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FAULT DETECTION AND DIAGNOSIS IN CONTINUOUS STIRRED TANK REACTOR (CSTR)

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***Abstract*—Continuous Stirred Tank Reactor (CSTR) here is considered as a nonlinear process. The CSTR is widely used in many chemical plants. Due to changes in process parameters the accuracy of final product can be reduced. In order to get accurate final product the faults developed in CSTR during the chemical reaction need to be diagnosed. If not, the faults may lead to degrade the performance of the system. For this purpose there are various fault diagnosis methods are to be considered. Among the methods, the neural network predictive controller can be used to detect faults in CSTR. Servo response is performed to understand the behavior of CSTR. By detecting various faults and with suitable control techniques, the accuracy of the desirable products in CSTR can be improved.**

***Index Terms*—Continuous Stirred Tank Reactor, Neural Network Predictive Controller, Fuzzy Logic Controller, Fault detection and estimation.**

I. INTRODUCTION

The Continuous Stirred Tank Reactor (CSTR) system is highly nonlinear, exothermic, irreversible first order process. In CSTR, when the reactants are added into the tank the stirrer will stir the reactants to give desired product. Once the equipment is running, it is usually operated at steady state and designed to achieve well mixing. The CSTR also known as back mix reactor is commonly used as perfect reactor type in chemical engineering. A CSTR is a model which is used to estimate individual operation variables while using a continuous agitated tank reactor in order to obtain the required output. CSTR is widely used in the organic chemicals industry for medium and large scale production. The reactor is widely operated by three control loops that will regulate the outlet temperature and the inlet flow rate of the reactant tank level. During the process the heat will be generated and hence the heat of reaction can be removed by a coolant medium that flows through a jacket around the reactor. During the CSTR process the faults occur which further leads to inaccurate result. A fault is defined as an unexpected change of the system functionality which may be related to a failure in a physical component such as sensor and actuator. In order to detect various types of faults in CSTR the Neural Network Predictive Controller can be applied.

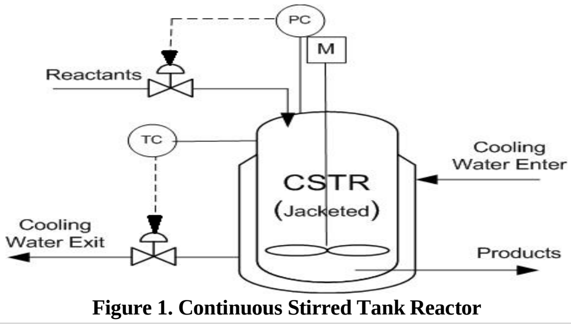

Figure 1. Continuous Stirred Tank Reactor

II. MATHEMATICAL MODELING OF CSTR

A reaction will create new components while simultaneously reducing reactant concentrations. The reaction may give off heat or give required energy to progress the process [2]. Figure 1. shows the CSTR consists of one inlet reactants and one outlet flow rate. In CSTR the outlet concentration is controlled by changing the volumetric flow rate [8]. Figure 2. shows the characteristic of the concentration and volumetric flow rate. Figure 3. shows the servo response of Continuous Stirred Tank Reactor. If the outlet concentration is not equal to the set point then the volumetric flow rate is adjusted in order to make outlet concentration to reach the desired set point.

By the mass balance (typical unit, Kg/s),

The Rate of change of mass in the system=The Rate of mass flow in –Rate of mass flow out

$$\frac{dCa}{dt} = \frac{F}{V}[Cai - Ca] - K_0 e^{-\frac{E}{RT}} Ca$$

$$ra = K_0 e^{-\frac{E}{RT}} \qquad (1)$$

Cai = Inlet reactant concentration in reactor

Ca = Outlet reactant concentration in reactor

F =Inlet feed flow rate

V =Volume of reactor

K_0 =Frequency factor

E =Activation energy

R =Universal gas constant

T =Reactor temperature

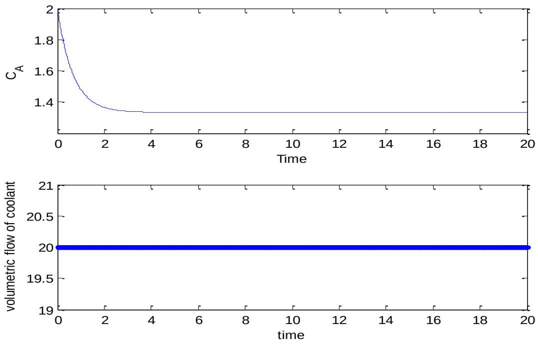

Figure 2. Behavior of Manipulated Variable- Controller Variable in Continuous Stirred Tank Reactor

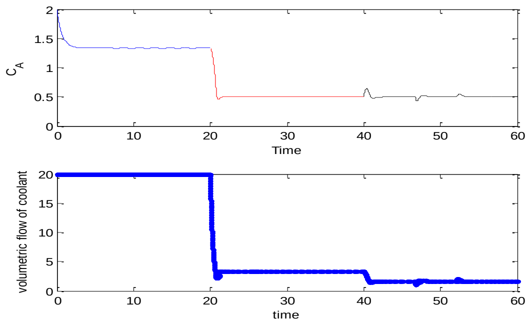

Figure 3. Servo Response of Continuous Stirred Tank Reactor

III. METHOD OF FAULT DIAGNOSIS

The term fault is generally defined as a departure from an acceptance range of an observed variable [6], [7]. Figure 4. shows that the faults developed in the plant diagnosed by the sensor and the sensor value will then be compared with the set point in the comparator. If there is any error in the sensor then the feedback controller generates a signal to the actuator. The actuator signal will be given to the diagnosis system. If any error occurs in the actuator, the diagnosis system will provide an alarm. The fault diagnosis system provides the supervision system with information about the onset, location and severity of the faults. Based on the system inputs and outputs together it will make fault decision information from the fault diagnosis system.

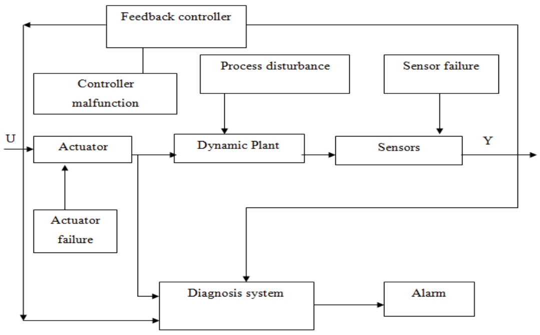

Figure 4. General Components of Fault Diagnosis Framework

FUZZY LOGIC CONTROLLER

Fuzzy logic is an extension of crisp set. A fuzzy logic system is a type of control system that work based on fuzzy logic. The fuzzy logic controller is based on mathematical system that evaluates input values for fuzzy logic system in terms of sensible variables. The logical variables take values in two ways they are continuous and discrete values. If the logical variable uses continuous value which ranges from 0 to 1 in contrast to digital logic and if logical variables for fuzzy logic operate on discrete values which is either 1 or 0 that is true or false respectively. Fuzzy system is useful in any situation in which the measurement depends strongly on the context or human opinion. A fuzzy reasoning algorithm establishes a preliminary fuzzy diagnosis system.

Fuzzy logic controller is commonly used in machine control operations. When the logic involved in fuzzy logic controller can deal with concepts which can be expressed in terms as neither true nor false but considerably as partially true. In such cases the rules are created to deal both with true, partially true, false and partially false. Fuzzy sets mean the input variables. The input variables in a fuzzy operating machine can be obtained by mapping the sets of membership functions. Fuzzificaion means the series of action for converting a crisp value to a fuzzy value.

The fuzzy logic controller uses inaccurate or not precise input and output variables by using membership function. The membership function can be expressed in terms of linguistic variables. In the fuzzy logic controller the if-then rules are used to identify the fault and fault free data. At the same time it provide the symptoms for faulty and fault less data by predefined fuzzy sets. The amount of fault that present is obtained by comparing the rules of reference model and with the rules of fuzzy reference model which is identified by using data obtained from CSTR plant [2],[3]. Here the process historical data is used [7]. The process historical data means data obtained from CSTR plant.

IV. FUZZY DECISION MAKING

The fuzzy logic controller is used for direct integration of the human operator into the fault detection and supervision of CSTR process. Changes in any variable in the process will reduce the accuracy of the final product. It also provides supervision of entire process. In the supervision of the process the alarm will be provided. If any error occurs in the process the alarm will be generated. For this purpose the fuzzy decision making is necessary. In order to avoid any incorrect decision which may cause false alarm then the fuzzy decision making is used to decide whether the fault has occurred and at which place in the process the fault has occurred. The fuzzy decision making is similar to the expert system and supervisory control.

V. FAULT ESTIMATION BY FUZZY LOGIC CONTROLLER

The fuzzy logic system handles the imprecision of input and output variables directly by defining them with memberships and sets that can be expressed in linguistic terms. The fuzzy reference models are made up from if-then rules which describe the symptoms of faulty and fault free of predefined fuzzy reference sets. A particular model is defined by specifying the values of the elements of its associated fuzzy relational array. Each element of the array is a measure of the credibility that the associated rules correctly describes the behavior of the system around the particular operating point. For fault detection and estimation in CSTR using Fuzzy Logic Controller. The fault level in CSTR depends on four variables such as feed flow rate (F_0), outlet reactant concentration (C_{A0}), coolant temperature (T_{C0}) and feed temperature (T_0). These four variables fault level depends on the volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and Jacket temperature (T_C) [5]. Based on these fault range the Fuzzy Logic Controller is developed. The Fuzzy Logic Controller consists of four inputs and four outputs. The membership function is developed for those four inputs and four outputs. The rules are created for these variables. Based on the input fault range the fault level is estimated by using Fuzzy Logic Controller.

The figure.5 shows various inputs to the Fuzzy Inference System such as volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and jacket temperature (T_C) and the fault outputs considered for Fuzzy Inference System are feed flow rate (F_0), outlet reactant concentration (C_{A0}), coolant temperature (T_{C0}) and feed temperature (T_0).

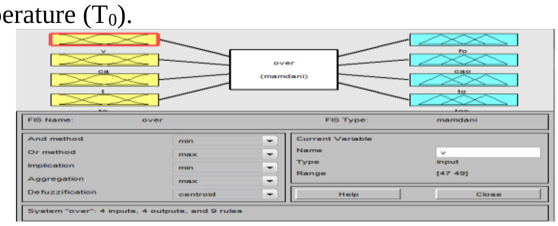

Figure 5. Fuzzy Inference System Editor for overall fault

With the help of Fuzzy Logic Controller, various faults considered are detected and estimated and the results obtained are shown in Table 1

Table 1: Fuzzy Logic Based Fault Estimation in CSTR

INPUT				PERCENTAGE OF FAULT			
$V(ft^3)$	C_A (lbmolA/ft³)	$T(\circ C)$	$T_C(\circ C)$	$F_0(ft^3/h)$	C_{A0} (lbmol/ft³)	$T_0(\circ C)$	$T_{C0}(\circ C)$
49	0.225	610	597	10	10	27.50	42.5
49	0.23	608	594	10	8.01	22.51	34.19
48.5	0.21	606	594	10	7.88	22.20	33.67
48	0.23	602	596	10	8.12	22.80	34.67
48	0.25	607	595	11.93	8.07	22.66	34.44
48.2	0.24	608	597	12.05	7.95	22.37	33.95

Similarly the fault level for individual variable can also be obtained. Figure.6 shows the fault in feed flow rate (F_0) depends on volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and jacket temperature (T_C). After developing the fuzzy logic controller the estimation of fault level in feed flow rate (F_0) can be done is shown in table 2.

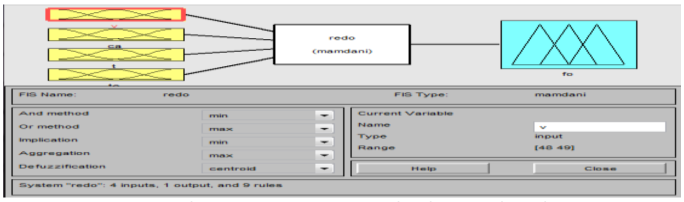

Figure 6. Fuzzy Inference System Editor for fault in feed flow rate (F_0)

Table 2: Fuzzy Logic Based Fault Estimation for Feed Flow Rate

INPUT				PERCENTAGE OF FAULT
$V(ft^3)$	C_A (lbmolA/ft³)	$T(\circ C)$	$T_C(\circ C)$	$F_0(ft^3/h)$
49	0.246	600.9	590.9	12.08
48	0.235	599.6	590.5	7.91
48	0.238	599.5	590.4	8.04
49.5	0.27	606	592	10
47	0.230	598	590	10

Similarly the fault level in outlet reactant concentration (C_{A0}) is based on volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and jacket temperature (T_C) as shown in the figure 7. Table 3 shows the estimation of fault level in outlet reactant concentration (C_{A0}).

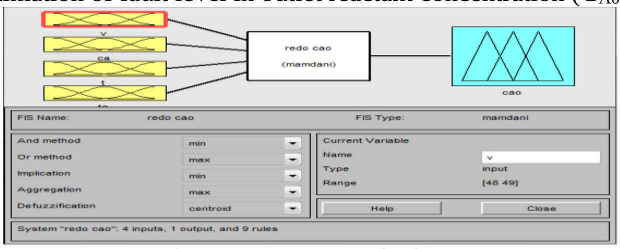

Figure 7. Fuzzy Inference System Editor for fault in outlet reactant concentration (C_{A0})

Table 3: Fuzzy Logic Based Fault Estimation for Outlet Reactant Concentration

INPUT				PERCENTAGE OF FAULT
$V(ft^3)$	C_A (lbmolA/ft³)	$T(\circ C)$	$T_C(\circ C)$	C_{A0} (lbmolA/ft³)
48	0.232	601	590.2	7.97
48	0.23	600	590.0	7.78
49	0.24	602	590.5	10
49.5	0.27	606	592	10

Similarly the fault level in coolant temperature (T_{C0}) depends on volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and jacket temperature (T_C) as shown in the figure.8. After developing the fuzzy logic controller the estimation of fault level in coolant temperature (T_{C0}) can be obtained as shown in table 4.

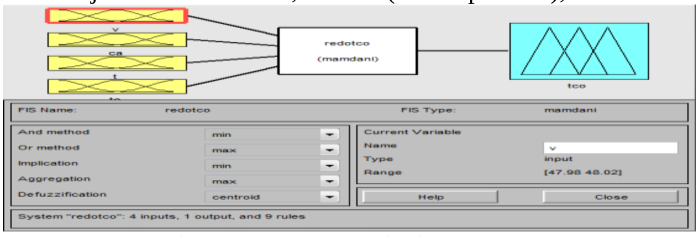

Figure 8. Fuzzy Inference System Editor for fault in coolant temperature (T_{C0})

Table 4: Fuzzy Logic Based Fault Estimation for Coolant Temperature (T_{C0})

INPUT				PERCENTAGE OF FAULT
$V(ft^3)$	C_A (lbmolA/ft³)	$T(\circ C)$	$T_C(\circ C)$	$T_{C0}(\circ C)$
48.02	0.23	610.5	597	51.75
48.01	0.225	610	596.5	51.17
48.005	0.215	609.5	596.4	50.22
47.99	0.19	600	595	42.50

Similarly the fault level in feed temperature (T_0) depends on volume of reactor (V), reactant concentration in the reactor (C_A), reactor temperature (T) and jacket temperature (T_C) as shown in the figure 9. Table 5 shows the estimation of fault level in feed temperature (T_0).

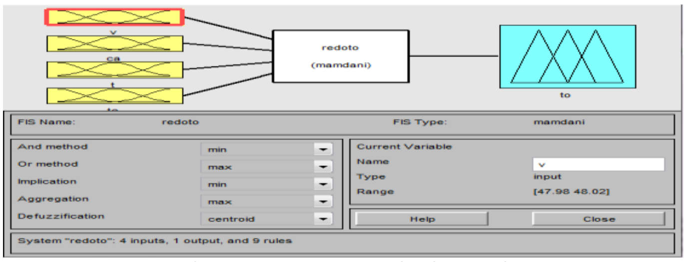

Figure 9. Fuzzy Inference System Editor for fault in feed temperature (T_0)

Table.5 Fuzzy Logic Based Fault Estimation for feed temperature (T_0)

INPUT				PERCENTAGE OF FAULT
$V(ft^3)$	C_A (lbmolA/ft³)	$T(\circ C)$	$T_C(\circ C)$	$T_0(\circ C)$
48.02	0.213	606	592	33.05
48.015	0.213	605	591.5	32.28
47.99	0.19	600	595	27.50

VI. NEURO PREDICTIVE XL SOFTWARE

Prediction means estimate, forecast and predict the future condition for this purpose the neural predictive XL software is used. In Microsoft excel the predictions can be done by a built in tool but the correctness of its results is greatly decreased when non-linear relationship occur or if any missing data are present. Neural networks are a tried, tested and most commonly used technology for most complex prediction operation. It is modeled by considering the human brain. The neural network is joined onto one another networks of separate processors [1], [4]. By changing the connections of these neural networks the finding answer to a problem can be identified. One of the major reasons that the analysts not using these latest methods such as neural networks in order to improve forecasts because the neural network method is very difficult to monitor. Neuro XL Predictor removes the mental process and practical limit by hiding the complicated nature of its latest neural network based methods while taking profit of analysts having present information in mind. Since users make the act of predicting the future through the commonly seen excel point of interaction, it reduces the learning time, greatly decreasing the intervening period between loading the software and performing useful predictions. The application is extremely known automatically and not difficult to use this neuro XL predictor software. In neural predictive XL by the knowledge of previous inputs and outputs it is able to predict what the future output for present input can be identified. In this neural predictive XL the sensor fault input and output data is loaded in the excel sheet by using neural predictive XL software the future output is predicted. Table.6 the fault in the output can be predicted by using neuro predictor XL. In Continuous Stirred Tank Reactor the sensor fault is considered. Neuro predictor XL is a spreadsheet which is used to detect fault in Continuous Stirred Tank Reactor. The sensor fault in CSTR is used [9]. In the sensor fault the flow rate of the liquid at the inlet (F_i), control valve opening (F_{cv}), temperature of the inlet reactant (T_i), control valve opening (L_{cv}), temperature of the tank (T_o), temperature of the outlet coolant (T_{jo}), flow rate of coolant (F_j), liquid level (L) are the variables considered in CSTR. By loading the sensor faults of CSTR in the spread sheet the neuro predictor XL software is used to predict future fault in CSTR. The neuro predictor XL software predict future fault in CSTR by seeing present and past faults in sensor of CSTR. So this neuro predictor XL software is useful for analysts to predict future fault in CSTR. By predicting the future fault the analysts can take some preventive measure to reduce the fault before its effect felt in the process. By doing these measure the final outcome of the process can be maintained.

Table.6 Prediction of Fault in CSTR

PROCESS VARIABLES	INPUT	OUTPUT
F_i (Inlet flow rate)	0.1	0
	0.95	1
	0.1	0
F_{cv} (Control valve opening)	0.5	1
	0	0
	0.5	1
T_i (Temperature of the inlet reactant)	0	0
	1	1
	0	0
L_{cv} (Control valve opening)	0.5	1
	0	0
	0.5	1
T_o (Temperature of the tank)	0	0
	1	1
	0	0
T_{jo} (Temperature of the outlet coolant)	0	0
	1	1
	0	0
F_j (Flow rate of coolant)	0.15	0
	0.8	1
	0.15	0
L (Liquid level)	0	0
	1	1
	0	0.227094

→ Predicted Output

Where,

F_i = Flow rate of liquid at inlet

F_{cv} = Control valve opening

T_i = Temperature of the inlet reactant(ºC)

L_{cv} = Control valve opening

T_o = Temperature of the tank (ºC)

T_{jo} = Temperature of the outlet coolant water (ºC)

F_j = Flow rate of coolant (cm^3/s)

L = Liquid level (cm)

VII. Neural Network Predictive Controller

The Mathematical Model of CSTR for two tank system is

A reaction will create new components while simultaneously reducing reactant concentrations [9]. The reaction may give off heat or give required energy to proceeds the process. Figure 10. shows the CSTR consists of two inlet reactants and one outlet flow rate. The two inlet reactants are W_1 which is inlet flow rate of concentrated feed and W_2 is inlet flow rate of diluted feed [2], [7].

By the mass balance (typical unit, Kg/s),

The Rate of change of mass in the system=The Rate of mass flow in –Rate of mass flow out

$$\frac{dh}{dt} = W_1 + W_2 - W_0 \tag{1}$$

$$W_0 = CV * \sqrt{h} \tag{2}$$

$$\frac{dh}{dt} = W_1 + W_2 - (CV * \sqrt{h}) \tag{3}$$

Where CV =0.2

$$\frac{dh}{dt} = W_1 + W_2 - (0.2 * \sqrt{h}) \tag{4}$$

Where

h =Liquid level (cm)

W_1 =Inlet flow rate of the concentrated feed (cm^3/s)

W_2 =Inlet flow rate of the diluted feed (cm^3/s)

W_0 =Outlet flow rate (cm^3/s)

The concentration of the continuous stirred tank reactor is given in the following equation

$$\frac{dC_b}{dt} = (C_{b1} - C_b)(\frac{W_1}{h}) + (C_{b2} - C_b)(\frac{W_2}{h}) - r_b$$

(5)

Where,

$$r_b = \frac{k_1 C_b}{(1 + k_2 C_b)^2} \tag{6}$$

Where,

C_b =The concentration of product at the output of the process (mol/cm^3)

C_{b1} =Inlet concentration feed (mol/cm^3)

C_{b2} =Outlet concentration feed (mol/cm^3)

W_1 =Inlet flow rate of the concentrated feed (cm^3/s)

W_2 =Outlet flow rate of the diluted feed (cm^3/s)

k_1, k_2 =The constants associate with the rate of consumption

h =Liquid level (cm)

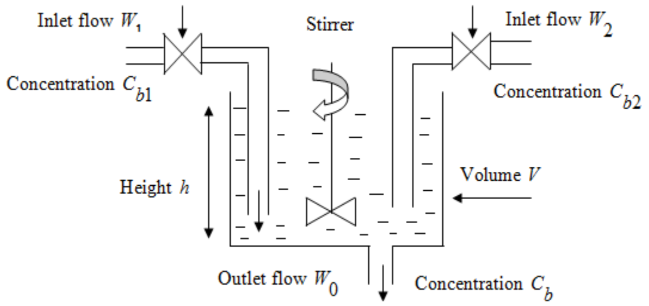

Figure 10.Continuous Stirred Tank Reactor

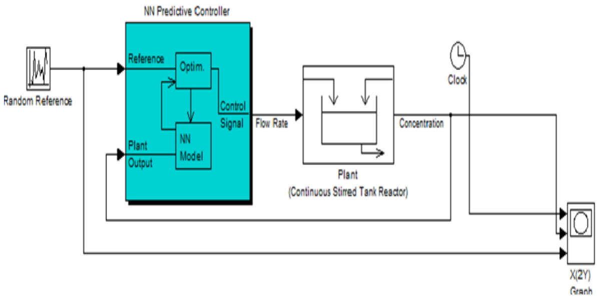

Figure 11. Neural Network Predictive Controller

The neural network predictive controller is a graphical user interface tool as shown in figure 11. From that neural network predictive controller select the plant identification which consists of neural network plant model. The plant model predicts the future plant outputs. The neural network plant model consists of one hidden layer. By generating training data by giving series of random reference signal the plant input and output data will be generated. By using trainlm the plant model training is done from this the training data for NN predictive controller will be obtained as shown in figure 12. and Validation data for NN predictive controller will be generated as shown in figure 13.

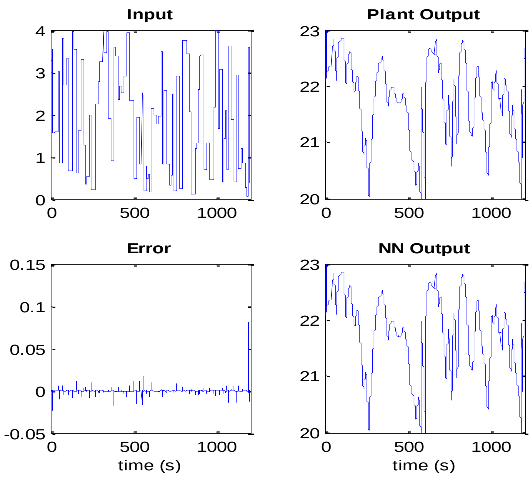

Figure 12. Training Data for NN Predictive Controller

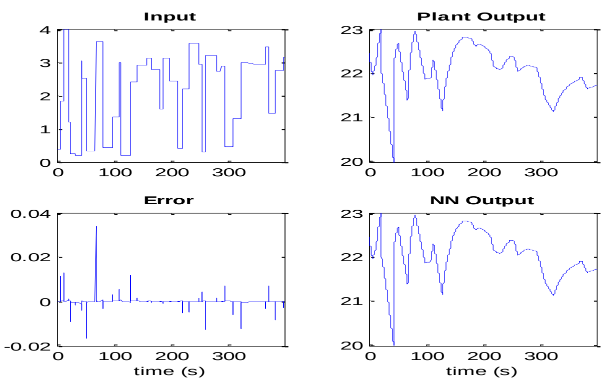

Figure 13. Validation Data for NN Predictive Controller

Figure 14. shows the servo response of CSTR. By using the neural network predictive controller plant model the characteristic of concentration in CSTR is obtained.

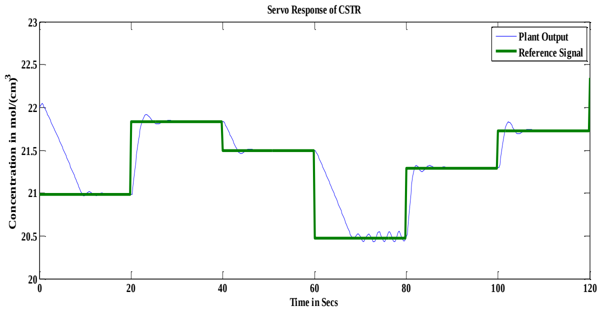

Figure 14. Servo Response of CSTR

VIII. Conclusion and Future Scope

The application of Continuous Stirred Tank Reactor is very essential nowadays. Using material balance condition, the CSTR process is effectively modeled which provides a better understanding of its characteristic behavior of the process. The modeling is effectively verified by its servo response. Various sensor faults considered in CSTR are detected and estimated in percentage by means of using Neural Network Predictive Controller and Fuzzy Logic Controller and found good results. This fault detection and estimation work can be further extended to actuator faults also.

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