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Original Article

Design of Multi-Input Multi-Output Hybrid Adaptive Neuro-Fuzzy Intelligent System for Primary Pressure Control System of Pressurized Heavy Water Reactor

Arshad H. Malik[1*] and Feroza Arshad[2]

[1]Department of Nuclear Instrumentation, Pakistan Atomic Energy Commission, Block-B, Kazimablad, Model Colony, Karachi, Pakistan
[2]Department of Management Information System, Pakistan Atomic Energy Commission, Block-B, Kazimablad, Model Colony, Karachi, Pakistan

Abstract: A new Multi-Input Multi-Output Hybrid Intelligent (MIMO-HI) system is designed for Primary Pressure Control System (PPCS) of a highly non-linear Pressurized Heavy Water Reactor (PHWR)-type Nuclear Power Plant (NPP). The MIMO hybrid intelligent system is a nonlinear control system which is synthesized using Adaptive Feedforward Neural Network (AFNN) and Mamdani-type Fuzzy Inference System (MFIS). In the proposed Mamdani Adaptive Neuro-Fuzzy System (MANFS), a supervised learning technique has been adopted using AFNN for learning the design parameters of membership functions. A Clustering Algorithm (CA) is used to select the initial number and type of membership functions with each variable. A reduced order nonlinear primary pressure control system is developed based on neural optimization for rule reduction. The MIMO- HI system is designed based on five Multi-Input Single-Output (MISO) adaptive neuro-fuzzy systems in the framework of parallel learning and parallel data processing. These five MISO adaptive neuro-fuzzy systems are designed for intelligent predictions of two feed valves, two bleed valves and one spray valve positions of a PPCS of an operating PHWR-type NPP in Pakistan. A severe transient has been imposed in training, validation and testing phases with proposed MIMO-HI system. The proposed MIMO-HI system is designed in MATLAB and a Graphical User Interface (GUI) is developed for variables transfer and simulations in Visual Basic. The designed MIMO-HI system is observed to be extremely efficient, robust, with reduced oscillations and better transient and steady state characteristics. The performance of the designed MIMO-HI system is tested and the estimated results are in agreement with conventional PID-type PPCS of PHWR.

Keywords: Adaptive neural network, Mamdani fuzzy system, multivariable system, soft computing, nonlinear control, feed-bleed system, nuclear power plant

INTRODUCTION

Artificial neural networks and fuzzy logic systems are capable of solving highly nonlinear and time varying real word problems. Due to their strong learning capabilities, these techniques do not need a mathematical model of system which may be difficult to obtain for complex systems [1].

The Nuclear Power Plant (NPP) is an integration of about 250 systems. The dynamics of these systems is very complex and it is very difficult to mathematically model these systems in detail. Amongst various control loops, Primary Pressure Control System (PPCS) is one of the most important control loops of Pressurized Heavy Water Reactor (PHWR)-type nuclear power plant. PPCS is a conventional control system using Proportional Integral Derivative (PID) control algorithm for pressure signals and ON-OFF control algorithm for surge tank level signal [2]. The problem is to design a new intelligent control system capable of adaptation and anticipation. Therefore, in order to design such an intelligent control system, a hybrid technology is adapted.

In hybrid neuro-fuzzy system, neural network can be used to learn system behavior based on system input-output intelligent data. This learned knowledge can be used to generate fuzzy logic rules and membership functions, significantly reducing the development time for embedded

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* Corresponding author: Arshad H. Malik; Email: mastermind_arshad@yahoo.com

control systems [3].

Different types of neuro-fuzzy systems are used for different applications of identification, modeling, control, fault detection and expert systems purposes. An Adaptive Network Fuzzy Inference System (ANFIS) neuro-fuzzy system has been reported in [1] for designing the maritime structures. In [3], an ANFIS-based modeling and feedforward control system has been developed for shape memory alloy actuators. An ANFIS-based PID controller has been developed for robot manipulator [4]. A radial basic function neural network based ANFIS neuro-fuzzy controller has been identified for robotic manipulator application [5]. Another application of neuro-fuzzy controller for the navigation of mobile robot using artificial neural network based on trigonometric series has been reported [6]. Computational accuracy of ANFIS and ANN as nonlinear models and Auto-Regenerative Integrated Moving Average (ARIMA) as linear model for forecasting applications have been analyzed and presented [7].

Neural networks have been extensively investigated in the context of system identification and simulation for nuclear research reactor [8-10]. Recurrent type ANN has been used for the prediction of flux and core power in different types of Pressurized Water Reactors (PWRs) [11, 12]. Ann attempt has been made for designing an intelligent Multi-Input-Multi-Output (MIMO) PWR core power controller using nuclear reactor code, recurrent type ANN and fuzzy system with fuzzifier and defuzzifier [13]. An improved intelligent MIMO PWR controller for axial off-set control using recurrent type ANN, fuzzy system with Singleton Fuzzifier, a Product Inference Engine and a Center of Gravity Defuzzifier (SF-PIE-CGD) has been reported [14]. A prediction of Channel Power Distribution (CPD) for an Indian PHWR has been proposed [15]. The identification of nonlinear dynamics of PHWR has been recently investigated using Adaptive Feedforward Neural Network (AFNN) [16]; and, thus, a research effort has been put for developing nonlinear models of different reactor system using feedforward neural network optimized by generalized delta rule with momentum weight and bias learning rules. A PPCS has been designed for Indian PHWR using fuzzy logic controller [17]. This fuzzy controller is a simple controller designed for feed and bleed system using seven triangular membership functions only.

In this research work, a new design approach is attempted for the successful replacement of primary pressure control system of a different PHWR-type nuclear power plant. Our proposed design methodology is one step ahead from research work reported [16, 17]. In this paper, a new MIMO hybrid intelligent adaptive neuro-fuzzy system is designed based on the integration of Adaptive Feedforward Neural Network [16] and Mamdani-type Fuzzy Inference System (MFIS) in the frame work of parallel learning of 24 each of triangular and trapezoidal membership functions for inputs and forty five triangular and sixteen trapezoidal membership functions for outputs. Therefore, a parallel learning and parallel data processing has been adopted with clustering algorithm for the selection of membership functions, advanced intelligent soft computing and neural optimization for fuzzy rule reduction for a different PHWR-type nuclear power plant. The Mamdani adaptive neuro-fuzzy intelligent system is better than ANFIS in expression of consequent part and intuitive fuzzy reasoning. In this MOMO-HI system, an operator and implication operator is product and aggregate operator is sum and defuzzification operator is centroid of area. Therefore, a composite inference method is evolved which results in excellent ability of learning because of differentiability while soft intelligent computing. It resolves some difficulties that are associated with other intelligent inference systems by providing multi-parameter computational facility and easy weight assigning facility to each input and fuzzy rules. Thus, it has a great flexibility with multi-parameter synthetic evaluation which is a main issue of T-S fuzzy inference system. The unique aspect of this control system is the hybrid intelligent critic which simulates an expert's operation in reality. This characteristic increases the degree of intelligence and robustness of the system and results in self tuning and adaptive controller design. This MIMO-HI has advantages in nonlinear modeling, membership functions in consequent parts, scale of training intelligent data and amount of adjusted parameters. The power of proposed MIMO-HI system is it's intuitive reasoning, widespread acceptance and it's well suited to human cognition which are not achievable in ANFIS model.

MATERIALS AND METHODS

Primary Pressure Control System (PPCS)

The primary pressure control system is one of the most important critical control system of PHWR-type nuclear power plant [2]. The purpose of primary heat transport system is to remove generated heat from the nuclear fuel. The design philosophy behind this heat removal system is to avoid fuel meltdown in case of core depressurization below 1427 psig and to avoid piping system burst out in case of over pressurization above 1581 psig. Therefore, the purpose of primary pressure control system is to maintain pressure of the reactor coolant system (P_P) around the pressure set-point (P_{Pset}) of 1500 psig. There are two types of set-points involved in this multivariable control loop. One for primary pressure regulation (P_{Pset}) based on PID control system and other for surge tank level control (L_{set}) based on ON-OFF control. The main pressure control system is a feed-bleed system used to increase and decrease pressure of primary heat transport system. Feed-bleed control system consists of two feed valves (FV_1, FV_2), two bleed valves (BV_1, BV_2) and one spray valve (SV). Both feed and bleed valves have split range control i.e. control transfer from one valve to other valve in a bump-less manner. Feed valves are provided to increase the system pressure in case of depressurization while bleed valves are provided to decrease the system pressure in case of over pressurization. Spray valve is also known as secondary bleed. Spray valve is operated in case of severe transients. Surge tank level control system is a support control system of main feed-bleed system. Surge tank is provided for pressure cushioning by regulating the surge tank level (L_V). Surge tank ON-OFF control system consists of three heaters. These three heaters turn ON-OFF at different threshold points. The block diagram of MIMO primary pressure control system is shown in Fig. 1. The dynamics of nuclear power plant is highly nonlinear in nature. Therefore, a nonlinear control synthesis is a better solution for the replacement of a conventional control system of PHWR. Thus, a hybrid adaptive neuro-fuzzy system is selected as an alternate modern design solution having nonlinear structure. All the nonlinearities and uncertainties due to system ageing effects and parametric variations are embedded in the plant closed loop dynamic operational data.

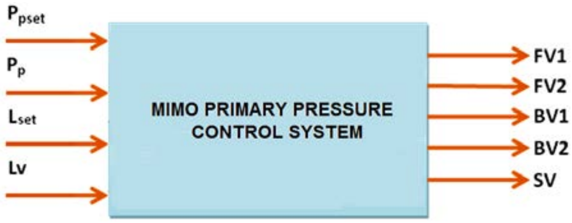

Fig. 1. Block diagram of MIMO primary pressure system.

In this paper, an adaptive neural network and Mamdani fuzzy inference system are combined to form Mamdani integrated adaptive neuro-fuzzy system for control synthesis of primary pressure control of a PHWR-type nuclear power plant. The basic set-up of integrated neuro-fuzzy system is shown in Fig. 2.

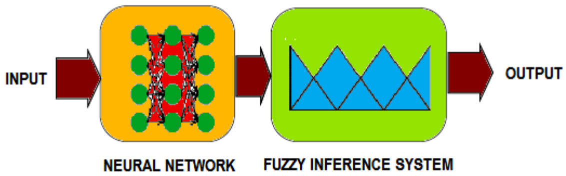

Fig. 2. Basic setup of integrated neuro-fuzzy system.

Hybrid Intelligent System Methodology

Mamdani adaptive neuro-fuzzy algorithm

Mamdani adaptive neuro-fuzzy intelligent system is an adaptive network based on Mamdani fuzzy inference system. Mamdani adaptive neuro-fuzzy intelligent system uses a supervised learning technique. The supervised learning is accomplished by adaptive feedforward backpropagation learning algorithm. The algorithm of adaptive feedforward backpropagation neural network is adopted from [16]. The Mamdani neuro-fuzzy system consists of five layers. The MIMO-HI adaptive neuro-fuzzy system is designed by decomposing the original MIMO system into five MISO adaptive neuro-fuzzy systems. The detailed architecture of two inputs and one output MISO Mamdani adaptive neuro-fuzzy system is shown in Fig. 3. The design philosophy of two inputs and one output MISO neuro-fuzzy intelligent system is explained below:

Form of Reasoning

Generalized Modus Ponens

Premise: u_1 is A_1

Implication: if u_1 is A_1 then u_2 is B_1

Consequence: y is C_1

where A_1, B_1 and C_1 are fuzzy sets and u_1, u_2 and y are symbolic names for inputs and output respectively.

Premise: u_1 is A_2
Implication: if u_1 is A_2 then u_2 is B_2
Consequence: y is C_2

where A_2, B_2 and C_2 are fuzzy sets and u_1, u_2 and y are symbolic names for inputs and output respectively.

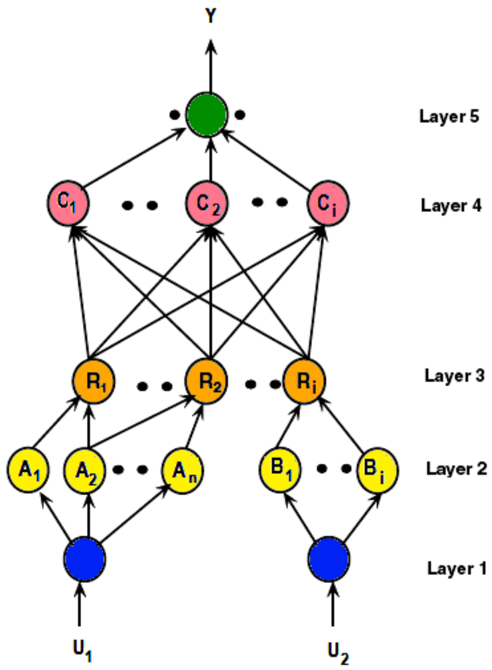

Fig. 3. Architecture of Mamdani adaptive neuro-fuzzy MISO system.

Similarly, the other control actions are designed. The design details of five layer hybrid intelligent system are as follows:

Layer 1: Layer 1 is an input layer and practically no computation is performed in this layer. Each node corresponds to one input variable in this layer. Therefore, the weights of layer 1 are unity.

Layer 2: Layer 2 is a fuzzification layer. Each node corresponds to one linguistic label. In this layer, output link presents the membership value. Basically, the degree to which an input belongs to a fuzzy set is computed in this layer. A clustering algorithm is used to select the initial number and type membership functions to be allocated to each of the input variables. The fuzzy sets in reality represent the shape of membership function. The final shapes of membership functions will be fine-tuned during network learning. Membership functions could be triangular, trapezoidal, generalized bell shaped, Gaussian curve, Sigmoid shaped, Z shaped or one can define any custom shaped membership function. In our proposed design, the selected membership functions fired by the clustering algorithm are mostly triangular and sometimes trapezoidal in shapes. These triangular and trapezoidal membership functions have the following forms:

$$\mu_{TRIANGULAR}(x) = \max\left[\min\left(\frac{x-a_i}{b_i-a_i}, \frac{c_i-x}{c_i-b_i}\right), 0\right] \quad (1)$$

and

$$\mu_{TRAPEZOIDAL}(x) = \max\left[\min\left(\frac{x-a_i}{b_i-a_i}, 1, \frac{d_i-x}{d_i-c_i}\right), 0\right] \quad (2)$$

where a_i, b_i, c_i and d_i are the nonlinear parameters referred to as premise parameters.

Layer 3: Layer 3 is a rule antecedent layer. A T-norm is used in this layer. The output of this layer 3 node corresponds to the firing strength (w_i) of the respective i^{th} fuzzy rule. The training data is divided into i disjoint clusters $R_1, R_2, \ldots\ldots, R_i$. Each cluster R_i corresponds to a control rule R_i.

Layer 4: Layer 4 is a rule consequent layer. This layer combines the incoming rule antecedents and determines the degree to which they belong to the output linguistic label. The number of nodes in this layer will be equal to the number of rules.

Layer 5: Layer 5 is a combination and defuzzification layer. This layer combines all rule consequents using a T-conorm operator and final crisp outputs are calculated after defuzzification. If consequent membership function is triangular then each membership function has three nonlinear parameters to be adjusted. Similarly when consequent membership function is trapezoidal then each membership function has four nonlinear parameters to be adjusted.

Computations of nonlinear parameters

In this paper, the adaptive feedforward backpropagation algorithm with generalized delta learning rule is adopted for modifications and fine tuning of nonlinear parameters of triangular and trapezoidal membership functions. The learning procedure involves the presentation of pairs of input-output patterns. The generalized delta rule allows a gradient descent in the sum squared error of the output, with the processing elements using nonlinear activation function. The error signal starts from output layer and goes backward layer by layer until the input layer is attained. The weights are computed and updated using gradient decent algorithm presented in [16].

Rule Reduction by neural optimization technique

Initially, a higher order nonlinear neuro-fuzzy system is designed but with an optimization algorithm unnecessary rules are eliminated by eliminating unnecessary input variables in the input vector for rules $R_1, R_2, \ldots\ldots, R_i$ by neglecting one input variable in one of the rules and comparing the control result with the one when the variable is not neglected. If the performance of the primary pressure control system is not influenced by neglecting input variable u_j in rule R_i, u_j is unnecessary for R_i and thus can be neglected. Therefore, a reduced order nonlinear neuro-fuzzy primary pressure control system is obtained.

Design of MIMO Hybrid Adaptive Neuro-fuzzy System for PPCS

Decomposition of MIMO intelligent system into MISO intelligent system

The multivariable MIMO hybrid adaptive neuro-fuzzy system is designed by decomposing it into five MISO adaptive neuro-fuzzy systems. The MIMO hybrid intelligent system is designed in a framework of parallel learning and parallel data processing. Primary pressure error signal (e_{P_p}), primary pressure error rate signal ($\frac{de_{P_p}}{dt}$) and surge tank level error signal (e_L) are identified as three input signals for MIMO adaptive neuro-fuzzy design. These three signals are computed using primary pressure set-point signal (P_{Pset}), primary pressure measured signal (P_P), surge tank level set-point signal (L_{set}) and surge tank measured level signal (L_V). Two feed valves positions (FV_1, FV_2), two bleed valves positions (BV_1, BV_2) and one spray valve of position (SV) are identified as five output signals for MIMO adaptive neuro-fuzzy design. The block diagram MIMO hybrid adaptive neuro-fuzzy intelligent system for primary pressure control system is shown in Fig. 4. The design of MIMO adaptive neuro-fuzzy system knowledgebase which is the heart of this design is shown in Fig. 5.

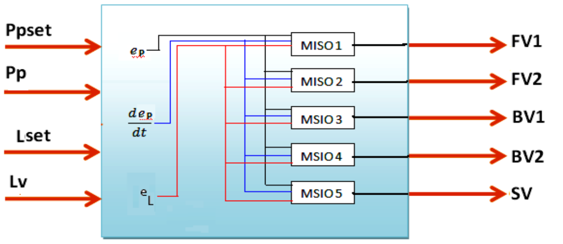

Fig. 4. MIMO adaptive neural-fuzzy design.

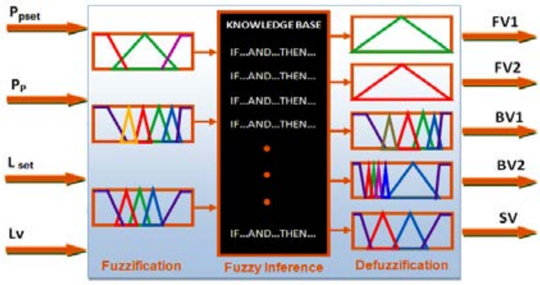

Fig. 5. Design of knowledgebase for MIMO adaptive neural-fuzzy system.

Closed loop data

A total of 410 patterns are obtained from closed loop primary pressure control system dynamics of PHWR-type nuclear power plant. These patterns are selected based on most representative samples set that depict the excellent closed loop dynamics without any noise and error in measurement because a highly dedicated and sophisticated measurement system has been employed for this purpose. Three different set of data patterns are prepared for adaptive feedforward neural network development; one set is comprised of 246 patterns (60% of total patterns) for training, second set is comprised of 82 patterns (20% of total patterns) for validation and third set is comprised of 82 patterns (20% of total patterns) for testing of design.

MISO adaptive neuro-fuzzy systems

Five MISO adaptive neuro-fuzzy systems are synthesized based three inputs and one output. The inputs of all five MISO adaptive neuro-fuzzy systems are common and are trained in a framework of parallel data processing. The intelligent predictions from five MISO adaptive neuro-fuzzy systems are the valve positions of two feed valves (FV_1, FV_2), two bleed valves (BV_1, BV_2) and one spray valve (SV).

RESULTS AND DISCUSSION

Training, validation and testing experiments are performed for five MISO adaptive neuro-fuzzy systems based on real data of PHWR-type nuclear power plant sampled at 1 second [2]. Therefore, for the purpose of simulations and performance analysis of proposed MISO adaptive neuro-fuzzy systems, the inputs and outputs are described in real time of signals that will basically correspond to number of patterns.

Training of Designed MIMO Adaptive Neuro-Fuzzy System

Training of five MISO adaptive neuro-fuzzy systems for primary pressure control system of PHWR-type nuclear power plant is carried in MATLAB environment. A Graphical User Interface (GUI) is developed in Visual Basic for variables transfer and simulation experiments. In Table 1, 15 linguistic variables are defined that are used to describe membership functions of inputs and outputs. In Table 2, the values of different design parameters of MIMO adaptive neuro-fuzzy intelligent system for primary pressure control are shown. In Fig. 6-8, membership functions for primary pressure error, primary pressure error rate and surge tank level error signals are shown. There are six, five and three membership functions for primary pressure error, primary pressure error rate and surge tank level error signals respectively. In Fig. 9-10, membership functions for feed valves 1 and 2 signals are shown. There is one membership for each feed valve. Membership functions for bleed valves 1 and 2 are shown in Fig. 11-12. There are six and seven membership functions for bleed valves 1 and 2 respectively. Membership functions for spray valve are shown in Fig. 13. There are four membership functions for spray valve.

Table 1. Linguistic variables for MIMO Mamdani adaptive neuro-fuzzy PPCS.

Linguistic Variables	Definitions
BN	Big Negative
MN	Medium Negative
SN	Short Negative
ZE	Zero
CZ	Close to Zero
ON	Short Slightly Positive
TW	Medium Slight Positive
TH	Big Slight Positive
FO	Very Big Slight Positive
SP	Short Positive
VSP	Very Short Positive
MP	Medium Positive
BP	Big Positive
VBP	Very Big Positive
HP	High Positive

Table 2. Design parameters of MIMO Mamdani Adaptive neuro-fuzzy PPCS.

Network Parameters	Values
Number of Training Patterns (60%)	246
Number of Validation Patterns (20%)	82
Number of Testing Patterns (20%)	82
Learning Rate	0.006
Thresholding Parameter	0.7
Number of Nonlinear Parameters for Triangular Membership Functions	69
Number of Nonlinear Parameters for Trapezoidal Membership Functions	40
Number of Epochs	100
Performance	4.17029×10^{-6}

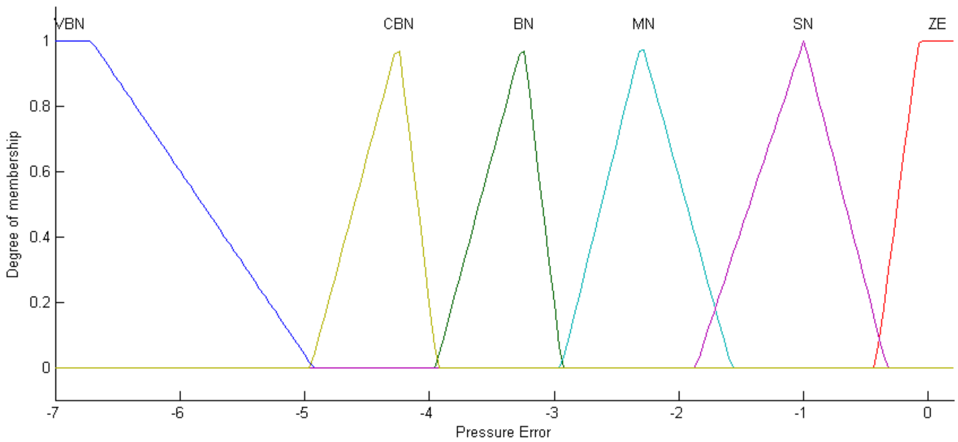

Fig. 6. Membership functions for primary pressure error.

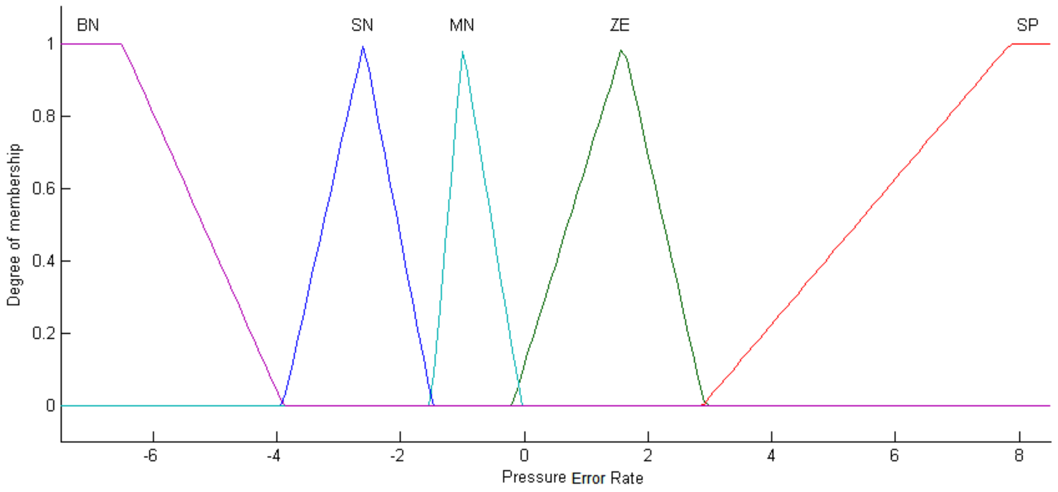

Fig. 7. Membership functions for primary pressure error rate.

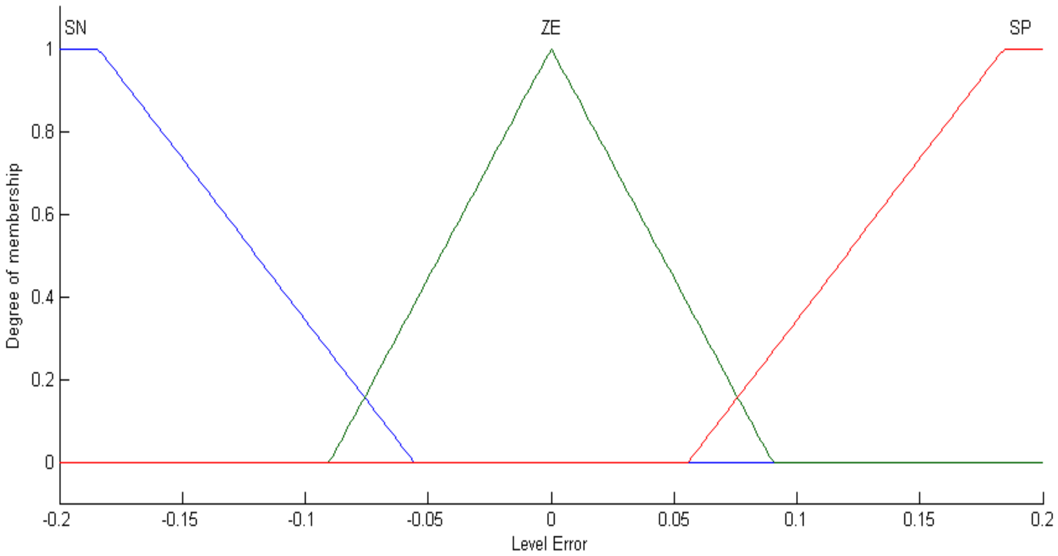

Fig. 8. Membership functions for surge tank level error.

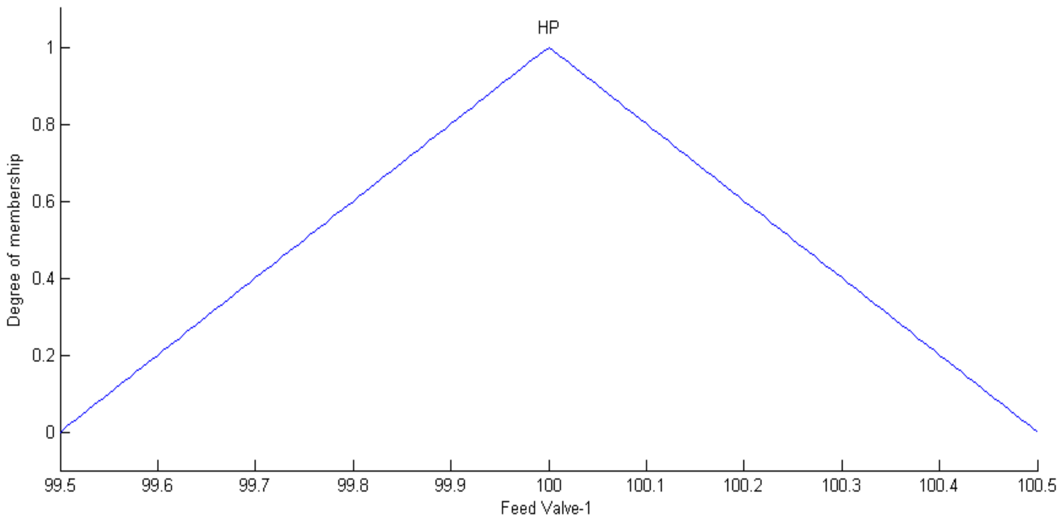

Fig. 9. Membership function for feed valve 1.

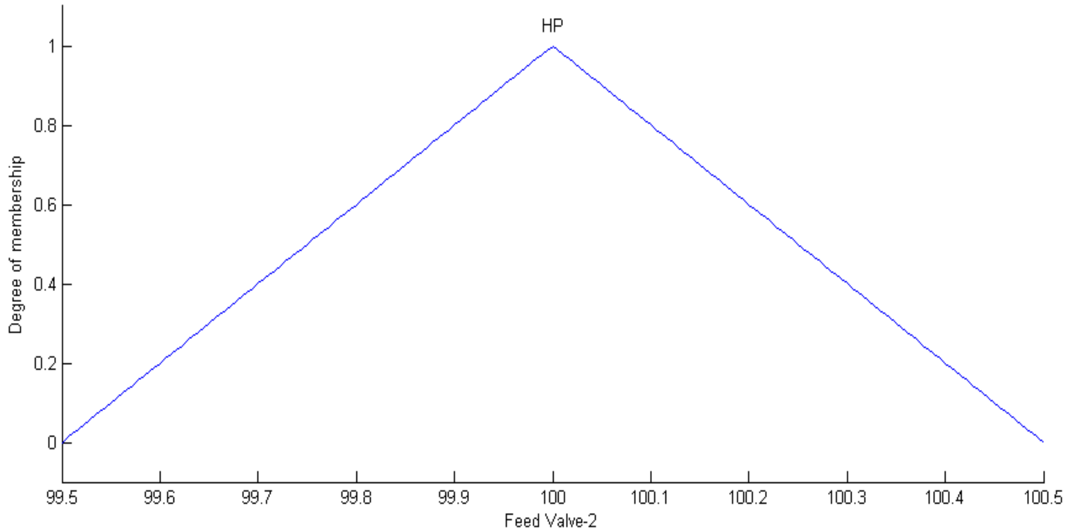

Fig. 10. Membership function for feed valve 2.

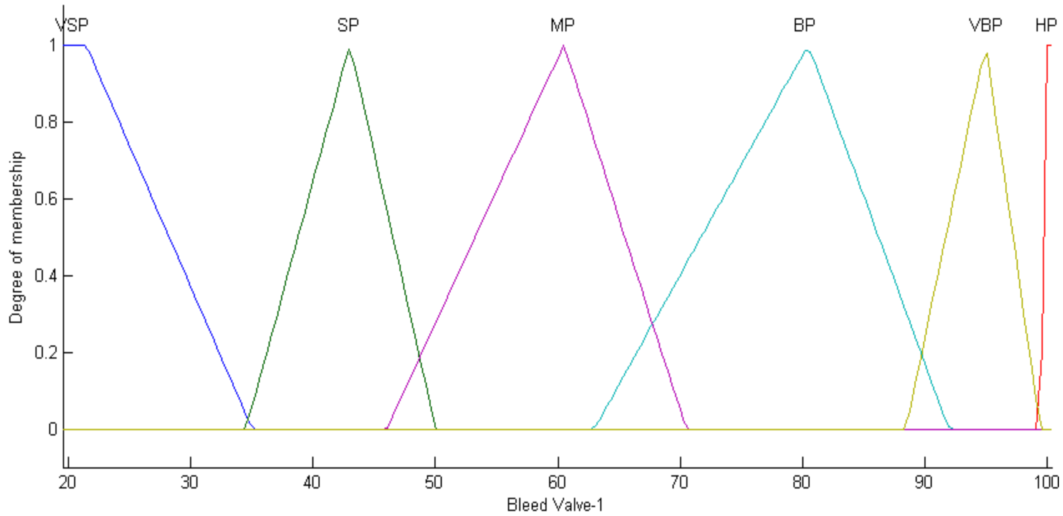

Fig. 11. Membership functions for bleed valve 1.

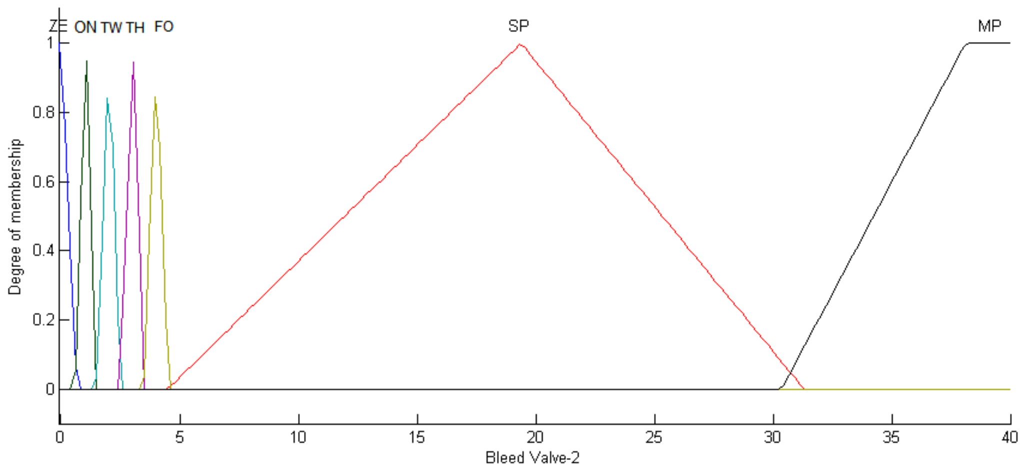

Fig. 12. Membership functions for bleed valve 2.

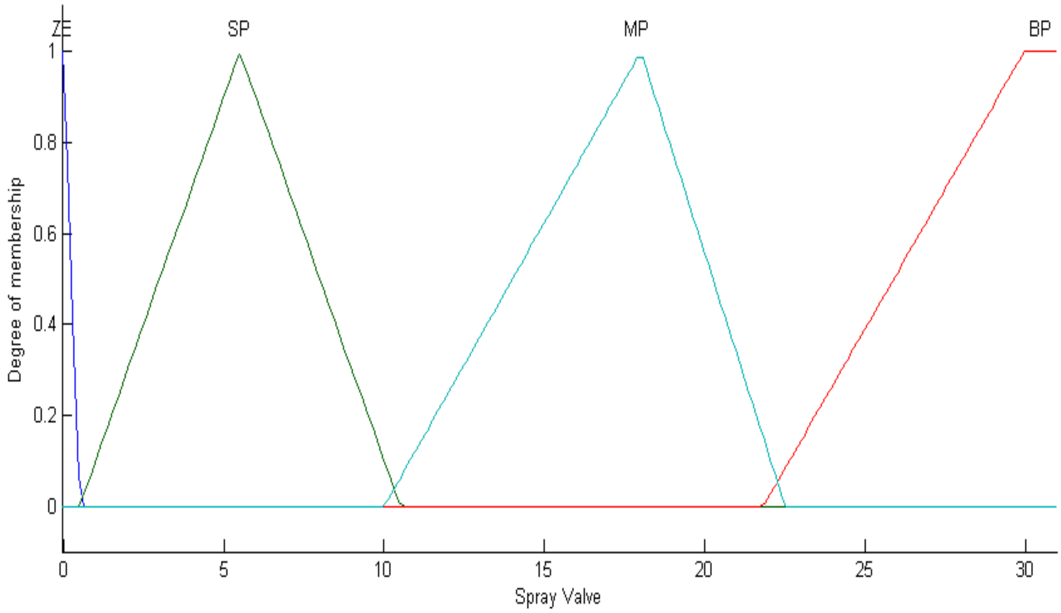

Fig. 13. Membership functions for spray valve.

Validation and Testing of Designed MIMO Adaptive Neuro-Fuzzy System

Since the proposed hybrid adaptive neuro-fuzzy intelligent system is a digital neural network, so its prediction error is computed against number of epochs. The performance of the proposed neuro-fuzzy system in training, validation and testing phase is computed in terms of MSE and shown in Fig. 14. The performance of the proposed design is found excellent against the target goal. All three performance curves for training, validation and testing, shown in Fig. 14, are almost identical which indicates that choice of patterns is very accurate and noise-free. And all membership functions are selected and fired exactly in accordance with the dynamics of control system covering all important modes of closed loop control system.

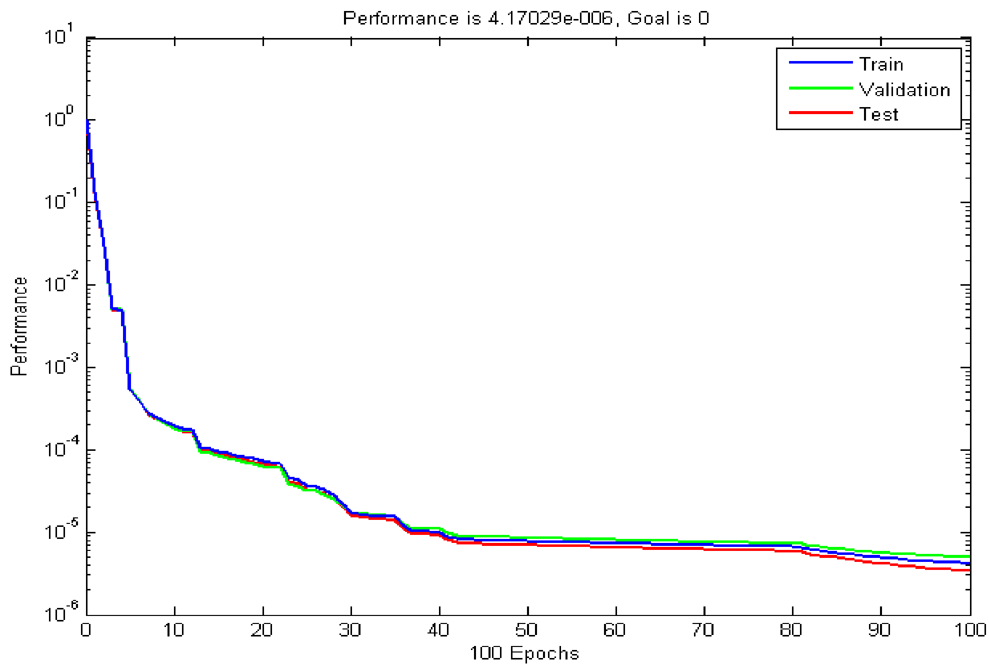

Fig. 14. MSE Performance of adaptive neural network in training, validation and testing phases.

When a neuro-fuzzy system has been trained, the next step is to evaluate it. The training and testing of neuro-fuzzy system is employed by considering a severe transient in PHWR-type nuclear power plant. In this severe transient, two feed valves are stuck open at 100% opening condition. The design of primary pressure control is such if two feed valves are stuck open at 100% opening condition then two bleed valves tries to compensate this 100% feed valve opening to avoid bursting out of primary headers and piping system. The level in the surge tank continuously increases during this transient. Therefore, a secondary bleed also appears to compensate this severe situation.

In this severe transient, performance of new MIMO-HI based closed loop control system is evaluated by comparing with conventional PID controller based closed loop control system. The system is initially at 1500 psig steady pressure. Suddenly, both feed valves are stuck open at 100% opening condition. In Fig. 15-16, MIMO-HI based closed loop control system response is compared with conventional PID controller based closed loop system response for both feed valve positions predicting the actual stuck feed valves opening condition. Initially, the level of the surge tank is 44.5 inches at 1500 psig. Later on, this level starts continuously increasing in the surge tank. In Fig. 17, comparison of MIMO-HI based closed loop control system response is compared with conventional PID controller based closed loop system response for bleed valve 1 opening demand. The bleed valve 1 attains the 100% valve opening demand in 24 seconds. In Fig. 18, MIMO-HI based closed loop control system response is compared with conventional PID controller based closed loop system response for bleed valve 2 opening demand. The bleed valve 2 takes a small transient in the beginning because bleed valve 1 tends to attain 100% feed valve opening in this period and finally the bleed valve 2 starts fluctuating after 68 seconds to cope 100% feed valves opening demand. During this bleed valve 2 opening, the level in the surge tank further rises. In Fig. 19, comparison of MIMO-HI based closed loop control system response is compared with conventional PID controller based closed loop system response for spray valve opening demand. In Fig. 19, the opening demand of secondary bleed i.e. spray valve is predicted. The spray valve remains 0% open upto 68 seconds and then starts fluctuating to cope excessive swell in the primary heat transport system. During the entire transient the primary pressure remains within ± 20 psig around 1500 psig which proves the robustness of the proposed MIMO adaptive neuro-fuzzy intelligent system for pressure control system. The final level of surge tank is 69. 5 inches during this transient. The performance of the proposed MIMO adaptive neuro-fuzzy intelligent system for primary pressure control system of PHWR-type nuclear power plant is highly efficient, fast and robust. The level of oscillations is much reduced and hence an excellent design is obtained which provides sound basis for the successful replacement of conventional primary pressure control system of PHWR-type nuclear power plant. Experimental results tell that this MIMO-HI model can achieve the desired targets and have a preferable capacity in traffic Level-Of-Service (LOS) evaluation for 410 patterns as is evident from Fig. 14.

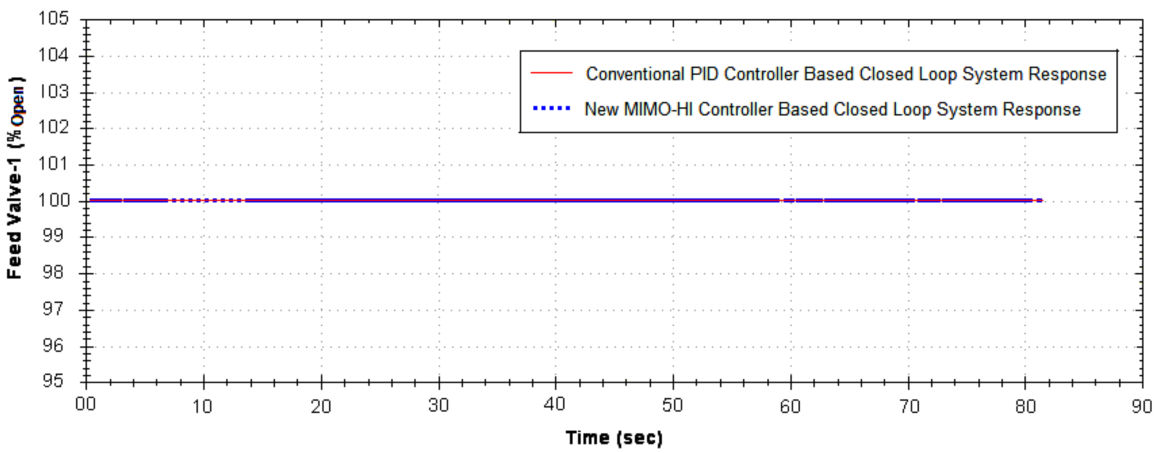

Fig. 15. Comparison of MIMO-HI and PID controllers based response for feed valve 1.

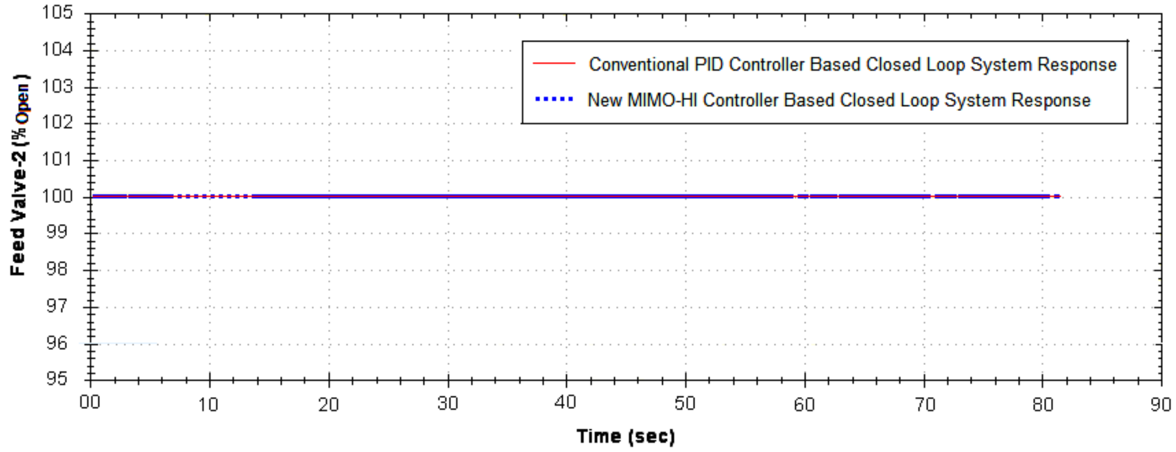

Fig. 16. Comparison of MIMO-HI and PID controllers based response for feed valve 2.

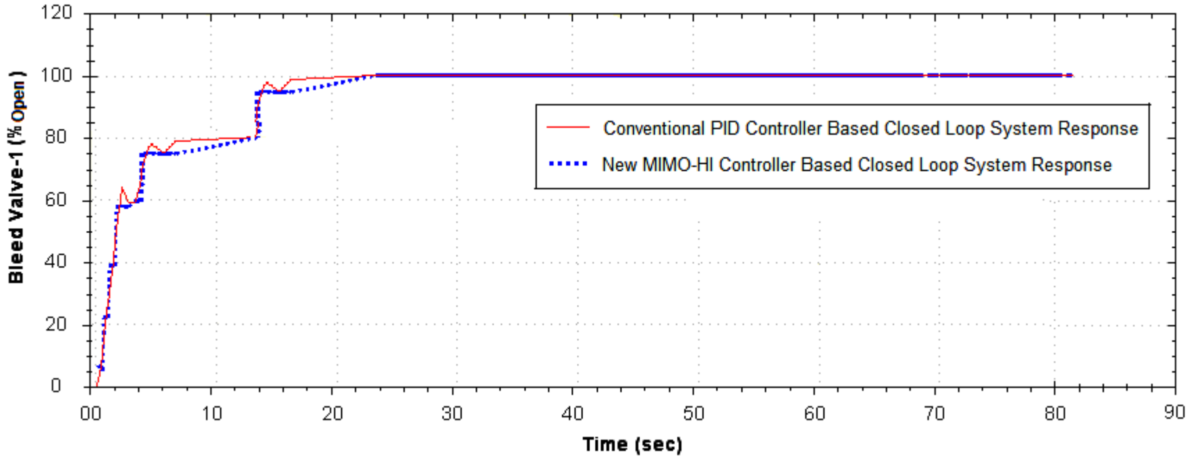

Fig. 17. Comparison of MIMO-HI and PID controllers based response for bleed valve 1.

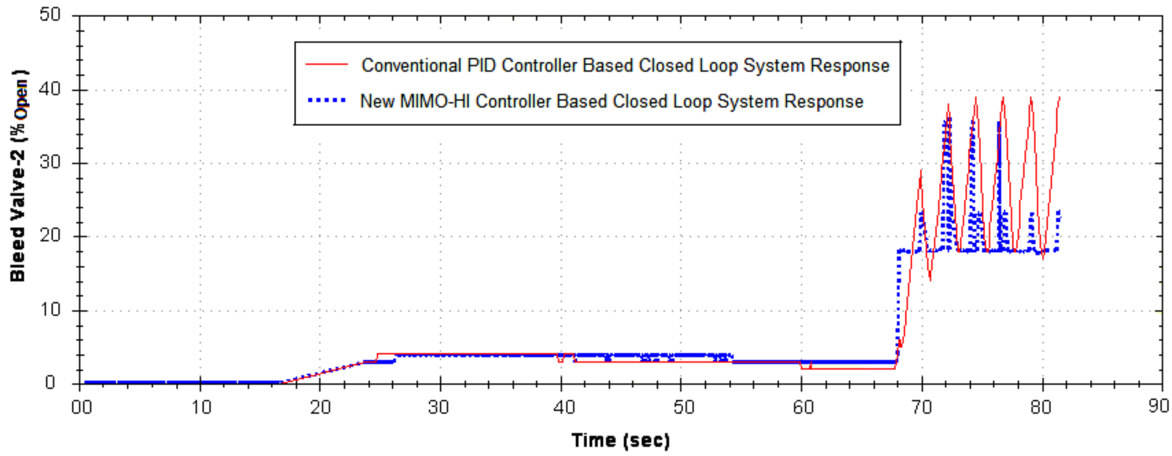

Fig. 18. Comparison of MIMO-HI and PID controllers based response for bleed valve 2.

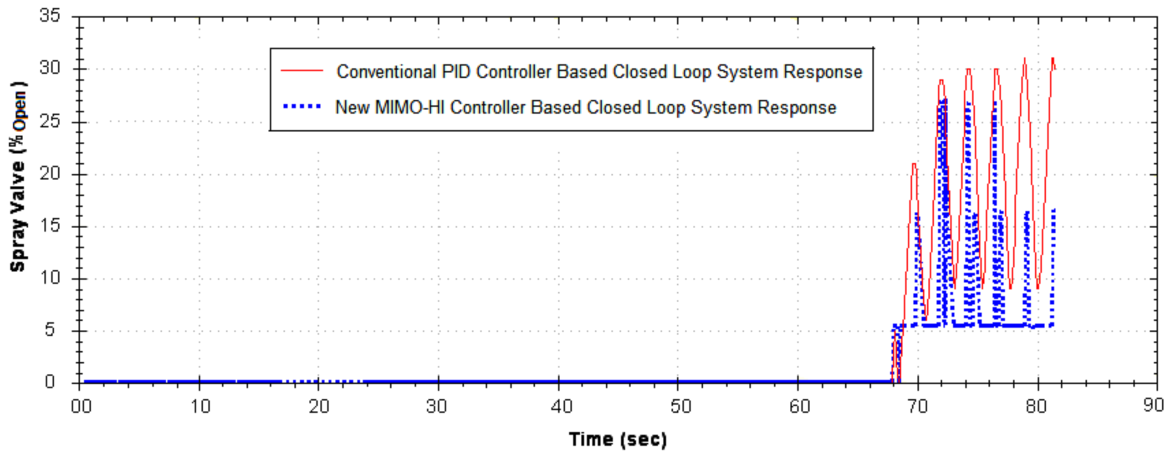

Fig. 19. Comparison of MIMO-HI and PID controllers based response for spray valve.

CONCLUSION

A hybrid neuro-fuzzy intelligent algorithm has been proposed for multivariable primary pressure control system of a PHWR-type nuclear power plant. The design of MIMO hybrid adaptive neuro-fuzzy intelligent system is based on the decomposition of MIMO system into five MISO adaptive neuro-fuzzy systems using adaptive feedforward neural network and Mamdani-type fuzzy inference system for the intelligent predictions of five control valve positions. The designed hybrid adaptive neuro-fuzzy intelligent system proves an excellent agreement with the PID-based closed loop experimental data and its effectiveness in a real world situation of nonlinear time-varying PHWR-type nuclear power plant.

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