A REAL -TIME TEMPERATURE CONTROL OF PLATE HEAT EXCHANGER BY ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The aim of present study is to maintain an optimal temperature of plate type heat exchanger. Controlling outlet fluid temperature is main purpose of using heat exchanger where it can transfer heat from a hot fluid to a cold fluid. A model of plate type heat exchanger has been identified using the step response from experimental data. It is obtained as first order system with transport delay with process parameters as Process gain =110 ⁰C/ (kg/min) and Time constant = 54 min and delay = 0.33min. In the present study a neural network based Model predictive controller(NNMPC) is designed for controlling temperature of the system. The simulation work is carried out with MATLAB and SIMULINK. The performance of NNMPC controller of the heat exchanger system is then compared with a conventional PID controller. The NNMPC is found to be faster without oscillations in comparison with conventional PID controller.

Keywords: *System identification, NN based Model predictive controller, plate heat exchanger, first order transport delay*

1.INTRODUCTION

Heat exchangers are important components in process lines in the liquid food industry. In heat treatment processes such as pasteurization and sterilization temperature control loops are often used with heat exchangers to maintain an accurate and stable temperature. In the case of food heating e.g. cream pasteurization, the temperature is a critical control parameter[1].During the last few decades plate heat exchangers has been an essential equipment in process dairy and other industries. extremely high rates of heat transfer, compactness, flexibility in design and operation, ease of cleaning and low liquid hold up are some of the advantages of plate heat exchanger[2] Most simulations of heat exchangers and other components of thermal systems have concentrated on their steady-state behaviors for heat rate predictions which are required for system design. The dynamic response of these devices, however, is also very important if these devices are to be controlled in any way[3]. Dynamic predictions are, of course, harder and it was not until recently that dynamical models started to appear in the literature [4-6].Most of them, in order to make the problem more tractable, rely on assumptions and simplifications that are not totally realistic[7-9].Artificial neural networks (ANNs) have been used in recent years to avoid the problems associated with deterministic approaches, and have been shown to approximate nonlinear functions up to any desired level of accuracy[10]. They are also less sensitive to noise and incomplete information than other approaches such as empirical models and correlations[3].Aminia[11]stated that plate heat exchanger weighs 95% less than comparable conventional shell and tube exchangers and provide 1000–1500 square meters of heat transfer per cubic meters of exchanger volume. Due to the importance of the plate heat exchangers, many researchers have investigated the modeling and the optimum design parameters for the system. Dynamic neural networks are good at modeling of nonlinear systems. Sen M [12] applied neural networks to predict the dynamic behavior and steady state of the heat exchangers. They established that using dynamic neural networks for modeling thermal process offer a reliable and fast way of prediction of their performance and the models can be updated continuously [10]. In the present study a first order with transport delay dynamic model has been developed performing a system identification method and used as model in SIMULINK closed loop shown in Section 3

2.IDENTIFICATION OF A PLATE HEAT EXCHANGER SYSTEM

The mathematical model of the plate heat exchanger is obtained from an "OPEN LOOP" experiment performed on the system. The controller is set into the manual mode and a step change either positive or negative is given to the Process. In the present experimental setup, the controlled variable is the "Process Fluid Temperature". The manipulated variable is "Steam flow rate" to plate heat exchanger. The manipulated variable is changed by the flow control valve. This operates in terms of percentage of opening. Three sets of experiments are carried out with different step changes in the present case to obtain the model of system. The Flow control valve which is steam valve initially set to 10% opening, this corresponds to steam flow rate of 0.2kgs/minute (i.e., plant input) and 35ºC of process fluid temperature (i.e., plant output). This indicates the initial steady state of plate heat exchanger system. At this steady state a positive change of 30% valve opening is given to the process by placing the controller in manual mode. The system reaches follows exponential response and reaches new steady state to a temperature of 92ºC. The plant input (i.e., steam flow rate) is oscillatory around average value of 0.45kg/min. Similarly. step change of 40% and 50% opening of valve are conducted. The time constant, process gain and dead time are determined using Cohen-Coon (CC) method. Thus, the transfer function model for the Plate Heat Exchanger system is obtained as

$$G_{\text{Plate Heat Exchanger}} = \frac{T(S)}{m(S)} = \frac{110}{54s+1}e^{-0.33s}$$

where, T(s)= Outlet Temperature of cold water, M(s)= Steam flow rate

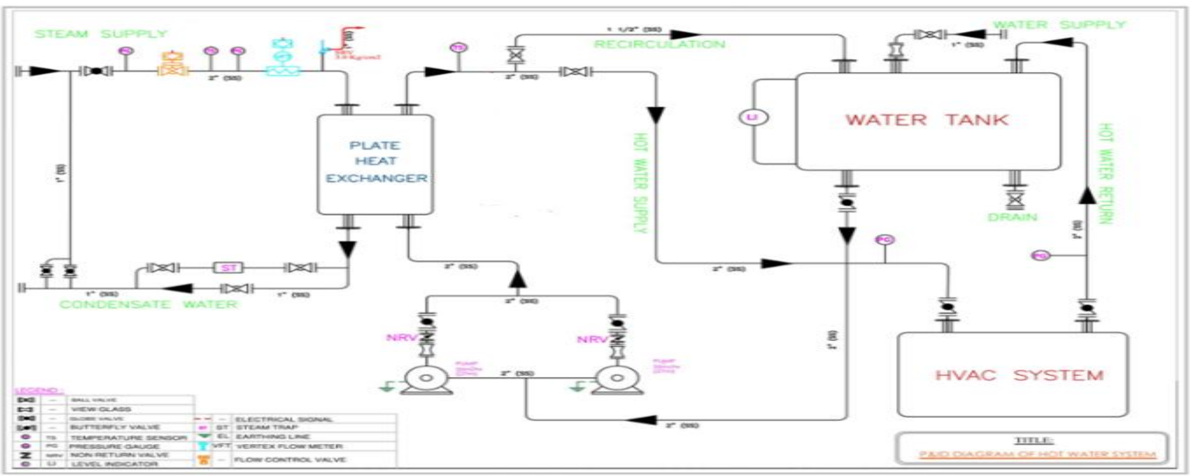

Fig. 1.Schematic diagram of Plate Heat Exchanger system

3.DESIGN OF A NEURAL NETWORKS BASED MODEL PREDICTIVE CONTROLLER

Artificial Neural networks controller design, involves mainly two steps: 1).System Identification, 2). Controller design In the system identification step, the neural network plant model has is developed using random input and output data. In the control design, here the neural network plant model is used to design the controller.

The neural network architecture shown in is Fig. 2 and optimum size of neurons in hidden layers is equal to 16. Fig. 3 gives NN based model predictive controller parameters. It shows cost origin of 50 and control origin of 20.

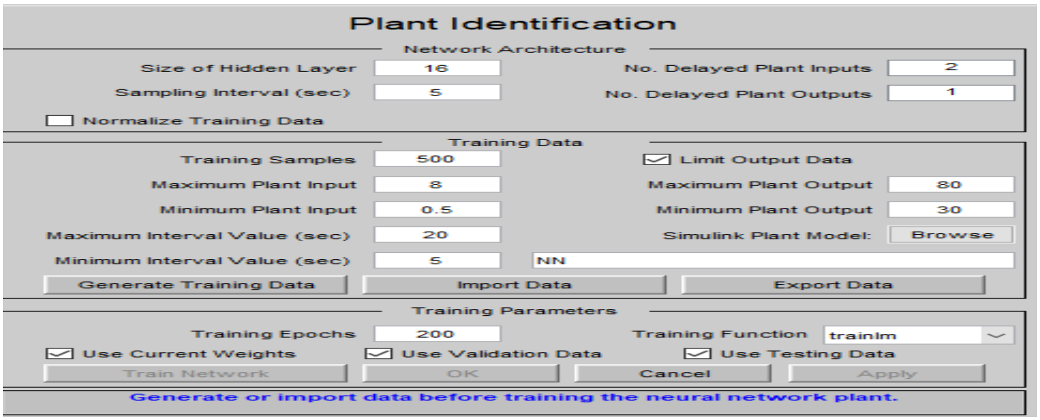

Fig. 2.Plant Identification block

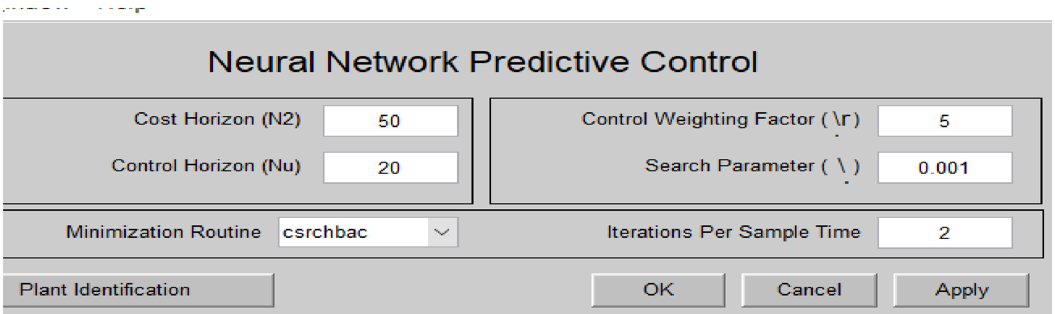

Fig. 3. Design Parameters of Neural Network based Model Predictive control

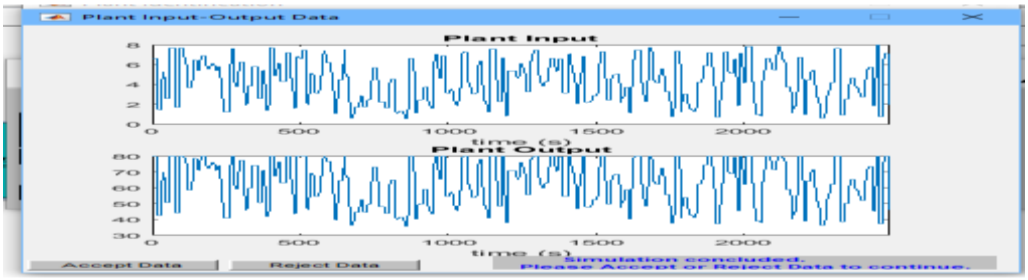

Fig. 4.Plant input and output data

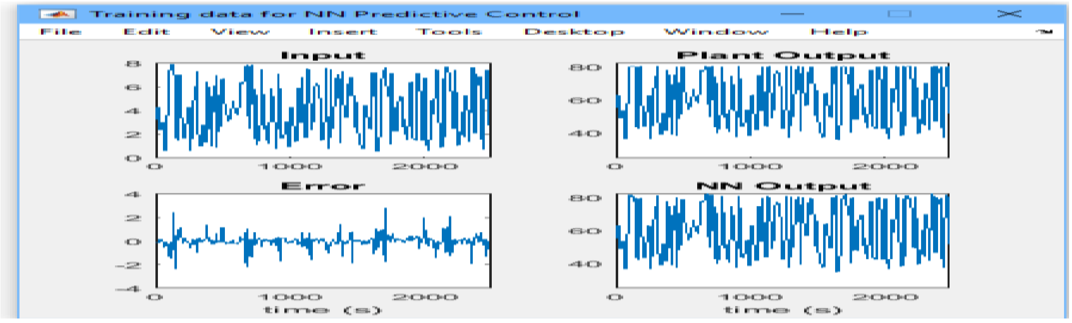

Fig. 5.Training data of NN Based Model Predictive Controller

4.RESULTS AND DISCUSSION

The closed loop simulation diagrams for PID and NNPC are shown in Fig. 6.

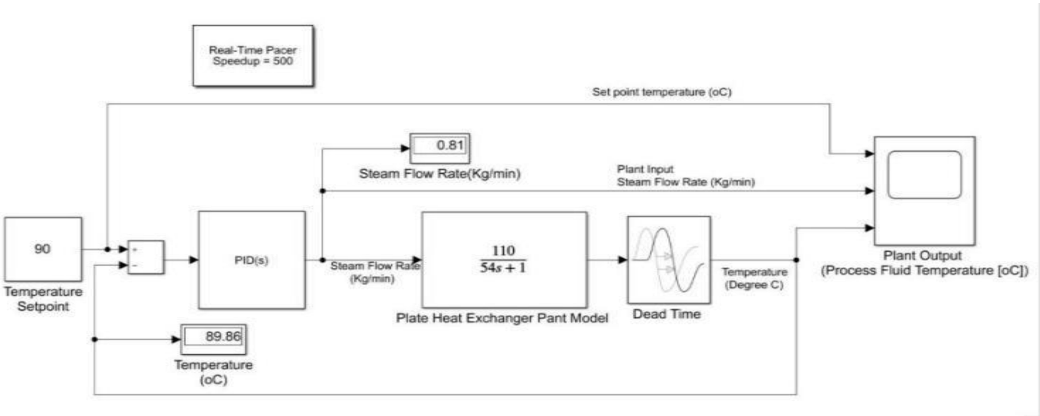

Fig. 6.Closed loop simulink diagram of PID Controller

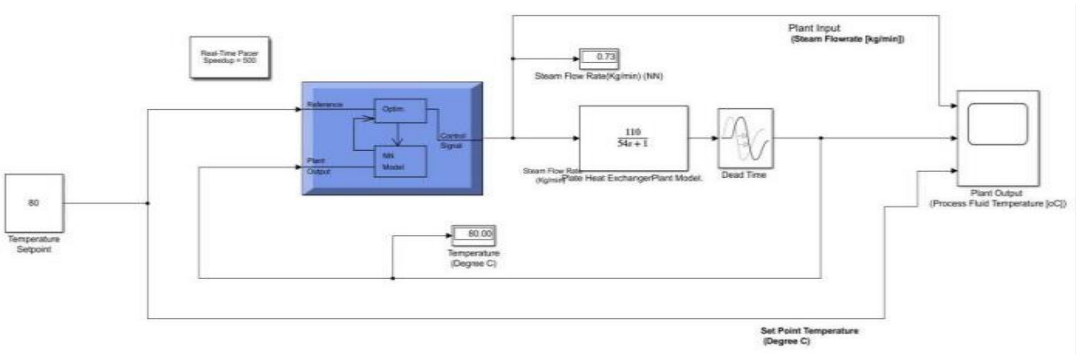

Fig. 7. Closed loop simulink diagram of Neural Networks based Model Predictive Controller

The closed loop response of the Artificial Neural networks Model predictive controller are shown in Fig. 8 for a set point of 80^{o}C. Here, NN controller shows faster response and without overshoot, whereas PID shows slower response with overshoot.

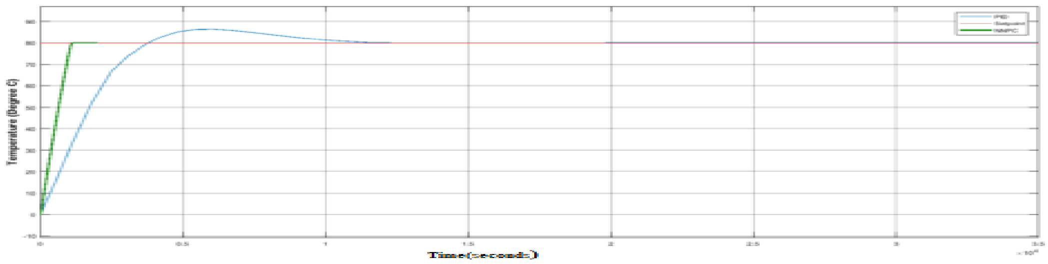

Fig. 8.Closed loop response in temperature of plate heat exchanger with NN based Predictive Controller and PID Controller

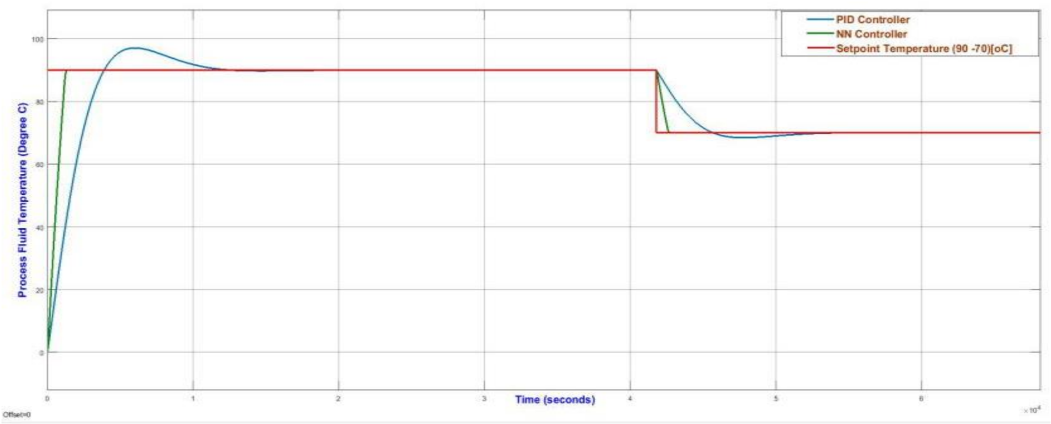

Fig. 9.Closed loop responses in Temperature of plate heat exchanger with NN Based Predictive Controller & PID controller for a negative step change of 90-70ºC in set point

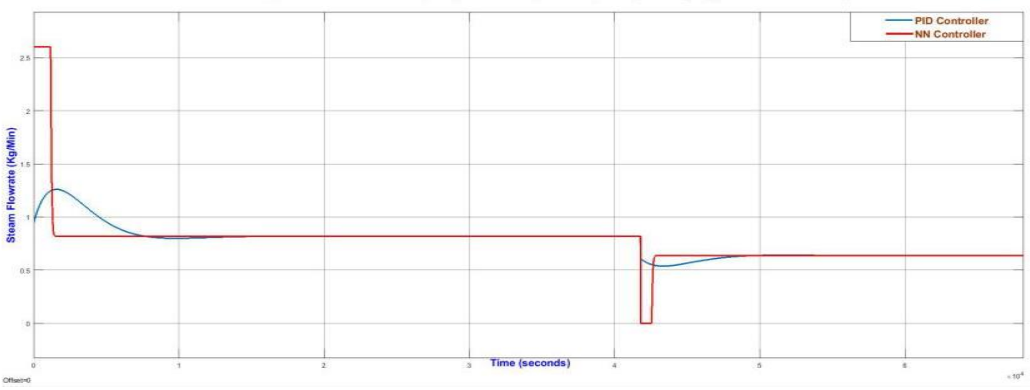

Fig. 10. Manipulated variable in steam flow rate versus time of NN based Predictive Controller and PID for the responses in Fig. 9

The closed loop response of NN based MPC controller and PID controller for a decrease in set point from 90-70 C is shown in Fig. 9. As expected, The NN based MPC gives superior performance. Fig. 10 gives manipulation in steam flow rate for the responses of Fig. 9.

5. CONCLUSIONS

The first part of present study includes identification of plate heat exchanger system using experimental data and ait is model as first order with time delay model using Cohen - Coon technique. The identified model of the process is used in the design of Artificial neural networks based Model predictive controller. Based on the closed loop simulation studies of advanced Neural Network based Predictive control of plate heat exchanger, it is concluded that the controller performance of Neural Network Predictive controller is found to be superior with faster and without overshoot than conventional PID controller for a set point change. Here, the data based Neural Networks Predictive controller is found to follow closely the dynamics of the Plate Heat Exchanger process.

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