Original Research Paper

Fault-Tolerant Control of a Nonlinear Uncertain System: A Neural Network-Based Passive Approaches and Comparative Study with State-of-the-Art Control Approaches

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Abstract: This article suggests passive methods for designing Fault-Tolerant Control (FTC) for nonlinear uncertain systems with actuator and leak faults. To anticipate the Fault-Tolerant Control (FTC) action to overcome the actuator and leak faults, two-layer Feed-Forward Back-Propagation Neural Network (FFBPNN) and two-layer Cascade Forward Neural Network (CFNN) have been used, it will also tolerate external process additive disturbances. We employ the passive approach for fault-tolerant control using Proportional Integral Derivative (PID) control methodology to create a fault-tolerant controller without a fault detection mechanism. Further, we use the four residue signal features (i.e., mean, variance, skewness and normalize data of residue signal) to train the neural network in this study to tackle the issue originating from having less faults and uncertainty from residue signal. To show the efficacy of the suggested approach, simulations are run. The measurement of the residue signal was done using a healthy and a faulty uncertain non-linear system model. A comparison of findings utilizing a state of-the-art control methodology provided in (Dutta *et al*., 2014) was also presented to validate the proposed FTC methodology.

Keywords: Actuator Fault, MIMO Uncertain System, Passive Fault Tolerant Control, Neural Network

Introduction

Fault Tolerant Control (FTC) is a research area for industrial processes that aims to preserve satisfactory control performance and system stability under faulty conditions (Patel and Shah, 2018a). The FTC's major goal is to prevent simple defects from becoming catastrophic failures, increasing system availability and lowering the possibility of a potential hazard (Patel and Shah, 2018a-c; 2019c). For the past three decades, FTC has been the topic of extensive research (Patel and Shah, 2018b; 2019e). Many actual industrial applications have resulted from this research (Bhandare and Kulkarni, 2015; Bonivento *et al*., 2004; Noura *et al*., 2000; Morse and Ossman, 1990). For FTC, there are two primary structured approaches: Active FTC and passive FTC (Patel and Shah, 2018d) Passive FTC has designed a robust controller for the system based on predetermined conditions and magnitude of system faults. On the other hand, in an active FTC approach, Fault Detection and Diagnosis (FDD) is a key component required. FDD has three important functions that begin with the detection of faults in the process, then isolation and

finally identification (Patel and Shah, 2018b; 2019d). The appeal of passive FTC algorithms stems from their inherent capacity to analyze all types of conceivable design flaws. The second major reason is that the operational principles are understood and reasonably simple to explain to practitioners, which appears to be a significant factor in the introduction of a new control scheme in industry.

Many industrial applications and chemical processes require level control processes for a variety of reasons (like liquid material handling, storage, transfer, pack-aging etc.). As a result, a lot of work has gone into controlling the Single Input Single Output (SISO) and Multi Input Multi Output (MIMO) level control processes under various scenarios. Some advanced control algorithms have previously been evaluated on benchmark SISO and MIMO level control processes with various uncertainty (i.e., actuator fault, system component fault, sensor fault and process disturbances) (Patel and Shah, 2019b; 2021a-b; Patel *et al*., 2021).

Failure of sensor and system components is a critical challenge in the control of SISO and MIMO level control processes (Patel and Shah, 2019f). However, a partial

failure of the actuator could result in a dangerous condition, leading to system instability and the loss of control action. This results in a waste of resources such as money, time and even people. As a result, we apply analytical redundancy in terms of advanced control schemes like Passive Fault-Tolerant Controller to improve the system's availability while performing the task in the presence of partial failure or fault in the actuator (PFTC). As a result, FTC is critical in the event of a partial failure of the main actuator. The author of a recent paper (Patel and Shah, 2020) employed a hybrid control system to build a passive FTC algorithm, combining a standard PID controller with a fuzzy logic based controller for SISO and MIMO level control processes with all conceivable faults. Passive FTC algorithms, as mentioned in (Luzar *et al*., 2014; Chen and Mei, 2014), have attained a high level of maturity, particularly for linear systems. However, dealing with nonlinear systems still presents a number of challenges. Modeling of nonlinear processes, state estimation and fault detection or fault tolerant control continue to be problematic (Chen and Mei, 2014; Shen *et al*., 2017).

Many passive FTC approaches for SISO/MIMO level control systems have been developed to date, including PID + type 1 fuzzy logic control, PID + type-2 fuzzy logic control, fractional order PID + type-1 fuzzy logic control and fractional order PID + type-2 fuzzy logic control (Patel and Shah, 2019a; Raval *et al*., 2021a-b). Without a question, neural net-works are the most widely utilized models. They are exceedingly adaptable, universal and willingly employed in situations when a precise mathematical model of the process is unavailable (Chen and Mei, 2014). Although neural network-based control is not a novel paradigm (Luzar *et al*., 2014; Chen and Mei, 2014; Patel and Shah, 2019a), however, we employed FFBPNN to develop PFTC and examined the performance of the MIMO uncertain level control system under partial actuator defect and additive process disturbances.

The following are the primary contributions of our paper. (1) There is no failure detection method in the fault-tolerant controller. (2) We create a healthy and faulty model for generating the residue signal in the MIMO level control process. (3) Determine four parameters to examine the residue signal (i.e., mean, variance, skewness and normalized data of residue signal). We train the FFBPNN and CFNN with this four-parameter data, which produces the controller output as an output signal. (4) The external disturbances are presumed to be unknown in a real application. These uncertainties are taken care by PFTC.

The following is a synopsis of the paper's structure. Following the introduction, Section II describes the MIMO uncertain level control process for which the fault tolerant control system was developed. The Passive FTC architecture combining FFBPNN and CFNN is then proposed in Section III. Section IV shows and discusses the simulation results as well as the implementation of the proposed strategy, moreover the proposed FTC using NN compared with existing FTC using LQR (Dutta *et al*., 2014). Conclusions and future scope are presented in the final section.

Uncertain MIMO Level Control System Model

Uncertain MIMO Level Control System

The benchmark Two-Tank Level Control System (TTLCS) is seen in Fig. 1. It comprises of two cylindrical water tanks, one sump tank, a pneumatic control valve and an electric pump. Figure 1 depicts the system. The system's controlled variable is the tank's height, h_1 and the manipulated variable is the control valve CV's inlet flow control. A tank, a storage vessel and a control valve with a positioner, a pump and transducers to measure process variables are all part of the system. The tank is designed as a horizontally placed cylinder, which brings significant nonlinearity into the system's static characteristic. Matlab/Simulink software was used to create the level control system laboratory stand. Real data from the physical installation was used to successfully verify the simulation model. Table 1 gives a detailed overview of the process variables. Acronyms CV_1, h_1, h_2, q_1 stand for actuator/final control element, tank 1 height, tank 2 height and inlet flow rate respectively. The simulator has an advantage over real processes in that it allows you to test the behavior of the pro-posed advanced control in the presence of potentially erroneous circumstances. Table 2 lists the defects and their descriptions. Problems in various aspects of the installation, such as actuator and component (leak) faults, are proposed. Figure 1 shows the location of the faults. As a result of the proposed set of faults, it is possible to study the suggested Passive FTC scheme's fault tolerance features in the probable faults.

The one defect considered in this study is an actuator error, in which the final control element does not deliver enough regulated variable inlet flow rate (f_2), resulting in a significant reduction in control performance. The second fault is consider in system component which is tank bottom leak fault represent situations where the tank level reducing drastically by additional outlet flow rate (f_1) and control valve not coup the faulty situation and hence control performance is degraded.

The system parameter uncertainty p_u consider in the two-tank level control system in terms of mathematical modeling inaccuracy, the variation of time constant τ parameter from 0 to +/- 10% and system gain k variation of 0 to +/- 10%. Also one fault consider in this study which is partial actuator failure in which the final control element is not provide sufficient amount of manipulated variable inlet flow rate (q_1) hence control performance is degraded drastically.
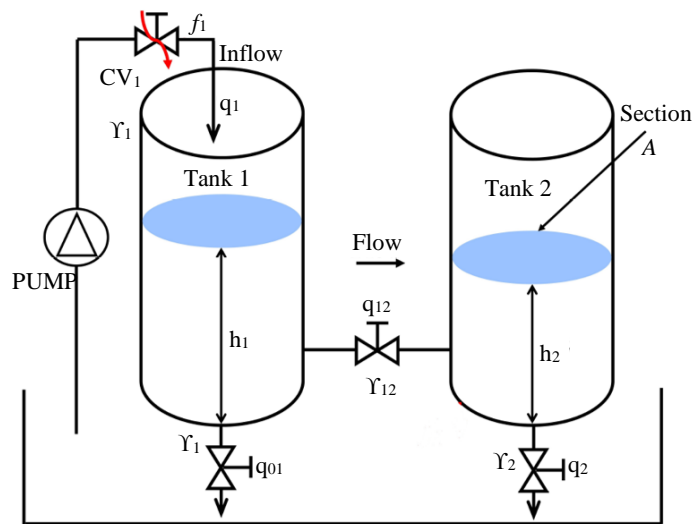
Fig. 1: Graphic illustration of the benchmark two-tank level process Raval *et al.* (2021a)

Table 1: Conditions of process variables Raval *et al.* (2021a)

Variable	Specification	Range
A_1 and A_2	Area of tank 1 and tank 2	0.0270 m^2
q_1	Inlet flow rate	0.000162 m^3/sec
γ_1	Discharge coefficient of tank 1	6.3795
γ_2	Discharge coefficient of tank 2	1.614
γ_{12}	Discharge coefficient of coupling valve	4.372

Table 2: Provisions of faulty circumstances in the benchmark two-tank level process

Faulty	Description	Type	Nature	Size/Unit
f_2	Actuator faulty in CV$_1$	Multiplicative	Abrupt	0-40%
f_1	Leak faulty in Tank 2	Additive	Abrupt	0-40%
d	Process disturbances	Additive	Abrupt	0-40%

Two-Tank Level Control System Mathematical Modeling

The Mass-Balance Equation and the Bernoulli Equation are used to model the TTLCS mathematically. In any event, the liquid input, liquid exit and tank interaction can all be used to represent the rate of change in the volume of liquid present within the tank (Patel and Shah, 2018c). Numerically:

$$A_1 \frac{dh_1}{dt} = q_1 - q_{o1} - q_{12} \tag{1}$$

$$A_2 \frac{dh_2}{dt} = q_{12} - q_2 \tag{2}$$

According to Bernoulli's Equation, the flow rates (Patel and Shah, 2018c) q_{01}, q_{12} and q_2 are given by,

$$q_{o1} = \gamma_1 \sqrt{h_1} \tag{3}$$

$$q_2 = \gamma_2 \sqrt{h_2} \tag{4}$$

$$q_{12} = \gamma_{12} \sqrt{h_1 - h_2} \tag{5}$$

Table 1 shows the operational parameters and system parameters for a bench-mark two-tank level control system.

Proposed Methodology for Passive FTC

Data generation layer, pre-processing layer, training layer and control output prediction layer are the four steps of the proposed approach for Passive Fault Tolerant Control (PFTC). Figure 2 depicts the proposed methodology, which is further detailed in the subsections. The operations in the proposed approach are divided into four stages: (1) Data creation, which creates residue signals from healthy and flawed TTLCS models. The second stage is pre-processing of the data generated in the first stage (data generating layer). In this step, four statistical data are created, including mean, variance, skewness and normalized

data and it is the indirect features parameters of the defective circumstances in the system.

The suggested PFTC scheme's third stage involves training the neural network, which can be done with data generated during the second (pre-processing) data stage. The fourth and final stage is critical for incorporating all uncertainties into the TTLCS process while maintaining stable control performance.

Data Generation Layer

The residue (r) signal verses manipulated variable/control valve opening signal data for this study is acquired in the data generation layer.

Data was generated using contextual information such as a faulty TTLCS model-2 and a healthy mathematical model-1 of the TTLCS uncertain level control system, as well as a faulty TTLCS model-2 and a healthy mathematical TTLCS model-1 of the uncertain level control system. Consider intermittent actuator (f_a) fault, system component (f_{sys}) fault, additive process disturbances (d) and system parameter uncertainty (p_u) ware for data production in faulty TTLCS level control model-2. In (Raval *et al.*, 2021a) presents a mathematical model of a TTLCS process that includes and excludes fault. The data generation system is depicted in Fig. 3 as a conceptual diagram.

For the purpose of data creation, fault magnitude is considered (+/- 0 to 40%) and system uncertainty is considered (+/- 0 to 10%). Total 10000 data ware generated for distinct residual signals from the data production layer, with appropriate various 10000 vales generated for manipulated variable/control output signals in distinct 10 simulations. This data can be used for feed data for next level/layer (pre-processing layer). The data ware generated for the different four uncertainties into TTLCS two faults, one process disturbances and system modeling.

Pre-Processing Layer

In this layer, data has been pre-processed in order to make it smooth for further pro-cessing. Different smoothing filter can be used for this purpose, such as moving aver-age, loess, lowess, Rloess, Rlowess, Savitsky-Golay and so forth. In this study, we have used the moving average method which is a very significant data smoothing filter used by various authors (Fayaz and Kim, 2018) for data smoothing. Equation (6) is the mathematical representation of moving average filter:

$$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} X(i+j) \tag{6}$$

In this equation, *x* [] is the input, *y* [] is the output and M is the number of points used in the moving average. In the pre-processing layer, first, we have calculated the statistical moments and concatenated with original data. The data-set comprises four parameters as input; mean (P_1),

variance (P_2), skewness (P_3) and normalized (P_4) and one parameter as output; namely control output/manipulated variable signal (M_1). The statistical moments, namely mean, variance, skewness and normalized (Fayaz and Kim, 2018) can be calculated using Eq. (7-10):

$$\mu = \frac{1}{n} \sum_{i=1}^{n} x_i \tag{7}$$

$$\sigma = \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2 \tag{8}$$

$$S = \frac{1}{n} \sum_{i=1}^{n} \frac{(x_j - \mu)^3}{\sigma} \tag{9}$$

$$x_{new} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{10}$$

where, μ, σ, S, x_{new} represent, respectively. P_i represents values of arithmetic mean of the data (P_1), standard deviation of the data (P_2), skewness of the data (P_3) and normalized data (P_4) of residue signal (r). Values, $i = 1,2$ to 4, x_{new} represent the output normalized value, x indicate the current value, x_{min} represents the minimum value in the set and x_{max} indicates maximum value (Fayaz and Kim, 2018). (M_1) denotes the additional control NN output which used for FTC control action apart from conventional PID control under faulty situations.

Training Layer

One of the most commonly used ANN models for regression is ANN. NNs are now being used by researchers to analyze various types of regression problems in a variety of circumstances. The Feed Forward Back-Propagation Neural Network (FFBPNN) and Cascade Feedback Neural Network (CFNN) are the ANN models used in the proposed work, as illustrated in Fig. 4 with original, normalized data and data with statistical moments. Normalized data and statistical moment's data are fed into the neural network as inputs. As indicated in the accompanying figures, we employed one parameter as inputs: Arithmetic mean of residue signal data (P_1), standard deviation of data (P_2), skewness of data (P_3), normalized data (P_4) and one output control valve opening/manipulated variable (M_1). A prominent artificial neural network model for estimation and prediction is the ANN model combined with the error propagation algorithm (FFBPNN) (Gonzalez and Zamarreno, 2005). In most cases, it contains three layers: An input layer, a hidden layer and an output layer.
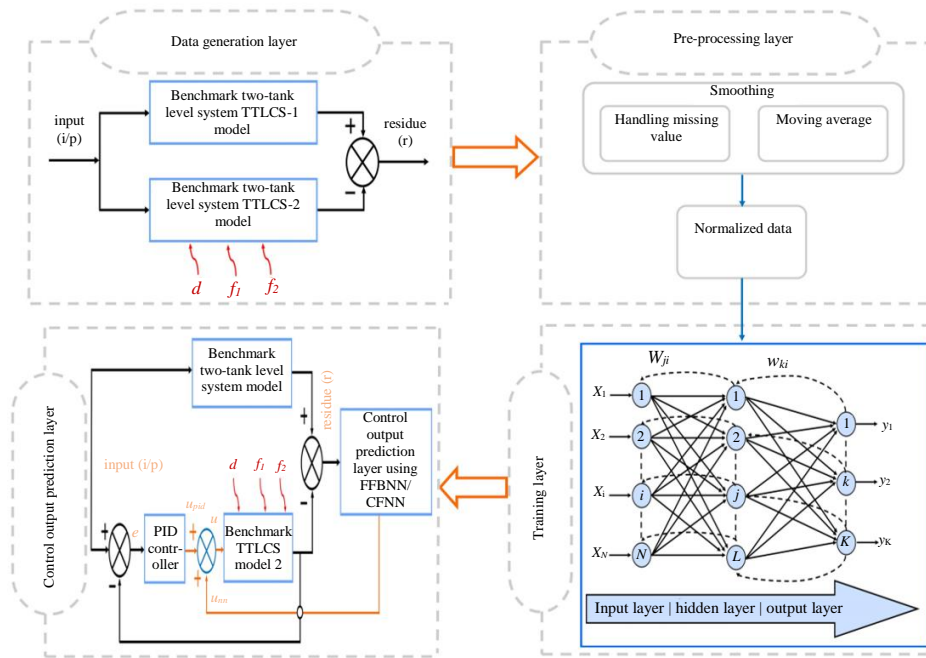
Fig. 2: Suggested approach for PFTC Raval *et al.* (2021b)
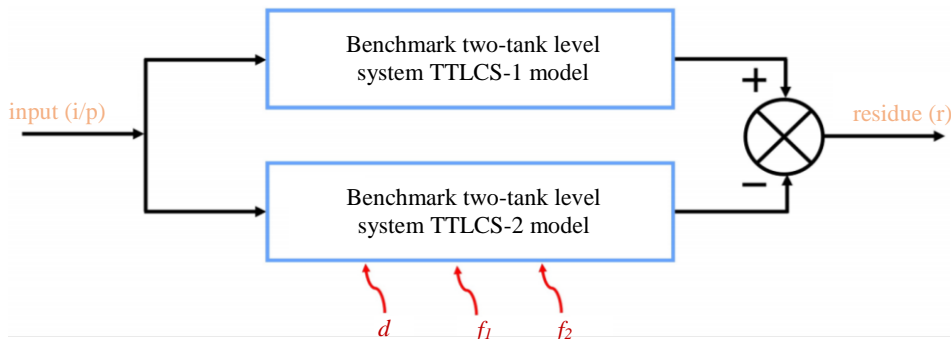
Fig. 3: Data generation system for two-tank uncertain level control system model Raval *et al.* (2021b)
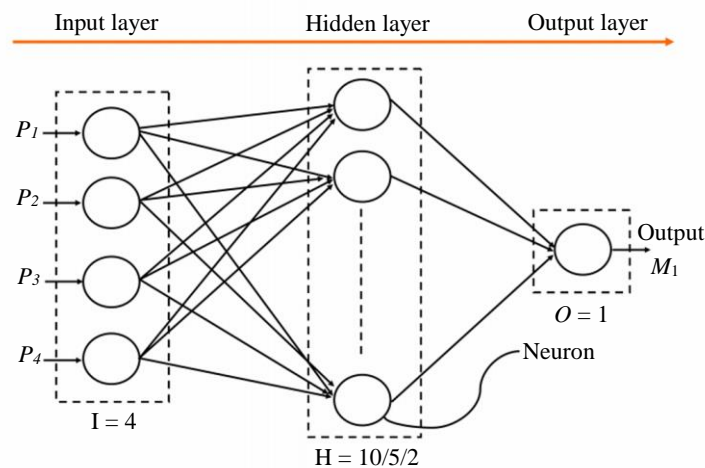
Fig. 4: Structure of ANN model for four inputs Raval *et al.* (2021b)

The following are the detailed mathematical formulations of the artificial neural network, which were extracted from Reference (Gibbs *et al.*, 2006). The following Eq. (11) can be used to compute the hidden layer value:

$$\vartheta_j = \left(1 + \exp\left(-1 \times \sum_{i=1}^{n} x_i w_i\right)\right)^{-1} \tag{11}$$

where, ϑ_j represents node j in the hidden layer, x_j represents node I the input layer and the weight between nodes are represented by w_{ij}. The output layer node value can be calculated by (12):

$$y = \left(1 + \exp\left(-1 \times \sum_{j=1}^{j} x_i w_{ij}\right)\right)^{-1} \tag{12}$$

where, y represents the output layer node (In this research, we have taken only one output node, multiple nodes can be used). Error E between observed and computed data can be calculated as (13):

$$Error(E) = 0.5(d - y)^2 \tag{13}$$

where, d represents the observed data propagation from the output layer and a hidden layer that is represented in Eq. (14) and (15) respectively:

$$\delta_y = (d - y)(1 - y) \tag{14}$$

$$\delta_y = \vartheta_j (d - \vartheta_j)(1 - y)\delta_y w_{j1}, j = 1,......J \tag{15}$$

The following values (16-17) can be used to change the weights of the hidden and output layers, as well as the input and hidden layer:

$$\Delta w_{ij} = \alpha\delta_y\vartheta_j, i = 1,......,I, j = 1,......,J \tag{16}$$

$$\Delta w_{ij}^{n} = \alpha\delta_y\vartheta_j, j = 1,......,J \tag{17}$$

where, α represents learning rate, additionally momentum can be measured using Eq. (18) and (19):

$$\Delta w_{ij}^{n} = \alpha\delta_y\vartheta_j + \beta\Delta w_{j1}^{n-1}, j = 1,......,J \tag{18}$$

$$\Delta w_{ij}^{n} = \alpha\delta_y\vartheta_j + \beta\Delta w_{j1}^{n-1}, i = 1,......,I, j = 1,......,J \tag{19}$$

where, n indicates iterations of error back-propagation; and β represents momentum constant. The training process in the flat region of the error surface and avoids fluctuations in the weights are accelerated by using this momentum method. Different types of activation functions can be employed in different layers of ANN, such as linear, tan-sigmoid, logarithmic sigmoid, sigmoid and so on. We employed the tan-sigmoid function in the hidden layer and a linear function in the out-put layer in the suggested study. The tan-sigmoid function is chosen in the hidden layer because it is the most appropriate activation function and its performance is deemed superior than that of other activation functions. Similarly, we employed the linear function on the output layer because we were dealing with a regression situation and wanted to employ a linear function. Equations (20) and (21) represent the linear and sigmoid functions numerically, respectively (Geem and Roper, 2009):

$$X(x) = linear(x) \tag{20}$$

$$\phi(x) = \frac{2}{\left(1 + 2e^{-2x}\right)} - 1 \tag{21}$$

Implementation and Results

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Implementation Setup

All of the proposed approach's implementations were carried out on an Intel Core i5 PC running Windows 7 with MATLAB R2010a version 7.10.0.499. In most cases, input features are critical to the success of any machine learning algorithm. As a result, the arithmetic mean of the data (P_1), standard deviation of the data (P_2), skewness of the data (P_3) and normalized data (P_4) were given as inputs to the feed forward back propagation with the error correcting neural network in this study. Because the FFBPNN is a supervised machine learning technique, it's best to divide the data into precise training and testing ratios. We separated the data into distinct training and testing ratios since we were predicting control output for distinct failure situations in a TTLCS uncertain level control system in this study. Equations (22) and (23) can be used to separate the data into training and testing categories:

$$T_s = P_k \times 600 \tag{22}$$

$$T_r = M_k - T_s \tag{23}$$

where, T_s, T_r, M_k represent testing data, training data, total number of running simulation data (complete data set) respectively and P_k represents single rune simulation base data. In the proposed work the k values are 1, 2, 3...10.

Possible variations of neurons in the hidden layer with input and output layers were tested and the best-suited combination of some neurons in the hidden layer (10,5) with an input layer and output layer was chosen, as illustrated in Fig. 5 from the ANN toolbox in MATLAB MathWorks Inc.: Natick (2013).

A second set of simulations was run with normalized data and 5 neurons in the hidden layer, five neurons in the input layer and one neuron in the output layer, as shown in Fig. 5 and 6, which were taken from the ANN toolbox in MATLAB MathWorks Inc.: Natick (2013). The second type of NN used in simulation presented in Fig. 6 is CFNN, in this the learning algorithm is same as for FFBPNN which is presented in above section, only the structure of the NN is changed remaining all the settings are same.

We employed four types of data in the proposed study: Residue signal data (P_1), standard deviation of data (P_2), skewness of data (P_3), normalized data (P_4), The data is derived from a MATLAB simulation and is divided into three categories: Training data, validation data and test data, with a ratio of 75:15:10. The mean square error is used to calculate the performance graph. For the buried layers, there are two and five neurons, respectively. The input layer has five nodes that characterize the input features, while the output layer has four nodes that characterize the target (output) classes. In the output, the activation function is pure linear (by default). The appropriate activation function in the hidden layers will be determined in this study by assessing the MSE of performance graphs, response graphs, regression co-efficient values and so on and the tan sigmoid function will be discovered.

The MSE of performance graph for tan sigmoid function activation functions for two neural networks is shown in Fig. 7 and 8. The tan sigmoid function and FFBPNN with 10 neurons in hidden layer 1 and 5 neurons in hidden layer 2 have a performance error of 0.070425, while the performance error for CFNN with 10 neu-rons in hidden layer 1 and 5 neurons in hidden layer 2 is 0.11259, So FFBPNN is the finest ANN.

As demonstrated in Fig. 9 and 10, a regression plot is another crucial aspect for verifying network performance. The desired value of Regression co-efficient (R) is equal to 1 for the best fitting of data by this network and any value approaching 0 is entirely unacceptable. The relationship between input and output parameters is represented by the Regression plot (Gonzalez and Zamarreno, 2005), which is given by the equation:

$$out\ put = learning - rate \times target + bias. \tag{24}$$

It is obvious from the regression plot that the regression plot for the ANN with configurations 1 and 2 has a value of *R* of 1.
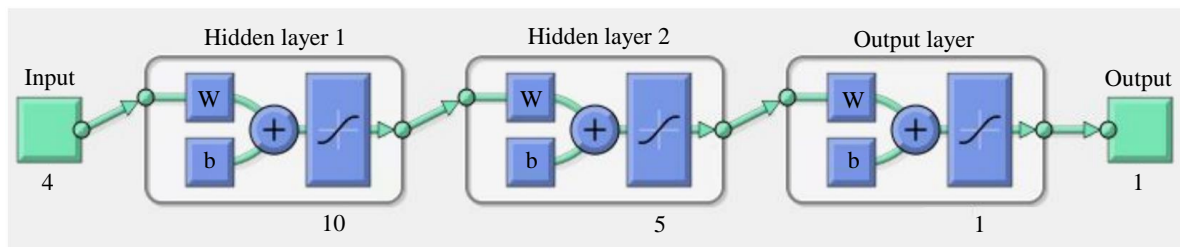

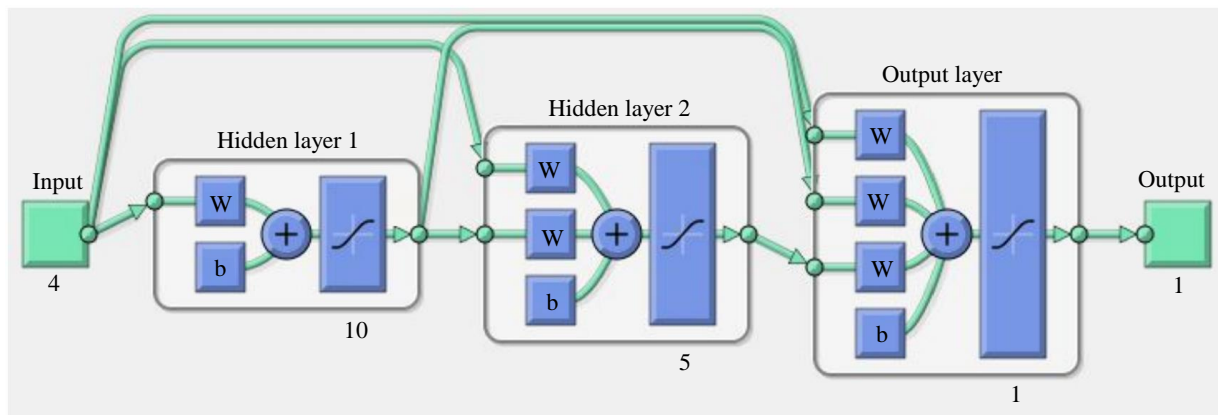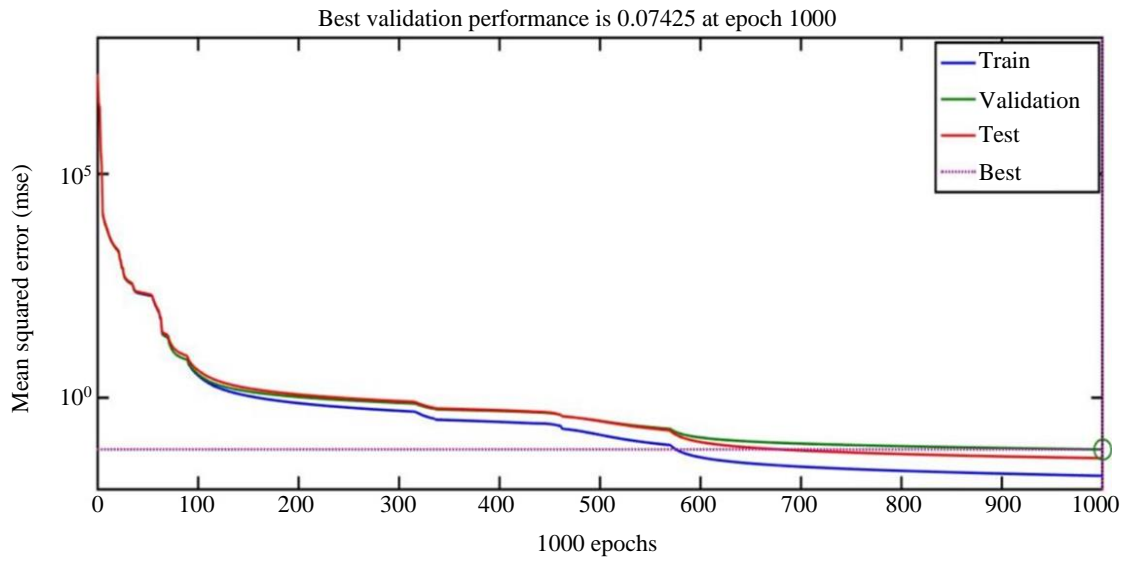**Fig. 5:** Artificial Neural Network (ANN) configuration with FFBPNN MathWorks Inc.: Natick (2013)
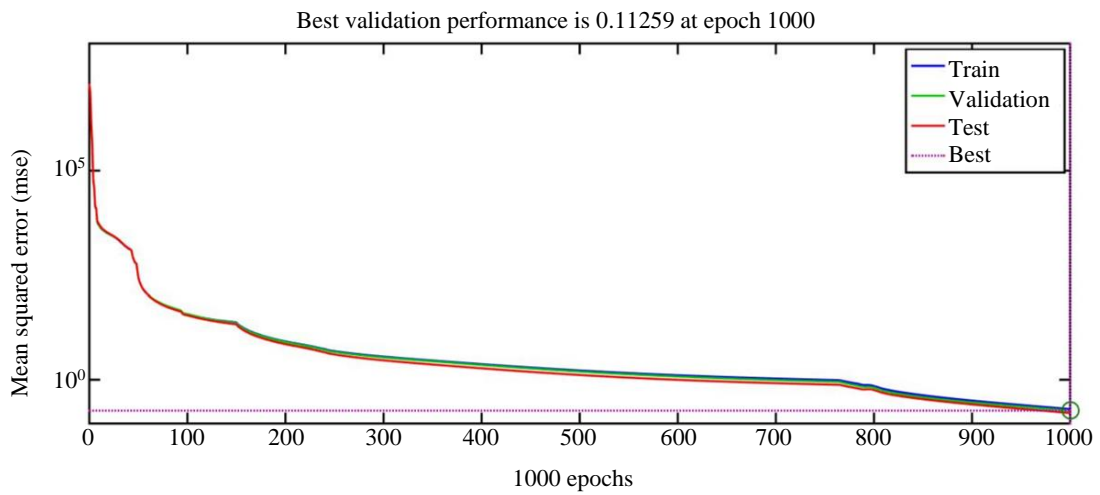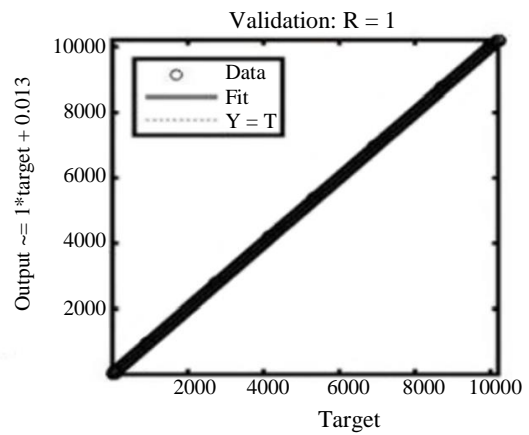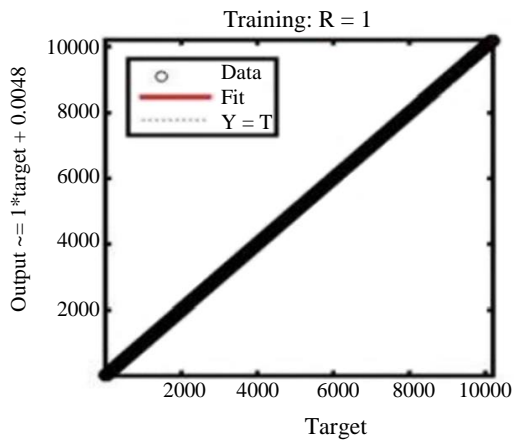

Fig. 6: Artificial Neural Network (ANN) configuration with CFNN MathWorks Inc.: Natick (2013)
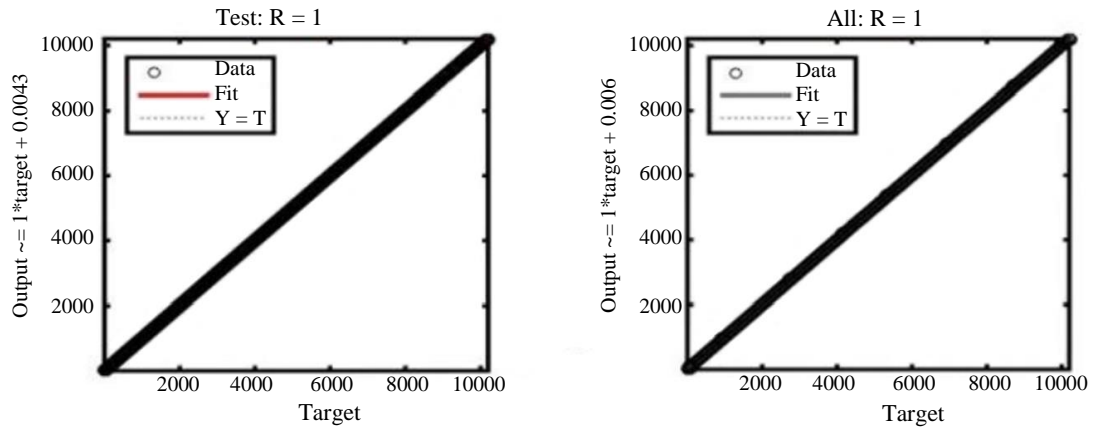
Fig. 7: The Performance graphs for FFBPNN with Tan-Sigmoid function and ANN configuration
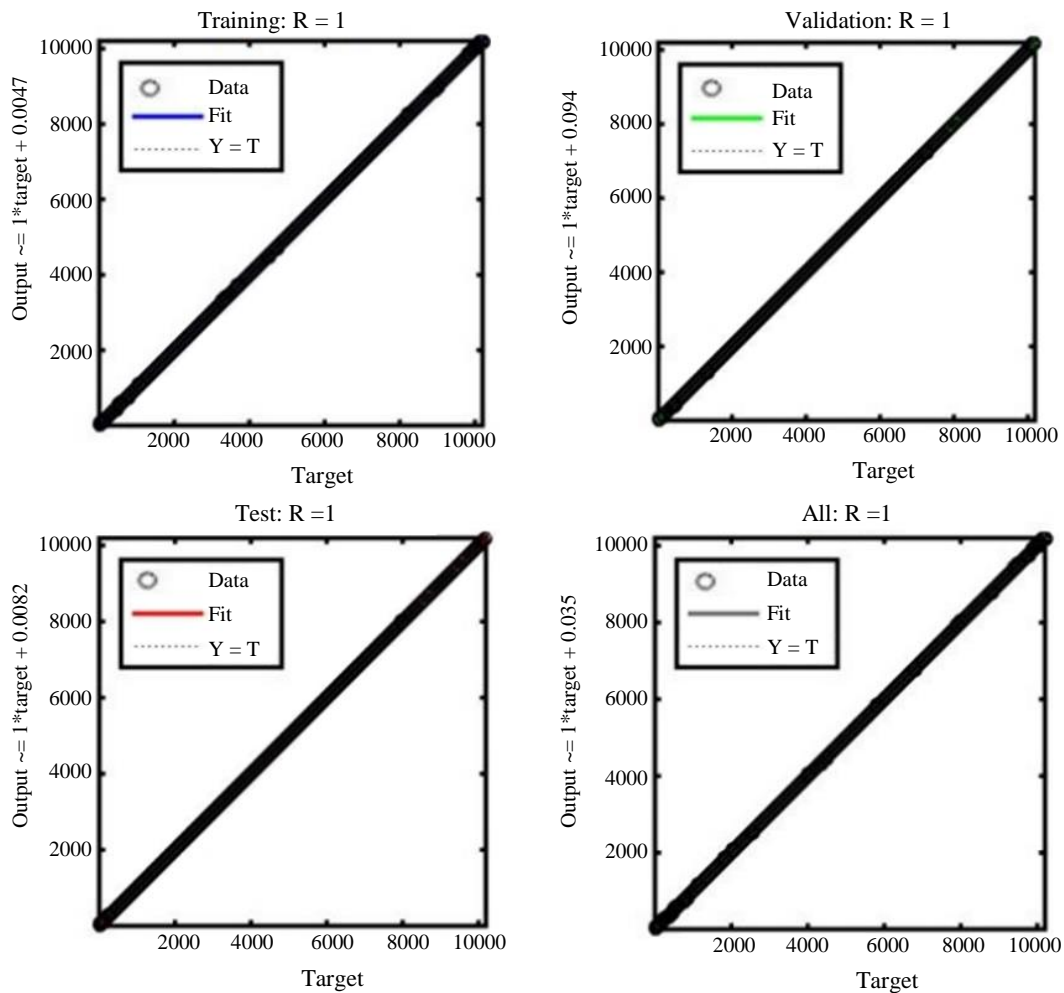

Fig. 8: The Performance graphs for CFNN with Tan-Sigmoid function and ANN configuration

Fig. 9: Regression (R) plots for the FFBPNN with ANN configuration

Fig. 10: Regression (R) plots for the CFNN with ANN configuration

Simulation Results

We employed two alternative neural networks in the proposed work: One configuration is FFBPNN with four inputs, two hidden layers with 10 and 5 neurons and one output neurons, while the other configuration is CFNN with four inputs, one output neurons and three cascade layers. The suggested control strategy is tested on a TTLCS

uncertain level control system that is subjected to actuator, leak and additive process disturbances. Its robustness is further tested with system parameter uncertainty.

Figure 11 shows a passive FTC scheme for a TTLCS uncertain system, in which a traditional PID controller is used in conjunction with an ANN to avoid system parameter uncertainty and faulty situations.

The Proportional Integral Derivative (PID) control settings are taken as following (Patel and Shah, 2018b):

$$K_p = 0.35, K_i = 0.04 \, and \, K_d = 0.15$$

where, K_p is proportional gain, K_i is integral gain and K_d derivative gain of the PID controller.

Figure 12-14 demonstrate simulation results for a TTLCS process with an actuator, a system component (leak) and process disturbances, respectively. The blue color lines in the result figures indicate FTC's response using FFBPNN, whereas the black color lines show

FTC's response using CFNN. The bold yellow line shows the control response of FTC using LQR prosed in (Dutta *et al.*, 2014).

From observing the response of the proposed control scheme on TTLCS uncertain level control system, it is clearly reflects the effectiveness of the proposed scheme under the system parameter uncertainty, actuator and system component (leak) faults. In Table 3 quantitative analysis presented in terms of Integral Absolute Error (IAE) and Integral Square Error (ISE). The test 1 results carried out subject to actuator fault, test 2 results carried out subject to leak fault and system parameter uncertainty and test 3 results carried out subject to additive process disturbances and system parameter uncertainty. Also the PFTC with FFBPNN configuration is most efficient and more sensitive to the actuator and leak faults with system parameter uncertainty as compare to PFTC with CFNN configuration. However, the proposed passive FTC using two different NN are superior as compared to FTC scheme using LQR proposed in (Dutta *et al.*, 2014).
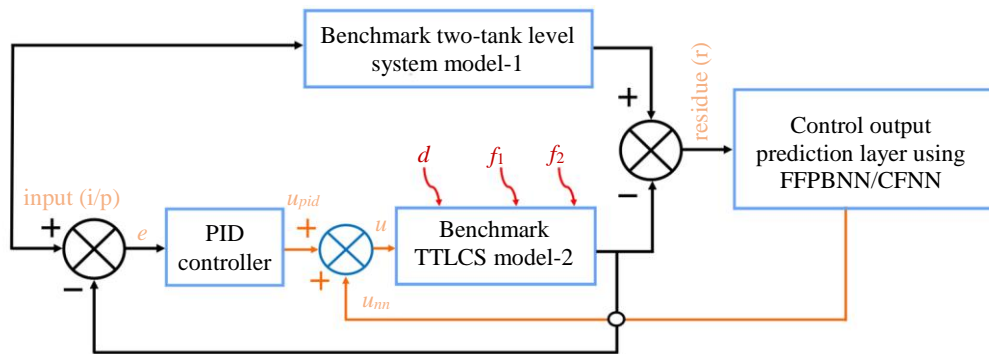

Fig. 11: Passive FTC scheme for TTLCS uncertain level control system
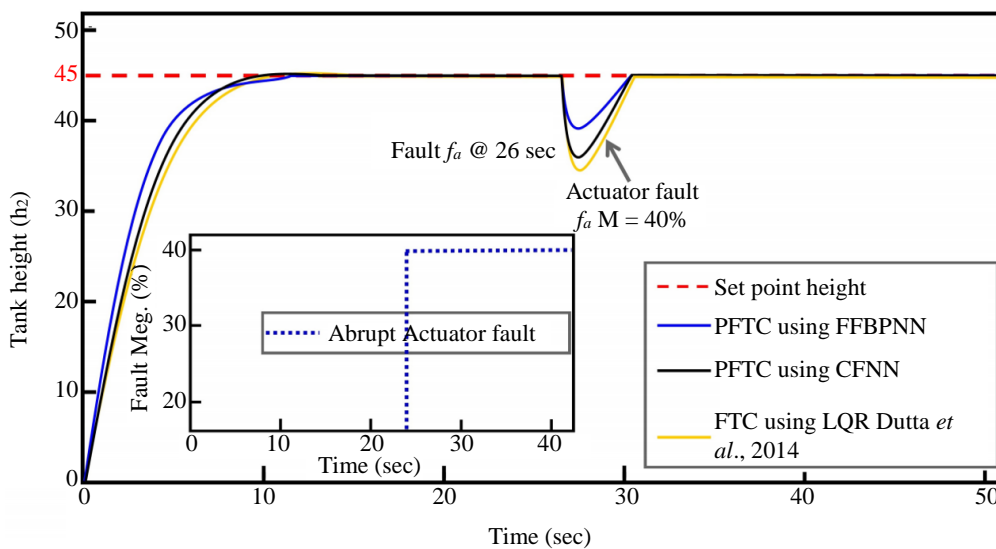

Fig. 12: The response of proposed control scheme with intermittent actuator fault and system parameter uncertainty
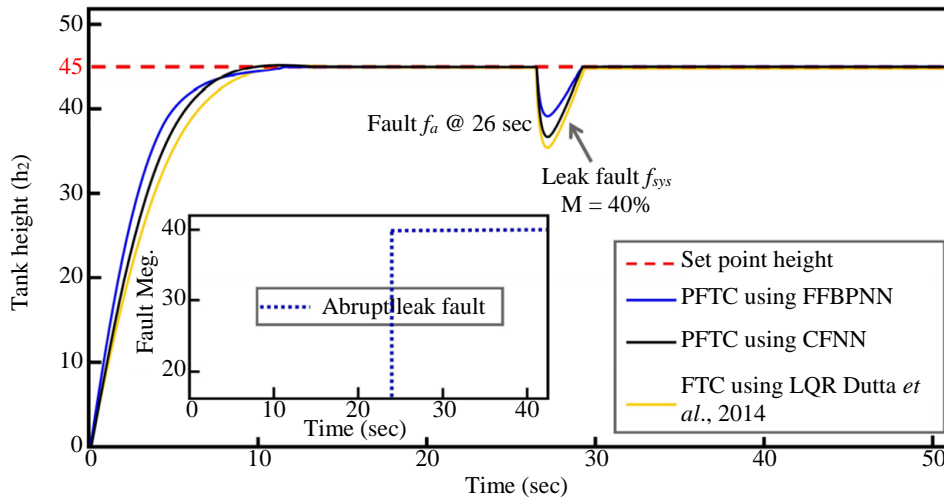
Fig. 13: The response of proposed control scheme with additive system component (leak) fault and system parameter uncertainty
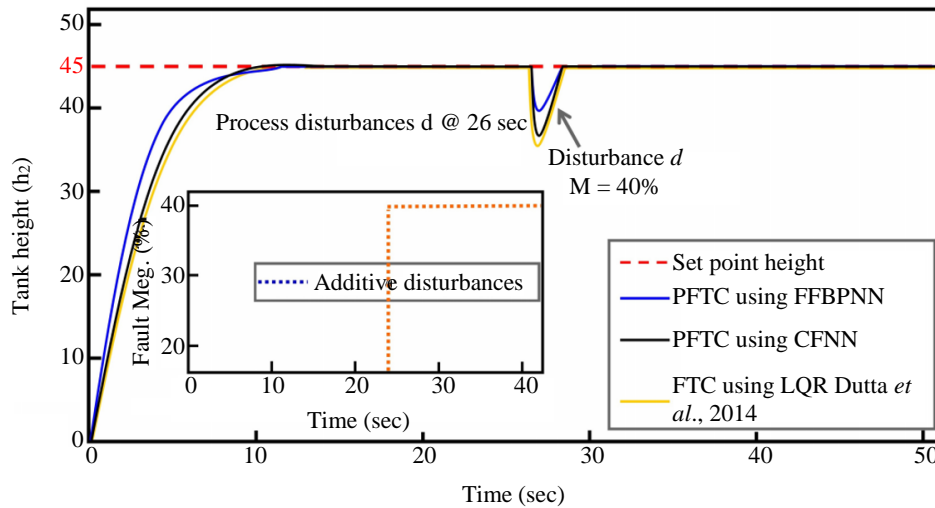

Fig. 14: The response of proposed control scheme with additive process disturbances and system parameter uncertainty

Table 3: Quantitative comparison between the proposed controller, with leak faults, actuator faults and process disturbance along with system parameter uncertainty

Test	Control scheme	IAE h_2	ISE h_2
Test 1	**PFTC using FFBPNN configuration**	**1.0491**	**1.4721**
	PFTC using CFNN configuration	1.3118	1.8159
	FTC using LQR proposed in (Dutta *et al*., 2014)	1.5621	2.9812
Test 2	**PFTC using FFBPNN configuration**	**0.9129**	**1.4191**
	PFTC using CFNN configuration	1.1914	1.6916
	FTC using LQR proposed in (Dutta *et al*., 2014)	1.3479	2.4319
Test 3	**PFTC using FFBPNN configuration**	**0.7829**	**1.2411**
	PFTC using CFNN proposed in (Dutta *et al*., 2014)	1.0241	1.4911
	FTC using LQR proposed in (Dutta *et al*., 2014)	1.1895	1.7099

Conclusion and Future Work

The research proposes a new control technique for two-tank uncertain level control systems called Passive Fault Tolerant Control, which combines a machine learning method with a traditional PID controller. Under system parameter ambiguity and unpredicted defective situations, control action prediction and modelling has always been a difficult issue. A robust and more flexible control method for predicting control action and taking appropriate control action in two-tank level control system uncertain level control systems has been developed in this study to address the difficulty. For actuator, system component (leak) failures and system parameter uncertainty, the prediction was carried out with FFBPNN and CFNN using normalized data and data with statistical moments of control output/manipulated variable in TTLCS uncertain level control system. We tested the FFBPNN/CFNN plus PID controller on a TTLCS uncertain system with an actuator defect and unknown system parameters and the findings show that PFTC with CFNN configuration outperforms PFTC with CFNN configuration. Different statistical measurements have been used to assess the performance of the system's algorithms (IAE, ISE). Furthermore, the suggested PFTC system with NNs was compared to the state-of-the-art control method offered in (Dutta *et al.*, 2014) and the results clearly show that the suggested PFTC scheme outperforms the control system described in (Dutta *et al.*, 2014). However, more data must be tested on the model and the findings must be compared to those of other algorithms, which will be the focus of future research.

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Author's Contributions

Sejal K. Raval and Himanshukumar Rajendrabhai Patel: All simulation/experiments, coordinated the data-analysis and contributed to the writing of the manuscript.

Vipul A. Shah: Supervisor, guide

Ethics

This article is original and contains unpublished material. The paper contains the extended research work of the published paper by Raval *et al.* (2021a). The corresponding author confirms that all of the other authors have read and approved the manuscript and no ethical issues involved.

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