is employed as a nonlinear autoregressive with exogenous input model (NARX), in which the network uses a number of past (delayed) plant inputs and outputs to predict the future system output. A NARX model is a subset of the general NARMAX model in which additional moving average terms are present for modelling the stochastic components of a dynamic process. Neural Networks are typically over parameterized; an important training issue that arises involves when to stop the training. A simplified version of the statistical technique of cross validation, called test set validation is usually employed [2].

2.1. Model Identification Steps

The first phase of the work will be generation of empirical model using neural network. The critically important issue is to generate a more accurate nonlinear model for process prediction and optimization problem.

2.1.1. Structure Selection

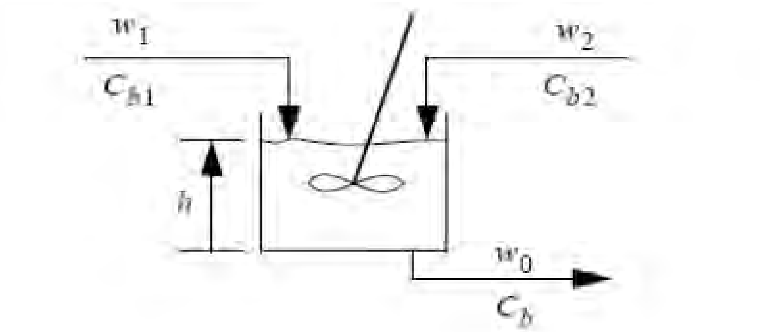


Figure 1. Continuous Stirred Reactor (CSTR)

$$\frac{dh(t)}{dt} = w_1(t) + w_2(t) - 0.2\sqrt{h(t)}$$

$$\frac{dC_b(t)}{dt} = (C_{b1} - C_b(t))\frac{w_1(t)}{h(t)} + (C_{b2} - C_b(t))\frac{w_2(t)}{h(t)} - \frac{k_1(t)C_b(t)}{(1+k_2C_b(t))^2}$$

Where h (t) is the liquid level, C_b (t) is the product concentration at the output of the process, w_1 (t) is the flow rate of the concentrated feed Cb_1 and w_2 (t) is the flow rate of the diluted feed Cb_2.[9]

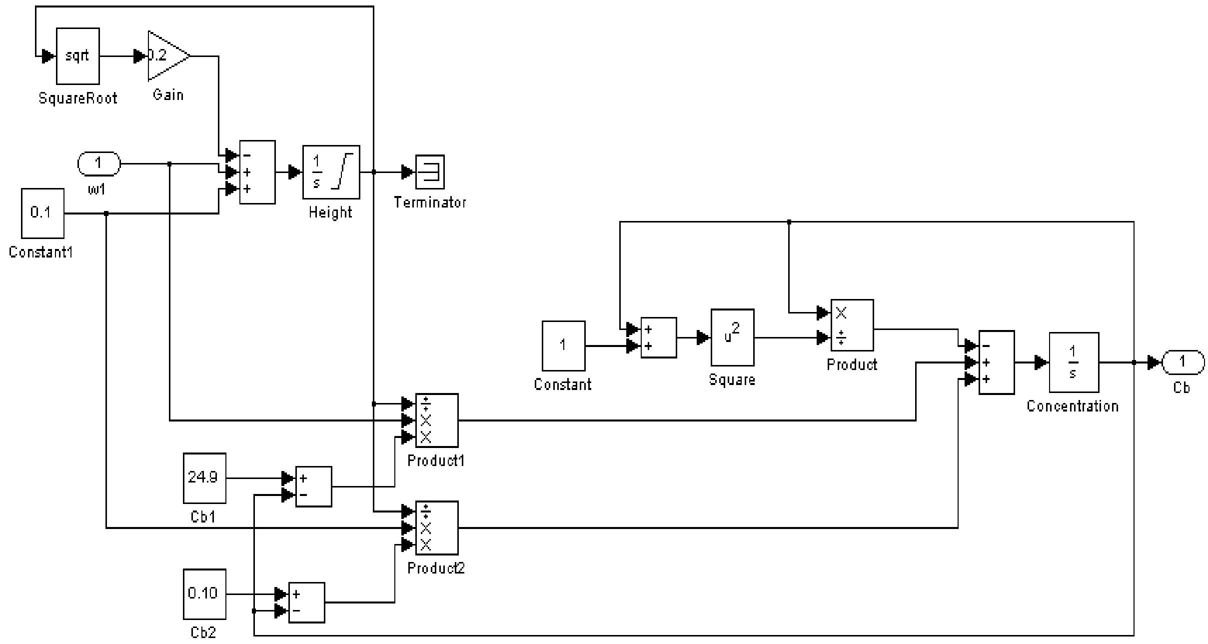


Figure 2. Continuous Stirred Reactor (CSTR) simulink model

2.1.2. Input sequence design

Determination of input sequence which is injected into the plant to generate the output sequence. The data set that is used is split into two parts, one for training and one for testing.[9]

2.1.3. Parameter Estimation

In this step estimation of model parameters is done by training the neural network. The initial training of neural network is typically done using backpropagation algorithm. Periodically, one stops training the network and calculates the error that the network with its current parameters produces on the testing data. Training is terminated when a minimum in the test set error is observed. By using this train-test approach, the fact that a network has too many parameters dose not results in a problem and accurate models can be achieved. A backpropagation feedforward network is used to model a single-input-single-output (SISO) system in the series-parallel approach and an external recurrent network resulting from the parallel identification of a feedforward network for an SISO system. [9]

2.1.4. Model Validation

Second part of data set is used for validation of the model. After application of input signal generated output from process and model are compared here. If the comparison is good then we can replace process by its equivalent model in control process.[9]

III. NONLINEAR PROCESS CONTROL

The main task of this work is to design a neural network controller which keeps the system stabilized. To control the nonlinear system use different approaches, such as: Model Predictive Control (MPC), Global Linearizing Feedback (GLF), and Generic Model Control (GMC).In this Model Predictive Control (MPC) is selected. In Model Predictive Control (MPC), model is used as a reference for controlling the plant.[9]

3.1. Model Predictive Control

The concept of model predictive control (MPC), in which a model is used as a reference for controlling the plant Fig.3.shows a block diagram of model predictive control represented in the Internal Model Control (IMC) structure allows the plant/model mismatch to be considered explicitly in the control problem formulation [4],[5].

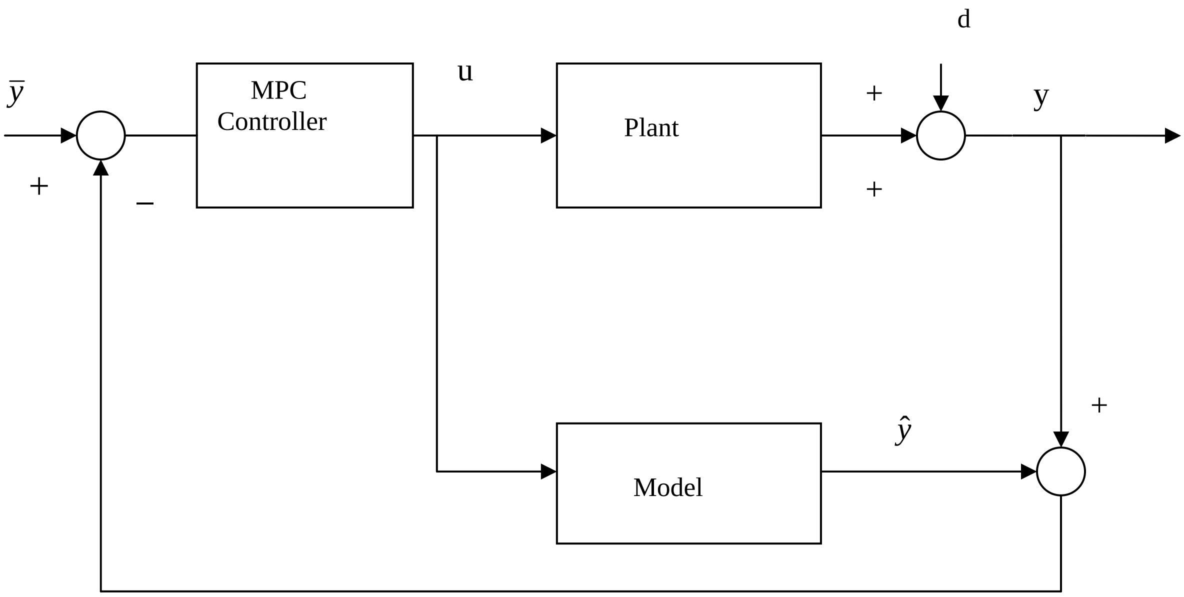


Figure 3. The MPC Controller in an IMC Structure

3.1.1. Model Predictive Control approach

In Fig.4.illustrates the basic idea is that a set of M control moves is calculated at every control interval so as to minimize an objective function defining the performance criterion over a prediction horizon (P steps into the future), and the first control move is implemented.

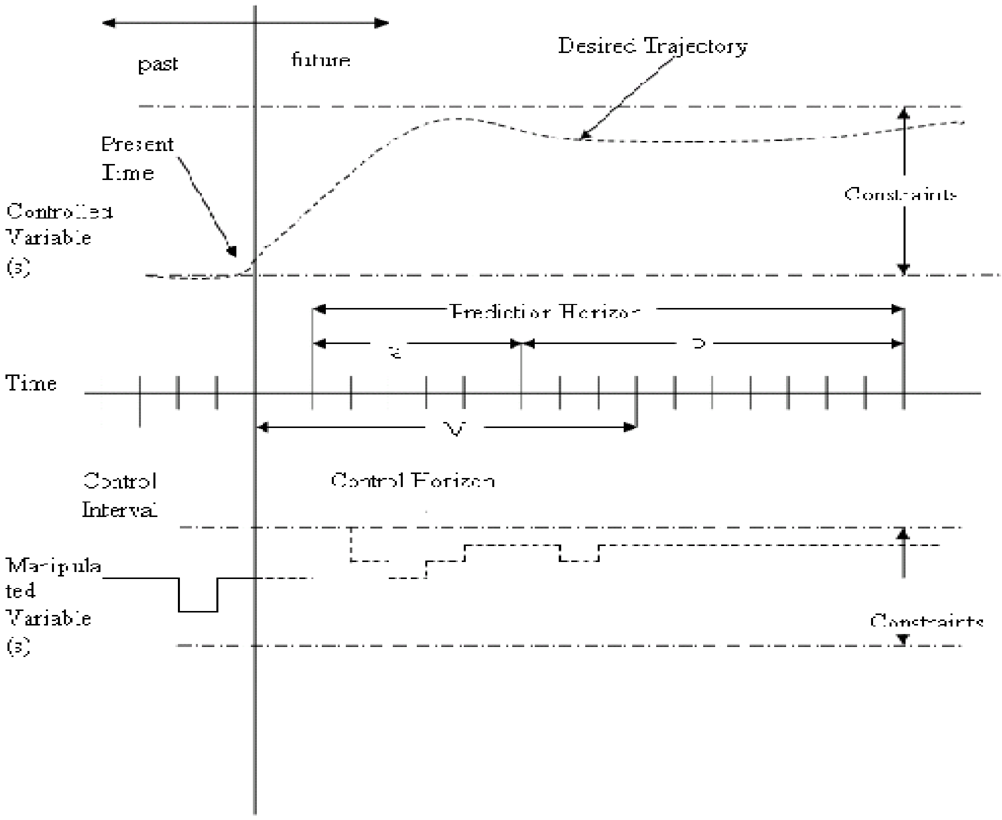


Figure 4. Model Predictive Control Approach

3.1.2. Model Predictive Control Formulation

In Nonlinear MPC is formulated using nonlinear programming (NLP) techniques.

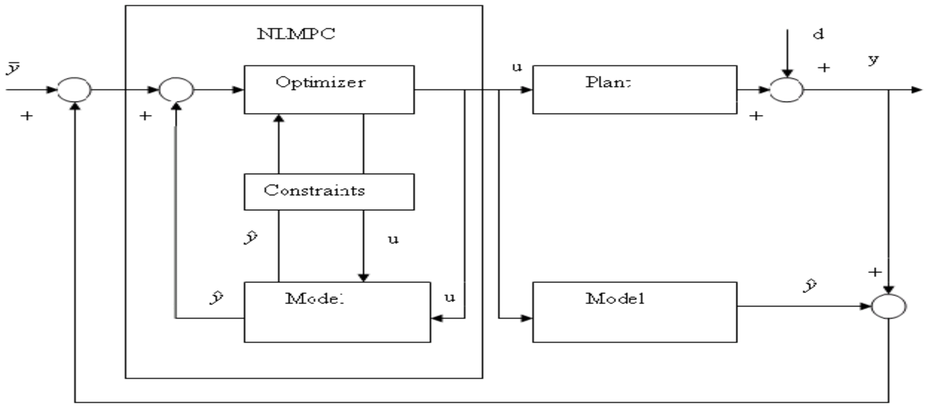


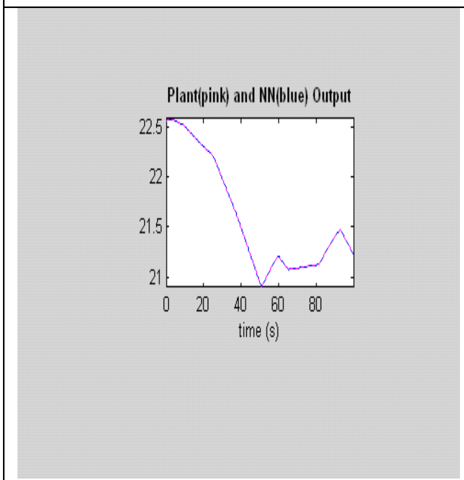
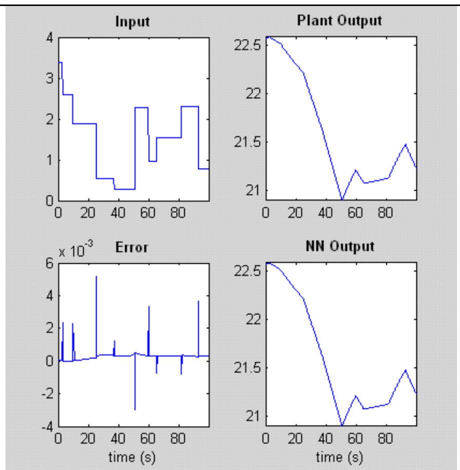
Figure 5. Structure of NLMPC Controller

Fig.5. illustrates a general IMC structure for an NLMPC algorithm. The various NLMPC algorithms differ in the way that the nonlinear model with constraints is solved.

IV. Simulation Results

1.1. Model Validation

TABLE 1. Size of Hidden Layer=7, Sampling interval=0.2, Training Samples=2000

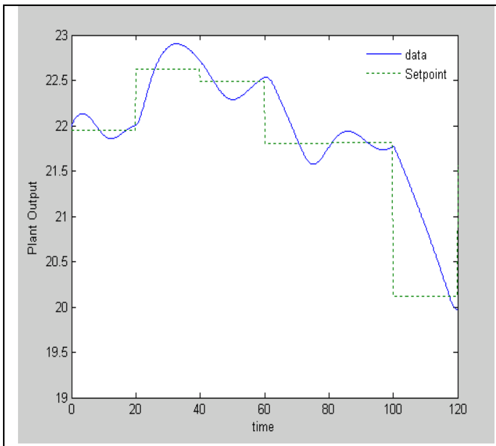
Comparison of Plant Output and NN Output	Validation data
	

Data set divided into two parts training and testing. Second part of data set is used for validation of the model. After application of input signal generated output from process and model are compared here. If the comparison is good then we can replace process by its equivalent model in control process.

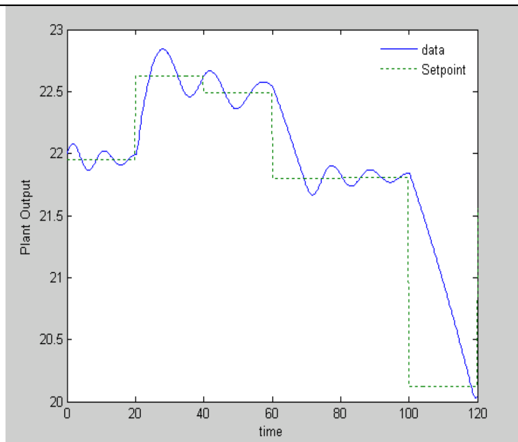
1.2 Nonlinear Process Control

TABLE 2.Different Prediction and Control Horizon and same Sample time

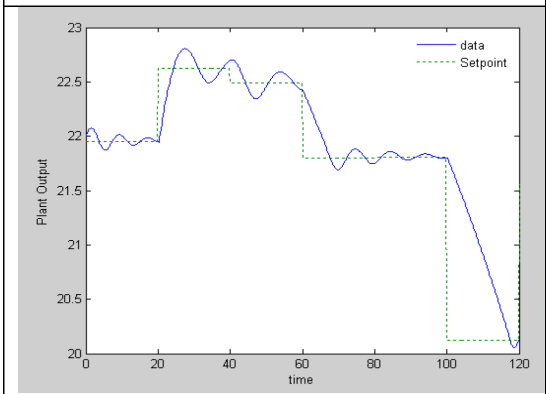
Prediction Horizon=2,Control Horizon=2,Sample time=20	Prediction Horizon=3,Control Horizon=2,Sample time=20



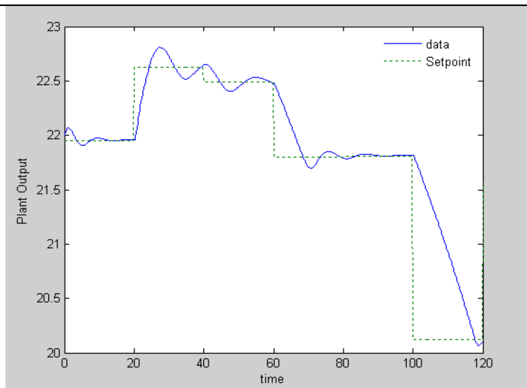
Prediction Horizon=4,Control Horizon=2,Sample time=20



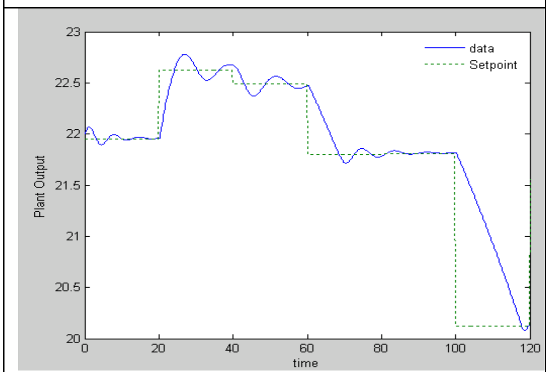
Prediction Horizon=4,Control Horizon=3,Sample time=20



Prediction Horizon=5,Control Horizon=2,Sample time=20



Prediction Horizon=5,Control Horizon=3,Sample time=20



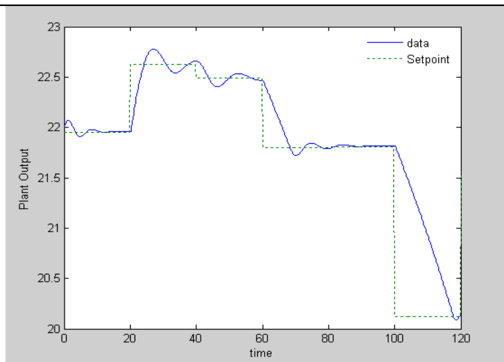
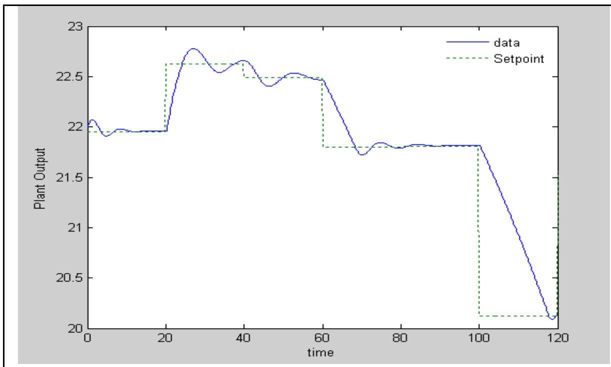
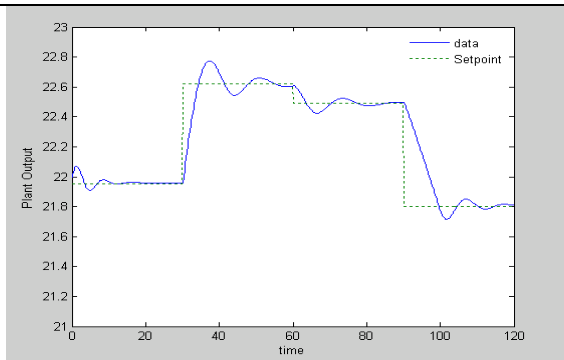


Table 3.Same Prediction and Control Horizon and Different sample time

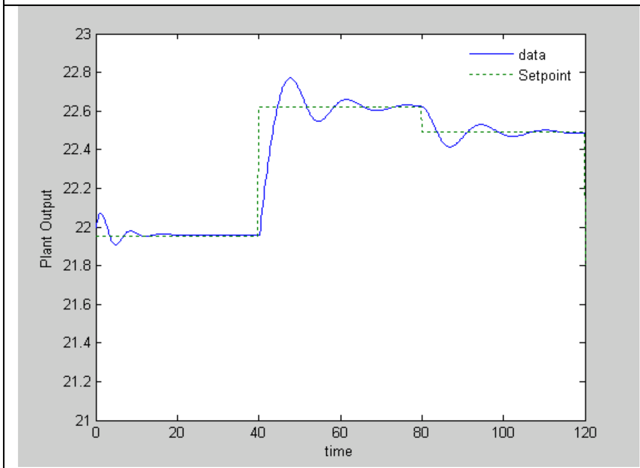
Prediction Horizon=5,Control Horizon=3, Sample time=20	Prediction Horizon=5,ControlHorizon=3, Sample time=30

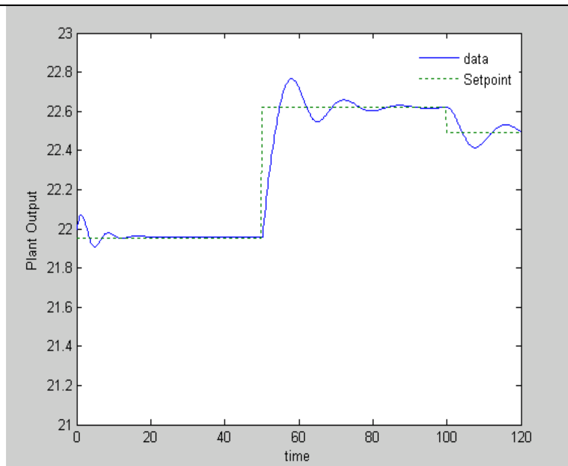


Prediction Horizon=5,Control Horizon=3, Sample time=40



Prediction Horizon=5,Control Horizon=3, Sample time=50





In Nonlinear Model Predictive Control, trained data are available from nonlinear process identification and used to control the nonlinear system for different prediction, control horizon and sample time.

V. Conclusion

In this paper we discussed about introduction to neural networks and their use for nonlinear identification and control. Neural networks have been used in a number of process control applications including: nonlinear predictive control, for dynamic modelling in nonlinear. This paper has explored in depth the use of multilayer perceptron networks for dynamic modelling and control. Neural networks hold great promise as process modelling tools. They are well matched to the modelling requirements of the process industries. Neural networks can be used to develop models from data. Initial results on their use in control systems have shown neural networks to be very robust to modelling errors. Once a process model is available then it can be used in many ways to improve process operation.

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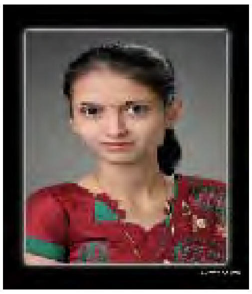

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