Advanced Materials Research Vols. 984-985 (2014) pp 1326-1334
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doi:10.4028/www.scientific.net/AMR.984-985.1326

Neural Network Predictive Controller based Nonlinearity Identification Case study: Nonlinear Process Reactor - CSTR

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I. KEYWORDS

Continuous Stirred Tank Reactor, Multi Input Multi Output, Neural Networks, Chebyshev Neural Networks, Predictive Controller.

II. ABSTRACT

In the last decades, a substantial amount of research has been carried out on identification of nonlinear processes. Dynamical systems can be better represented by nonlinear models, which illustrate the global behavior of the nonlinear process reactor over the entire range. CSTR is highly nonlinear chemical reactor. A compact and resourceful model which approximates both linear and nonlinear component of the process is of highly demand. Process modeling is an essential constituent in the growth of sophisticated model-based process control systems. Driven by the contemporary economical needs, developments in process design point out that deliberate operation requires better models. The neural network predictive controller is very efficient to identify complex nonlinear systems with no complete model information. Closed loop method is preferred because it is sensitive to disturbances, no need identify the transfer function model of an unstable system. In this paper identification nonlinearities for a nonlinear process reactor CSTR is approached using neural network predictive controller.

III. INTRODUCTION

Several information exists for explaining the nonlinear performance of processes such as CSTRs, distillation columns, evaporators and biotechnological processes. Nonlinearity behavior in the process control reactor occurs from various parameters such as temperature dependence of reaction rates [1]. It may also result from process limitations such as valve limits, leading to input saturation (i.e., flow rate manipulation) or from physical constraints on output variables (e.g., mole fractions of chemical species) [2], [3]. Optimization and control of process systems usually requires a precise process model [4]. Essential first principles models can be difficult to build up if the original process is not well understood [5]. The resulting fundamental models have numerous unknown parameters and severe complexity[7]. As existing nonlinear chemical processes are persistently faced with the requirements of becoming safer, more consistent, and more economical in operation, the need for a rigorous, yet practical, approach for the design of effective chemical process control systems that can meet these demands becomes increasingly evident [8]. However, the control design problem is highly non insignificant because most chemical processes are essentially Multi-Input Multi-Output (MIMO) and nonlinear, and the use of controllers only designed on the basis of the approximate linearized process can direct to traditional, besides reduced, control performances[6]. In addition, the unavoidable presences of physical constraints on the process variables and in the capacity of control actuators not only limit the nominal performance of the controlled system, but also can influence the stability of the overall system [10]. Process nonlinearity is the most dominant issue in system

identification problems which will be used to identify the model for a system from measured input/output data, without having the basic knowledge about the physical laws governing the controlling the system [9], [11].

IV. CSTR SYSTEM DESCRIPTION

The Continuous stirred Tank Reactor (CSTR) having a wide application in process control industries. The detailed diagram of CSTR is presented in the Fig.1. The nonlinear process control reactor (Continuous Stirred Tank Reactor) is taken for NN predictive controlled based nonlinearity identification problem.

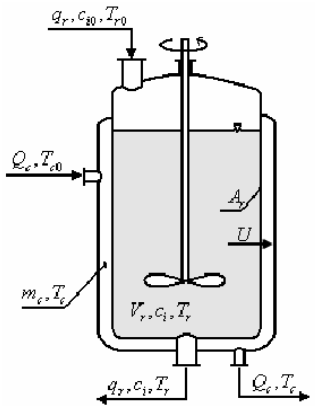


Fig.1 Schematic Diagram of the CSTR

In order to reduce the heat created in the CSTR, a cooling jacket has been used which will be carrying out the Vander Vusse reaction scheme described by the following reactions:

$$A \xrightarrow{k1} B \xrightarrow{k2} C \quad (1)$$

$$2A \xrightarrow{k3} D \quad (2)$$

Here B is the required product,
C and D are the undesired byproducts
k_1, k_2 and k_3 are considered as the reaction rate constants.

In this reactor, a product A is to be transformed to the desired product B by an exothermic reaction in CSTR, but the product B is again degraded to product C. In addition to this successive reaction, a high order parallel reaction occurs and A is converted to by product D. The mathematical modeling of this non linear process control reactor is explained as the four set of Ordinary Differential Equations (ODE) is derived from material and heat balances inside the reactor.

$$\frac{dC_A}{dt} = \frac{q_r}{V_r}(C_{A0} - C_A) - k_1 C_A - k_3 C_A^2 \quad (3)$$

$$\frac{dC_B}{dt} = -\frac{q_r}{V_r} C_B + k_1 C_A - k_2 C_B \quad (4)$$

$$\frac{dT_r}{dt} = \frac{q_r}{V_r}(T_{r0} - T_r) - \frac{h_r}{\rho_r c_{pr}} + \frac{A_r U}{V_r \rho_r c_{pr}}(T_c - T_r) \quad (5)$$

$$\frac{dT_c}{dt} = \frac{1}{m_c c_{pc}}(Q_c + A_r U(T_r - T_c)) \quad (6)$$

Where $C_A \geq 0$, $C_B \geq 0$

In the differential equations, t denotes time, c denotes concentrations, T denotes temperatures, c_p represents the specific heat capacities, q represents the volumetric flow rate, Q_c represents the heat removal, V represents the volumes, ρ represents the densities, A_r is the heat exchange surface and U represents the heat transfer coefficient. Indexes $(.)_A$ and $(.)_B$ represents the compounds A and B, $(.)_r$ given for the reactant mixture, $(.)_c$ denotes the cooling liquid and $(.)_0$ denotes the feed (inlet) values. The mathematical modeling of the nonlinear process control reactor has been derives by considering the four states namely concentrations of the product A (C_A) and the concentration of the product B (C_B), temperature of the reactor T and the temperature of the coolant T_c.
The model of the reactor describes the nonlinear process control reactor. Nonlinearity calculated in reaction rates (k_j) which are described via Arrhenius law:

$$k_j(T_r) = k_{0j}.\exp\left(\frac{-E_j}{RT_r}\right), for\ j = 1,2,3 \quad (7)$$

Where k_0 denotes the pre-exponential factors and E denotes the activation energies.
The reaction heat (h_r) in the equation (2) is expressed as:

$$h_r = h_1k_1c_A + h_2k_2c_B + h_3k_3c_A^2 \quad (8)$$

Where h_j means reaction enthalpies.

Table 1: PARAMETERS OF THE REACTOR

$k_{01} = 2.145 \cdot 10^{10}$ min^{-1}	$k_{02} = 2.145 \cdot 10^{10}$ min^{-1}	$k_{03} = 1.5072 \cdot 10^{8}$ min^{-1}mol^{-1}
$E_1/R = 9758.3$ K	$E_2/R = 9758.3$ K	$E_3/R = 8560$ K
$h_1 = -4200$ kJ.kmol^{-1}	$h_2 = 11000$ kJ.kmol^{-1}	$h_3 = 41850$ kJ.kmol^{-1}
$V_r = 0.01$ m^3	$\rho_r = 934.2$ kg.m^{-3}	$c_{pr} = 3.01$ kJ.kg^{-1}.K^{-1}
$U = 67.2$ kJ.min^{-1}m^{-2}K^{-1}	$c_{pc} = 2.0$ kJ.kg^{-1}.K^{-1}	$A_r = 0.215$ m^2
$c_{A0} = 5.1$ kmol.m^{-3}	$T_{r0} = 387.05$ K	$U = 67.2$ kJ.min^{-1}m^{-2}K^{-1}
$m_c = 5$ kg	$c_{B0} = 0$ kmol.m^{-3}	

This reaction describes the nonlinear chemical reaction, under ultimate environment, of an inflow of substance A to a product B. a heat exchanger with coolant flow has been used for controlling the heat created inside the reactor due to chemical reaction. In order to make easier the problem, some of the assumptions has been considered:

- The mixing of the liquid has been carried out ideally.
- The density and the physical properties are assumed to be constant.
- The tank liquid level h is assumed as constant and water flows in the input and output are considered as equal: Q1 = Q2.
- The first order reaction with a temperature relation was carried out based on the Arrhenius law.
- The work in the shaft was neglected.
- The temperature increase in the coolant on the coil was neglected.

In the CSTR, it is considered that the reaction has been carried out in the two chemicals to produce a product compound A with the concentration $C_A(t)$, with the reactor temperature T(t). The heat created by the exothermic reaction slows down the reaction. A coolant is used with coolant flow-rate $Q_c(t)$, the temperature is to be reduced which will control the concentration of the product. C_A denotes the concentration of the inlet feed, Q denotes the process flow-rate, T represented the temperature of the inlet feed and T_C denotes the temperature of the coolant, all of which are understood as constant at nominal values.

V. SYSTEM IDENTIFICATION

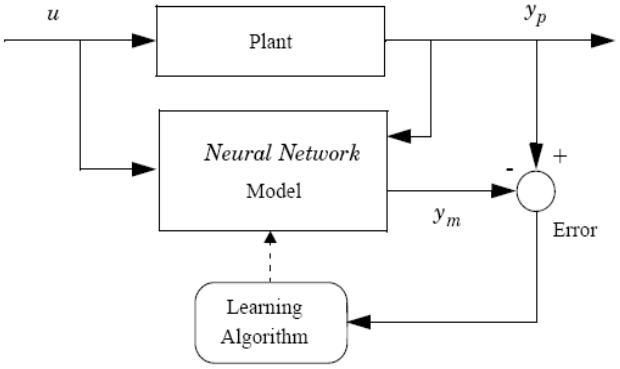


Fig.2 System Identification Block diagram

System identification block diagram is given in Fig. 2. The System identification algorithm is mainly applied for identification of nonlinearities in all engineering fields. The identification algorithm is to be divided into two type's namely non-parametric type model identification and parametric type model identification or online identification and offline method of identification. The three principles of identification algorithm are least square method, the gradient correction procedure and maximum likelihood method. The least square offline parametric identification method was implemented for identification of given nonlinear process control reactor Continuous Stirred Tank Reactor. The real modeling from the data acquisition data for model establishment is quite complex due to the drawback like complexity and diversity of the nonlinear system and its calculation is quite complicated. The System Identification Toolbox in the MATLAB programming can able to make the process easy and simplifies the computation process and increases the identification efficiency.

The first procedure step of the forward dynamics is the training of the neural network, and the future values can be predicted by analyzing the previous input and output of the system. The model structure of the neural network model is specified in the following Fig.3. The training of the network can be carried out in offline (batch mode), with the data collected in the working of the plant. System identification based on MATLAB is highly resourceful. Primarily The computation process is very straightforward and the identification system is direct-viewing and easy to adapt.

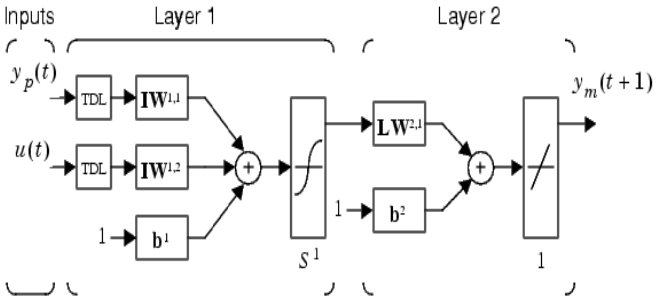


Fig.3 Structure of Neural Network Plant model

The neural network based nonlinear predictive control algorithm having two components, first one is the nonlinear model to identify the behavior of the system, and the second one is the optimization algorithm to generate the control signal in order to minimize the performance function (which is having high influence of the current and predicted errors). In the neuro-predictive control, Levenberg-Marquardt algorithm is used to attain a superior performance which is the second-order derivative-based optimization methods. Using such optimization methods, rather than steepest descent (first order ones), leads to better performance of control system, but the drawback is that it requires much more computation steps in comparison to first-order methods.

VI. NEURAL NETWORK PREDICTIVE CONTROL

Neural networks have been functioning very effectively in the identification and control of dynamic systems. The performance of the nonlinear process control reactor plant model is predicted with the implementation of the neural network predictive controller. In the next step, the controller will calculate the control input which will optimize performance of the plant over a specified time. The identification of the neural network plant model (system identification) is the first step of the predictive controller design. In feedback control, as the most common type of control, the control command is generated using the error which has already occurred, whereas, in predictive control the predicted error is utilized to generate control command to avoid the error before appearing to do so a model (for predict the system's response) and a control algorithm (to generate the control command) are needed.

VII. SIMULATION RESULT

The Proposed neural network predictive controller based nonlinearity identification on the Nonlinear Chemical Reactor CSTR was carried out. The experimental results shows that the NN identification is the appropriate approach for successful nonlinearity identification of CSTRs, because obtained model has best suited to predict the step response of the process. In the architecture of the NN Plant model hidden layers have been constructed. 8000 training samples with the sampling interval of 0.2 was carried in the NN Training stage with control weighting factor ρ as 0.05 and Search Parameter α as 0.001

The Simulation results of Plant Input and Plant Output of CSTR are given in the Fig. 4 and 5, Validation performance result of NN identifier is given in Fig. 6, Training State Result of NN identifier is given in Fig. 7, Training data for NN Predictive Control is given in Fig. 8, Validation data for NN Predictive Control and system response are given in Fig. 9 and 10 respectively..

Algorithm progressed

Training Function = Levenberg Marquardt (trainlm)
Performance = Mean Square Error (mse)
Data Division Specified (divideind)

Progress:

No of Epochs : 7 iterations
Time taken for the Progress: 0:00:00
Gradient : 0.000961
Mu : 0.000100
Validation checks: 6

Simulation results of Plant Input and Plant Output of CSTR:

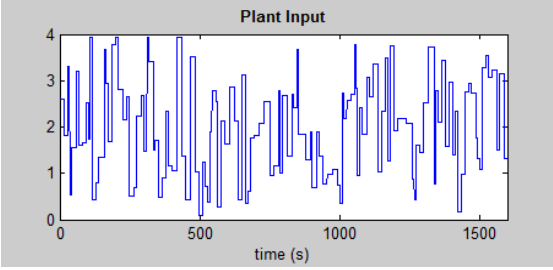


Fig. 4 CSTR Plant Input

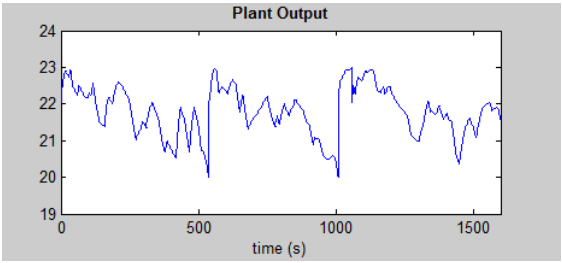


Fig. 5 CSTR Plant Output

Validation performance simulation result:

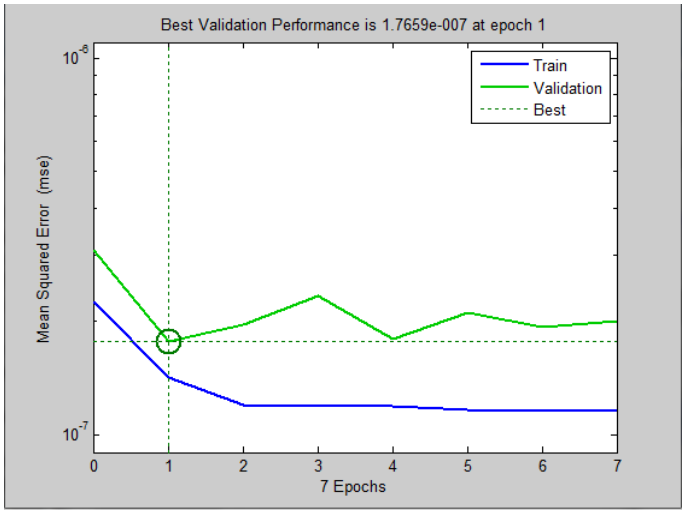


Fig.6 Validation performance of NN identifier

Training State Simulation Result:

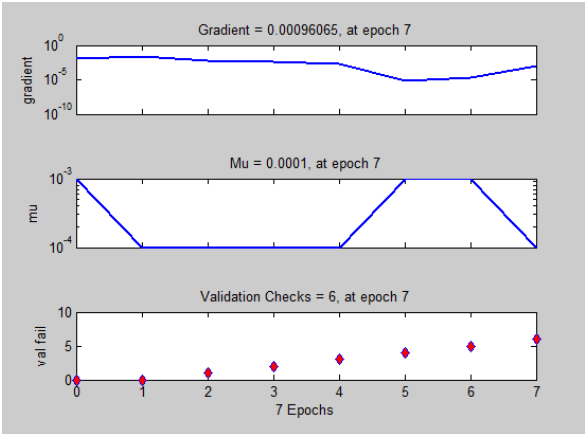
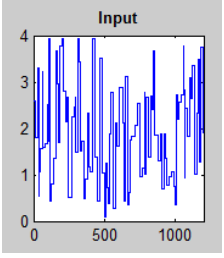
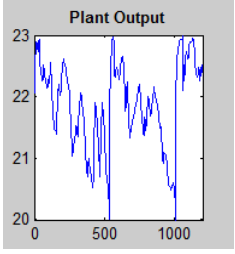


Fig.7 Training state of NN Identifier

Training data for NN Predictive Control





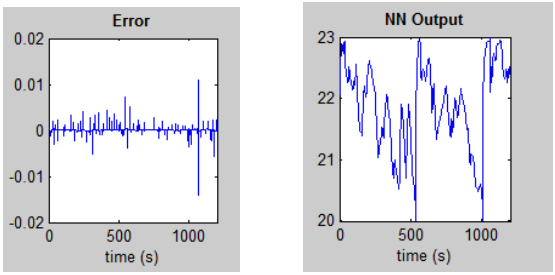


Fig.8 Simulation result of Training data of CSTR with NN predictive Control

Validation data of the NN Predictive Control

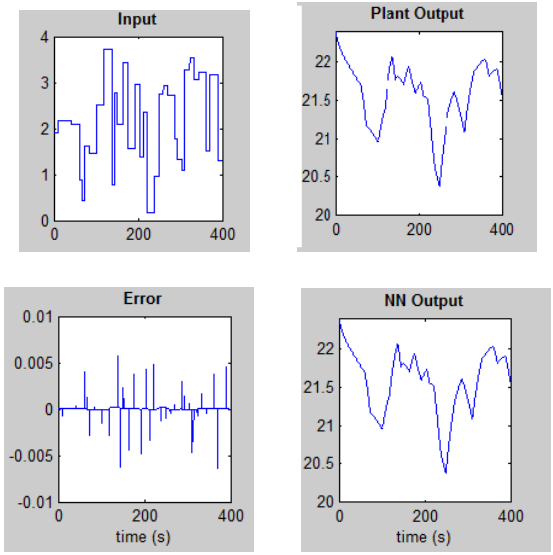


Fig.9 Simulation result of validation data of CSTR with NN predictive Control

System Response:

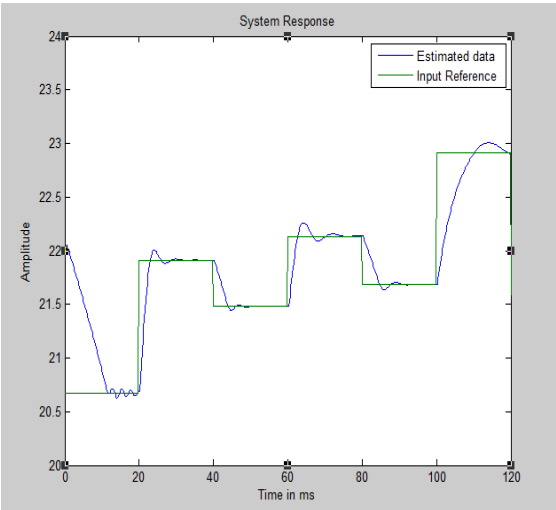


Fig. 10 Nonlinearity Identification of CSTR with NN Predictive Control

VIII. CONCLUSION

In this proposed approach, the neural network predictive controller design is implemented for nonlinear identification of CSTR is presented. It is processed with NN-based system nonlinearity identification method and nonlinear model predictive controllers which has an ability to reject the

disturbances which is slowly varying and unmeasured in nature. The control of nonlinear multivariable processes increases the complexity which creates challenges for researchers. The major importance for controller design to have the best performance of the nonlinear process control reactor system is the difficulty of identifying the mathematical model of the process. In order to solve this issue, the identification approaches have been getting considerable concentration in the present research scenario. In this issue, the neural networks predictive controller is an excellent method to deal with identification problems due to their functional approximation capabilities and the availability of effective learning algorithms. Uses of mathematical models are fundamental for analysis of system behavior including various scientific and engineering applications. A large class of dynamical systems can be given with good approximation by linear models which cannot be reproduced dynamical regimes which will result from system's nonlinear reactions. Nonlinear models will be required to capture these effects and this in turn leads to the complex problem associated which is used to identify the accurate nonlinear models from plant input data. This paper presents the use of chebyshev neural network models (CNN) with Levenberg Marquardt training scheme to identify the process. The performance of the proposed neural network predictive controller based identification approaches is demonstrated on a highly nonlinear time-varying multivariable continuous stirred tank reactor (CSTR) benchmark problem. Simulation results express the fine performances of all identification algorithms.

IX. AUTHORS

Mrs. M.Shyamalagowri received the B.E degree in Electrical and Electronics Engineering from KSR College of Technology, Thiruchengodu in 2001 and M.E., Control Systems from PSG College of Technology, Coimbatore in 2006. She is currently working for Ph.D degree in the area of Control Systems at Anna University of Technology, Coimbatore. Her area of interest is Control Systems, Process Control. She is working as a Associate Professor in EEE Department in the Erode Sengunthar Engineering College having the experience of 11 years 8 months.
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