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Research Article

Synthesis of a Novel Adaptive Wavelet Optimized Neural Cascaded Steam Blow-off Control System for a Nuclear Power Plant

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Abstract: In this paper, a new Multi-Input Multi-Output Adaptive Wavelet Neural Network based Steam Blow-Off System Controller (MIMO AWNN-SBOSC) is designed based on real time dynamic parametric plant data of steam blow-off system with conventional Single-Input Multi-Output Proportional plus Integral plus Derivative Controller (SIMO PIDC). The proposed MIMO AWANN-SBOSC is designed using three Multi-Input Single-Output Adaptive Wavelet Neural Network based Steam Blow-Off System Controllers (MISO AWNN-SBOSC). The hidden layer of each MISO AWNN-SBOSC is formulated using Mother Wavelet Transforms (MWT). Using nonlinear dynamic neural data of designed MIMO AWNN-SBOSC, a Multi-Input Multi-Output Adaptive Wavelet Neural Network based Steam Blow-Off System Model (MIMO AWNN-SBOSM) is developed in cascaded mode. MIMO AWNN-SBOSM is designed using two MISO AWNN-SBOSM. All training, testing and validation of MIMO AWNN-SBOSC and MIMO AWNN-SBOSM are carried out in MATLAB while all simulation experiments are performed in Visual C. The results of the new design is evaluated against conventional controller based measured data and found robust, fast and much better in performance.

Keywords: MIMO neural modeling, wavelet transforms, MIMO neural control, steam blow-off control system, nuclear power plant

1. INTRODUCTION

In this research work, a secondary of system of a Nuclear Power Plant was considered called Steam Blow-Off System (SBOS). This steam blow-off system is associated with steam generator or boiler [1].

A self tuning based decoupled PID controller has been designed using diagonal recurrent neural network in [2]. The dynamics of a nuclear research reactor has been captured by using locally recurrent neural network in [3]. A fuzzy logic based controller has been designed for pressure regulation in liquid zone control system for 540 MWe PHWR in [4]. The MIMO nonlinear dynamics of PHWR is identified using adaptive feedforward neural network in [5]. Another adaptive feedforward neural controller has been designed for nonlinear systems using simultaneous perturbation stochastic algorithm in [6]. A first principles model based wavelet neural controller has been designed for nuclear steam generator in [7]. A wavelet based optimization has been suggested for skeletal buildings with frequency domain constraints in [8]. A wavelet based neural transforms have been proposed for transmission line fault detection in [9]. A spline wavelet transform has been suggested for identification of liquid zone control model of 540 MWe Indian PHWR in [10]. A robust wavelet neural controller

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with sliding modes has been designed for motor control drive in [11]. An optimization algorithm has been developed for back propagation based wavelet neural network in [12]. An adaptive wavelet neural controller has been suggested for power converter using FPGA in [13]. A wavelet observer based control has been synthesized for uncertain time delayed systems in [14]. A first principles model based wavelet neural controller has been designed for automated generation control in [15]. A wavelet neural controller for first principles model based plant frequency control has been designed in [16].

In this research, a novel multi-objective optimized Multi-Input Multi-Output Adaptive Wavelet Neural Network based Steam Blow-Off System Controller was synthesized using Mother Wavelet Transforms with strong adoptability features. Based on proposed control algorithm, a Multi-Input Multi-Output Adaptive Wavelet Neural Network based Steam Blow-Off System Model was developed in cascaded neural network formulation rather than first principles based linearized modeling approach which is considered in [13-16]. Also, a cascaded neural model of the blow-off system was developed because the neural blow-off controller is series configuration of neural steam blow-off system and hence the neural blow-off controller driving the three blow-off control valves operating in coupled neural configuration for the excessive release of steam pressure in the nuclear boiler system.

2. MATERIALS AND METHODS

2.1. Steam Blow-off System

Steam blow-off system was associated with steam generators. Steam blow-off system was used in Pressurized Heavy Water Reactor (PHWR) type nuclear power plant of 137 MWe rating in which steam corresponding to 30 MWe was stored in the condenser while remaining excessive steam was released to the atmosphere. In contrast, the steam dump system was used in Pressurized Light Water Reactor (PLWR) type nuclear power plant in which 30–90% steam is dumped in the condenser while remaining 70–10% is released to atmosphere, depending on the electrical rating of the plant. The purpose of steam blow-off system was to release the excessive steam to atmosphere in case of grid loss, reactor trip or turbine trip. There were three blow-off control valves (CV_1, CV_2 and CV_3) mounted on the top of steam generator. Three blow-off control valves were provided for redundancy and fast release in case of unexpected severe transients.

2.2. Steam Blow-off Controller

The normal steam generator pressure was maintained at 550 Psig but under normal transient conditions, the steam pressure varies from 550 Psig and it should be with ± 20 Psig band. Under abnormal conditions, called unexpected severe transients, a Single-Input Multi-Output Proportional plus Integral plus Derivative Controller (SIMO PIDC) was used. This SIMO PID controller was used to actuate three steam blow-off control valves when steam pressure is increasing at a rate of 2 Psig/Sec and reaches to 620 Psig. Therefore, the set-point of the steam blow-off controller was 620 Psig. If the steam blow-off set-point is Ps_{SET} and measured steam pressure is Ps then e_P would be the steam pressure error signal controlled by a SIMO PID controller as shown in Fig. 1.

2.3. New Steam Blow-off Controller

Since the new steam blow-off controller was an adaptive wavelet neural controller, by using the adaptive wavelet neural network structure [15] and back propagation algorithm optimized by steepest decent learning rate [5], the performance index for CV_{1N} can be defined as:

$$J_{CV1N}(n) = \frac{1}{2}\sum_{n=1}^{p}[CV_{1N}(\bar{W}_{ki}(n), \bar{W}_k(n), \bar{W}_k(n), a_k(n), b_k(n)) - CV_1(n)]^2 \tag{1}$$

where CV_{1N} (.) and CV_1 (.) are neural and nonlinear dynamic functions for steam blow-off control valve CV_1 respectively while $\bar{W}_{ki}$, $\bar{W}_k$, a_k, b_k and n are weights matrix associated with input layer of i nodes, weights matrix associated with hidden layer of k nodes, dilation factors associated with k nodes, translation factors associated with k nodes and backward step number (n = 1,2,3,…,p samples) respectively. The structure of adaptive wavelet neural network controller is shown in Fig. 2.

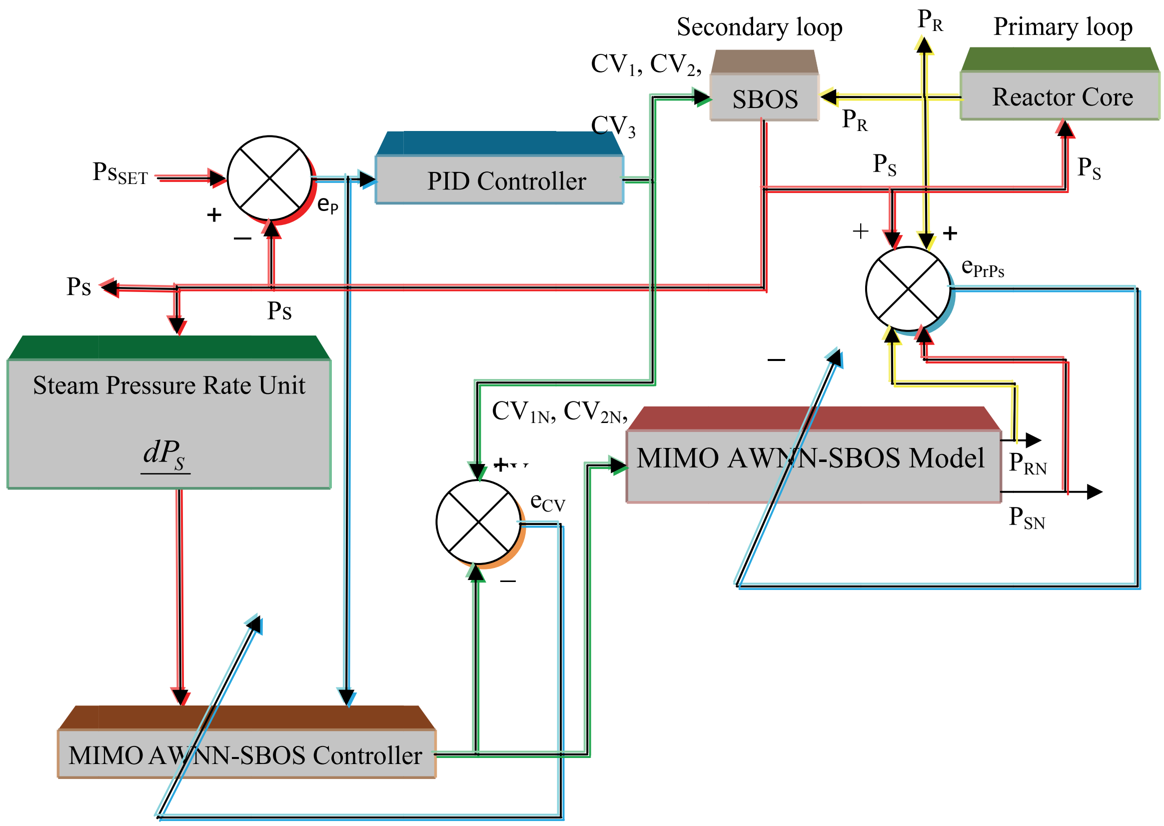

Fig. 1. Closed loop design architecture of existing and new blow-off control system.

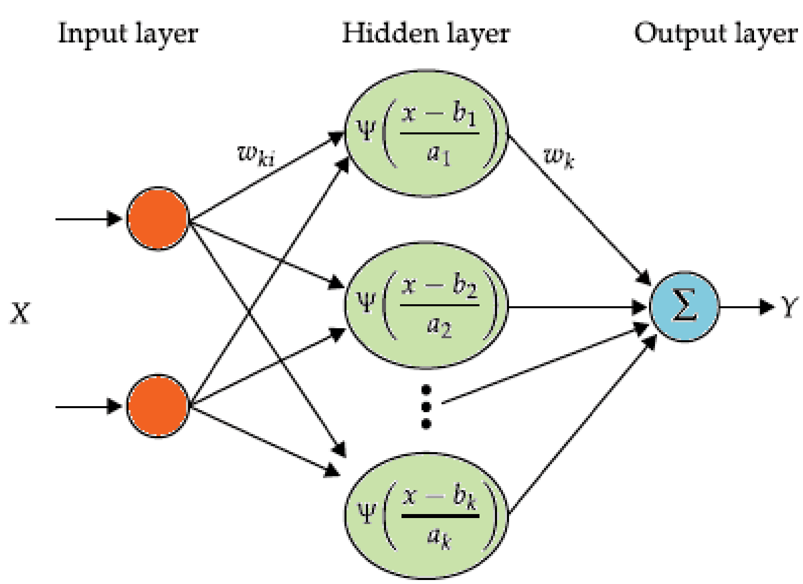

Fig. 2. Design architecture of adaptive wavelet neural network.

Similarly, the performance index for CV_{2N} can be defined as:

$$J_{CV2N}(n) = \frac{1}{2}\sum_{n=1}^{p}[CV_{2N}(\overline{W}_{ki}(n), \overline{W}_k(n), a_k(n), b_k(n)) - CV_2(n)]^2 \tag{2}$$

where all symbols have their usual meanings.

The performance index for CV_{3N} can be defined as:

$$J_{CV3N}(n) = \frac{1}{2}\sum_{n=1}^{p}[CV_{3N}(\overline{W}_{ki}(n), \overline{W}_k(n), a_k(n), b_k(n)) - CV_3(n)]^2 \tag{3}$$

where all symbols have their usual meanings.

2.4. Adaptive Wavelet Neural Optimization

2.4.1. Structure of Mother Wavelet Network

The term wavelet means little wave having minimum oscillations, with extremely fast decaying characteristics to zero. The function having such feature is called wavelet function. The wavelet function used for feed forward neural network is called mother wavelet function expressed by ψ. The wavelet transform measures the relationship between inputs and translated mother wavelet. The mother wavelet transform is given as:

$$\psi(a_k, b_k)(x_i) = \frac{1}{\sqrt{a_k}}\psi\left(\frac{x_i - a_k}{b_k}\right) \tag{4}$$

where x_i, a_k and and b_k are i^{th} input signal, k^{th} dilation factor and k^{th} translation factor respectively.

2.4.2. Steepest Decent Learning Rule and Wavelet Neural Network

Using the steepest decent learning rate [5], the change in input weights, hidden layer weights, dilation factors and translations factors can be formulated as:

$$\Delta\omega_{ki}(n+1) = -\alpha\frac{\partial J_{CV_{1N}}(n)}{\partial\omega_{ki}} + \beta\Delta\omega_{ki}(n) \tag{5}$$

$$\Delta\omega_k(n+1) = -\alpha\frac{\partial J_{CV_{1N}}(n)}{\partial\omega_k} + \beta\Delta\omega_k(n) \tag{6}$$

$$\Delta a_k(n+1) = -\alpha\frac{\partial J_{CV_{1N}}(n)}{\partial a_k} + \beta\Delta a_k(n) \tag{7}$$

$$\Delta b_k(n+1) = -\alpha\frac{\partial J_{CV_{1N}}(n)}{\partial b_k} + \beta\Delta b_k(n) \tag{8}$$

where α and β are learning rate and momentum term respectively.

Now, the input weights, hidden layer weights, dilation factors and translations factors updating logic can be formulated as:

$$\omega_{ki}(n+1) = \omega_{ki}(n) + \Delta\omega_{ki}(n+1) \tag{9}$$

$$\omega_k(n+1) = \omega_k(n) + \Delta\omega_k(n+1) \tag{10}$$

$$a_k(n+1) = a_k(n) + \Delta a_k(n+1) \tag{11}$$

$$b_k(n+1) = b_k(n) + \Delta b_k(n+1) \tag{12}$$

2.5. MIMO AWNN-SBOS Controller

2.5.1. Choice of New Inputs

The input of existing SIMO PID controller is e_P which is a function of Ps_{SET} and P. In the new proposed design, instead of one input signal two input signals were selected. One was a previous steam pressure error signal (e_P) and second was a steam pressure rate signal (*dPs/dt*). Therefore, the new proposed controller is a multi-input controller.

2.5.2. Synthesis of MIMO AWNN-SBOS Controller

The configuration of inputs and outputs for MIMO AWAN-SBOS controller is shown in Fig. 3. The new proposed MIMO AWNN-SBOS controller was synthesized based on three MISO AWNN-SBOS controllers. These three controllers were synthesized using soft parallel computing algorithm for estimating the valve opening positions of three blow-off control valves CV_{1N}, CV_{2N} and CV_{3N} expressed in %.

2.6. MIMO AWNN-SBOS Model Development

2.6.1. Choice of Neural Inputs

The inputs and outputs of steam blow-off system and nuclear reactor core acting like a plant for new proposed controller as shown in Fig. 3. CV_1, CV_2 and

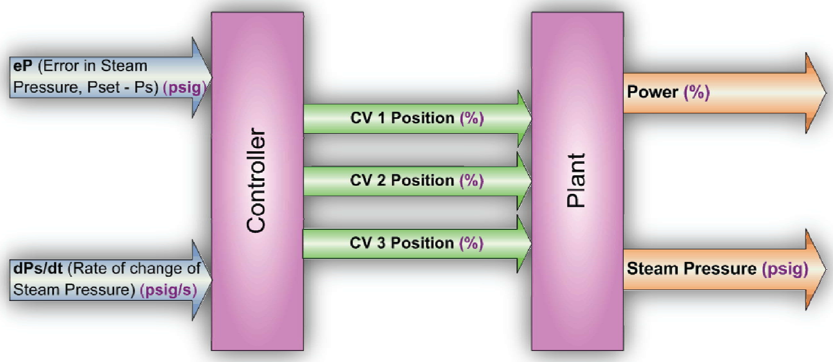

Fig. 3. New Interfacing set-up of controller with plant.

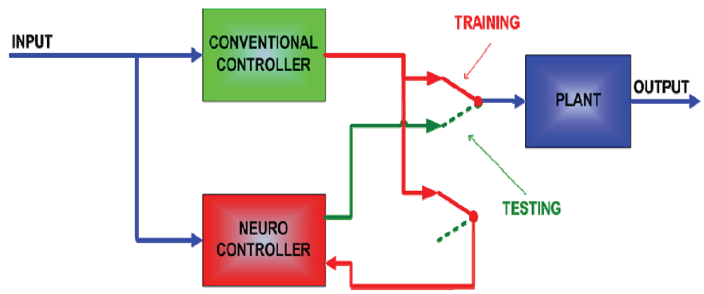

Fig. 4. Framework for training and testing of neuro-controller switchover logic.

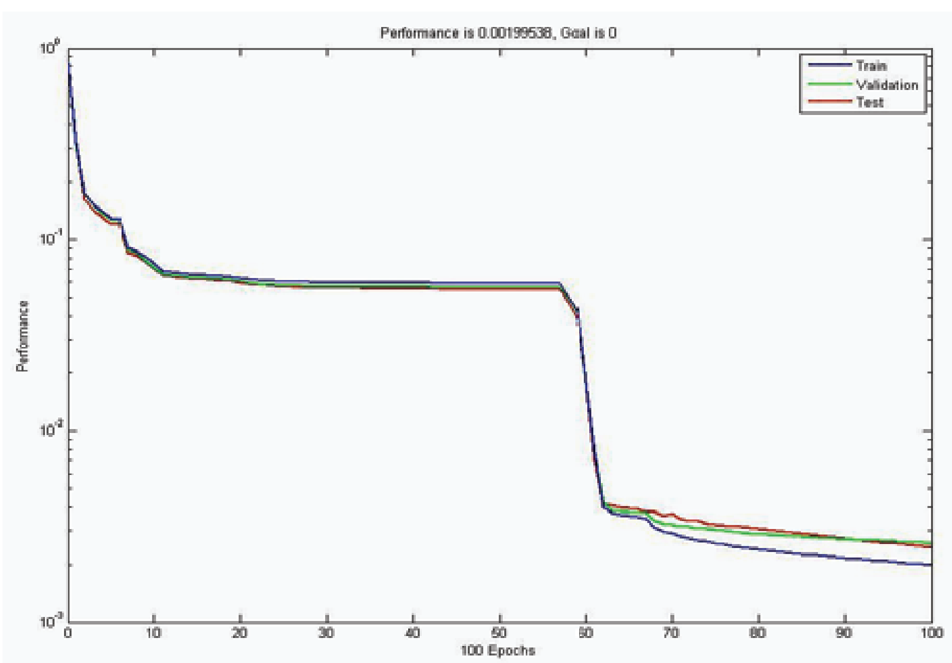

Fig. 5. Performance optimization during training, validation and testing phases of MISO AWNN-SBOS model for steam pressure.

CV_3 are the inputs and P_R and P_S are the outputs of steam blow-off system. Since the nonlinear model is developed in cascaded configuration, so in fact CV_{1N}, CV_{2N} and CV_{3N} are chosen as inputs and P_{RN} and P_{SN} are chosen as outputs for multivariable neural model development.

2.6.2. *Formulation of MIMO AWNN-SBOS Model*

The highly nonlinear dynamics of multivariable blow-off system was captured by synthesizing two MISO AWNN models using soft parallel computing algorithm. The parallel computing algorithm means the model is Multi-Input and Multi-Output (MIMO) which is designed based two parallel operating MISO neural models and all the model parameters are computed and optimized simultaneously. One MISO AWNN-SBOSM is synthesized for estimating reactor power while another MISO AWNN-SBOSM is synthesized for estimating steam pressure.

Similar to equation (1), the performance index for P_{RN} can be defined as:

$$J_{P_{RN}}(n) = \frac{1}{2}\sum_{n=1}^{p}[P_R(\overline{W}_{ki}(n), \overline{W}_k(n), a_k(n), b_k(n)) - P_R(n)]^2 \tag{13}$$

where P_{RN} (.) and P_R (.) are neural and nonlinear dynamic functions for reactor power P_R respectively while $\overline{W}_{ki}$, $\overline{W}_k$, a_k, b_k and n are weights matrix associated with input layer of i nodes, weights matrix associated with hidden layer of k nodes, dilation factors associated with k nodes, translation factors associated with k nodes and backward step number (n = 1,2,3,…,p samples) respectively.

Similarly, the performance index for P_S can be defined as:

$$J_{P_{SN}}(n) = \frac{1}{2}\sum_{n=1}^{p}[P_{SN}(\overline{W}_{ki}(n), \overline{W}_k(n), a_k(n), b_k(n)) - P_S(n)]^2 \tag{14}$$

where all symbols having their usual meanings.

3. RESULTS AND DISCUSSION

The closed loop cascaded configuration of MIMO AWNN-SBOS controller and MIMO AWNN-SBOS is shown in Fig. 1.

3.1. MIMO AWNN-SBOS Controller Model Estimation

100,000 data points were obtained in real time sampled over 0.01 Sec controller parameters under the severe transient prevailing sudden grid loss. Three sub-data points were generated from these 100,000 data points for training, testing and validation purposes. The performance indices described in equation (1) to equation (3) were optimized using equation (5) to equation (12) and the optimized parameters of three MISO AWNN-SBOS controllers are tabulated in Table 1 to Table 3, respectively.

Table 1. Design parameters for MISO AWNN-SBOS Controller for CV_1.

Network Parameter	Value
Input Parameters	e_P, dPs/dt
Output Parameter	CV_1
Total Patterns (100%)	100, 000
Number of Training Patterns (70%)	70, 000
Number of Testing Patterns (15%)	15, 000
Number of Validation Patterns (15%)	15, 000
Sample Time (Sec)	0.01
Number of Neurons in Input Layer of MISO	2
Number of Neurons in Hidden Layer of MISO	49
Number of Neurons in Output Layer of MISO	1
Learning Rate	0.05
Momentum Term	0.6
Number of Dilation Parameters	49
Number of Translation Parameters	49
Total Epochs	100

Table 2. Design parameters for MISO AWNN-SBOS Controller for CV_2.

Network Parameter	Value
Input Parameters	e_P, dPs/dt
Output Parameter	CV_2
Total Patterns (100%)	100, 000
Number of Training Patterns (70%)	70, 000
Number of Testing Patterns (15%)	15, 000
Number of Validation Patterns (15%)	15, 000
Sample Time (Sec)	0.01
Number of Neurons in Input Layer of MISO	2
Number of Neurons in Hidden Layer of MISO	37
Number of Neurons in Output Layer of MISO	1
Learning Rate	0.05
Momentum Term	0.6
Number of Dilation Parameters	37
Number of Translation Parameters	37
Total Epochs	100

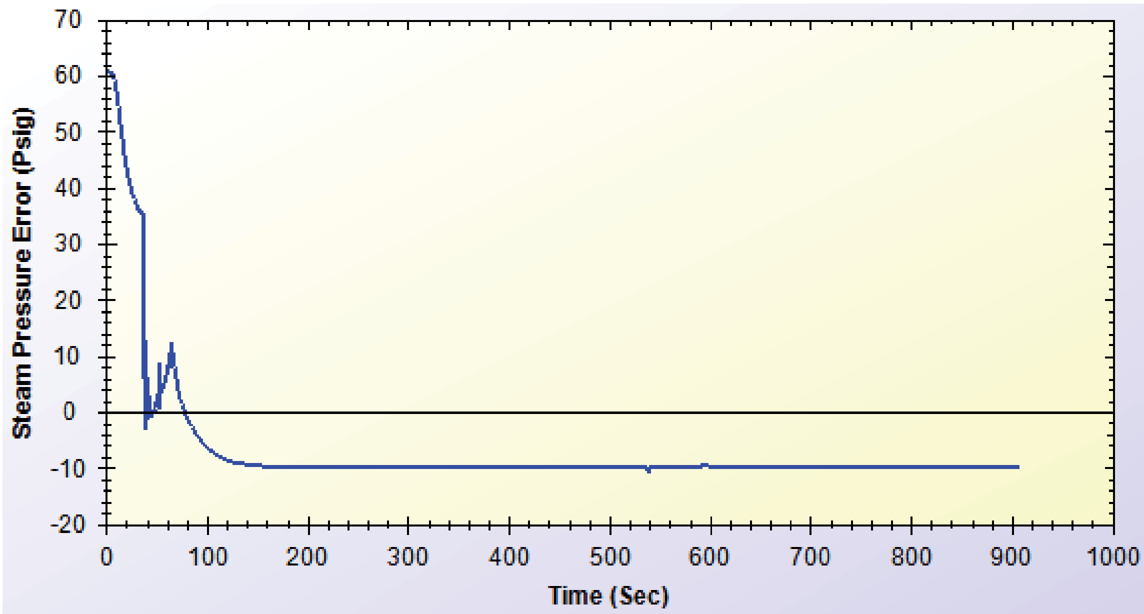

Fig. 6. Simulation of steam pressure error signal.

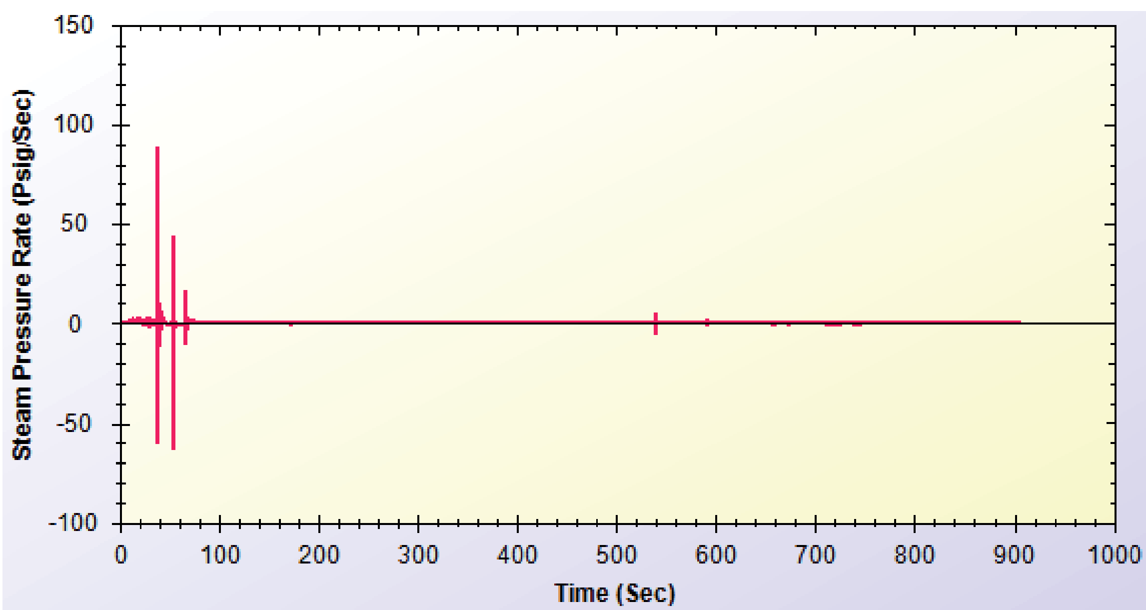

Fig. 7. Simulation of steam pressure rate signal.

Table 3. Design parameters for MISO AWNN-SBOS Controller for CV_3.

Network Parameter	Value
Input Parameters	e_P , dPs/dt
Output Parameter	CV_3
Total Patterns (100%)	100, 000
Number of Training Patterns (70%)	70, 000
Number of Testing Patterns (15%)	15, 000
Number of Validation Patterns (15%)	15, 000
Sample Time (Sec)	0.01
Number of Neurons in Input Layer of MISO	2
Number of Neurons in Hidden Layer of MISO	20
Number of Neurons in Output Layer of MISO	1
Learning Rate	0.05
Momentum Term	0.6
Number of Dilation Parameters	20
Number of Translation Parameters	20
Total Epochs	100

3.2. MIMO AWNN-BOS Model Estimation

Since, the MIMO AWNN-BOS model was optimized in cascaded with MIMO AWNN-SBOS controller, so 100,000 data points were required to be utilized for model estimation. Thus, 100,000 neural data points obtained from CV_{1N}, CV_{2N} and CV_{3N} were used in real time sampled over 0.01 sec for estimating plant parameters under the same grid loss transient. These sub-data points were generated from these 100,000 neural data points for training, testing and validation purposes. The performance indices described in equation (13) and equation (14) were optimized using equation (5) to equation (12) and the optimized parameters of two MISO AWNN-SBOS models are tabulated in Table 4 and Table 5, respectively.

Table 4. Design parameters for MISO AWNN-SBOS Model for P_R.

Network Parameter	Value
Input Parameters	CV_1, CV_2, CV_3
Output Parameter	P_R
Total Patterns (100%)	100, 000
Number of Training Patterns (70%)	70, 000
Number of Testing Patterns (15%)	15, 000
Number of Validation Patterns (15%)	15, 000
Sample Time (Sec)	0.01
Number of Neurons in Input Layer of MISO	3
Number of Neurons in Hidden Layer of MISO	39
Number of Neurons in Output Layer of MISO	1
Learning Rate	0.05
Momentum Term	0.6
Number of Dilation Parameters	39
Number of Translation Parameters	39
Total Epochs	100

Table 5. Design parameters for MISO AWNN-SBOS Model for P_S.

Network Parameter	Value
Input Parameters	CV_1, CV_2, CV_3
Output Parameter	P_S
Total Patterns (100%)	100, 000
Number of Training Patterns (70%)	70, 000
Number of Testing Patterns (15%)	15, 000
Number of Validation Patterns (15%)	15, 000
Sample Time (Sec)	0.01
Number of Neurons in Input Layer of MISO	3
Number of Neurons in Hidden Layer of MISO	39
Number of Neurons in Output Layer of MISO	1
Learning Rate	0.05
Momentum Term	0.6
Number of Dilation Parameters	39
Number of Translation Parameters	39
Total Epochs	100

3.3. Validation of Proposed Closed Loop AWNN Based Control Scheme

The closed loop framework for the training and testing of new proposed neuro-controller switchover logic is shown in Fig. 4. All inputs, outputs and closed loop optimization scheme are shown in detail in Fig. 1. All three MISO AWNN-SBOS controllers and two MISO AWNN-SBOS models were analyzed during training, testing and validation phases. Since, fourth and fifth MISO AWNN-SBOS models werre cascaded outputs of three MISO AWNN-SBOS controllers, so, a fifth MISO AWNN-SBOS was selected covering the whole performance of closed loop framework. The performance of MISO AWNN-SBOS model for predicting steam pressure during training, testing and validation phases is shown in Fig. 5. The performance curves show an excellent agreement in optimization. A steam pressure error signal was applied at input of classical SIMO PID controller while two input signals of steam pressure error signal and steam pressure rate signal were applied at the input of MIMO AWNN-SBOS controller for performance analysis purposes. Simulations of these signals are shown in Fig. 6-7. In Fig. 6, stabilization of pressure error signal is shown. Since the steam blow-off pressure set-point was 610 psig and normal steam pressure was 550 psig, during the steam blow-off transient, the normal steam pressure changed from 550 psig and keep on increasing towards 610 psig set-point and when the set-point was reached then the process of

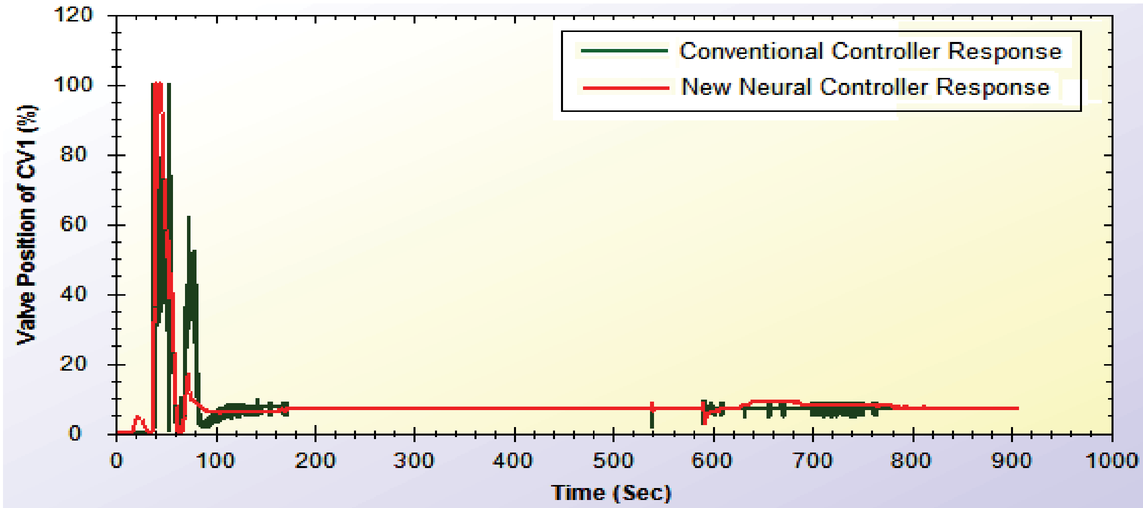

Fig. 8. Comparison of SIMO PID controller and new neural MISO AWNN-SBOS controller response for blow-off control valve – CV1.

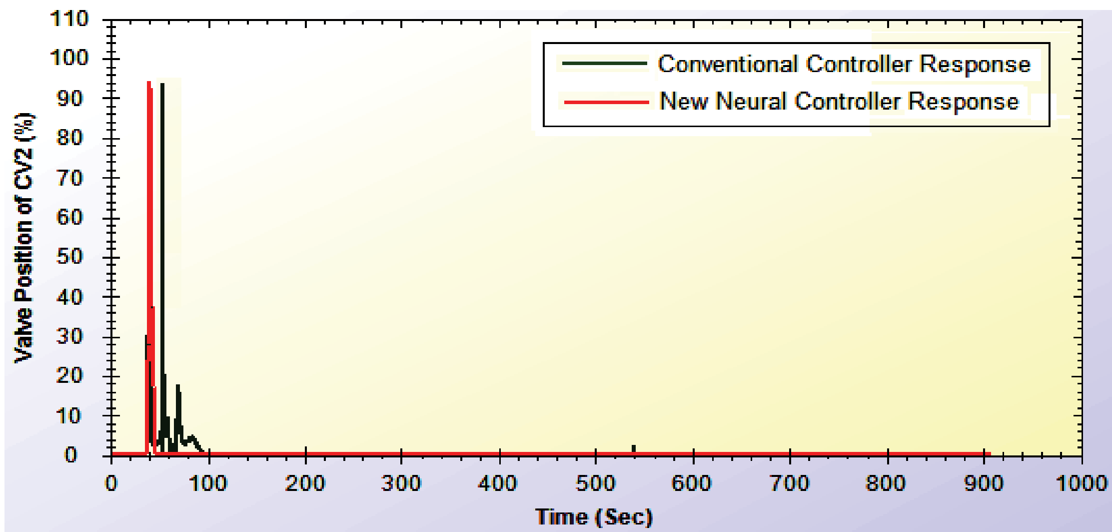

Fig. 9. Comparison of SIMO PID controller and new neural MISO AWNN-SBOS controller response for blow-off control valve – CV2.

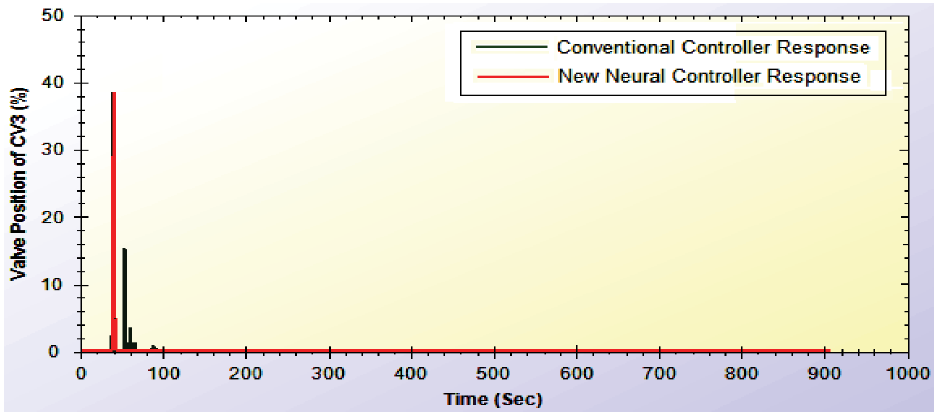

Fig. 10. Comparison of SIMO PID controller and new neural MISO AWNN-SBOS controller response for blow-off control valve – CV3.

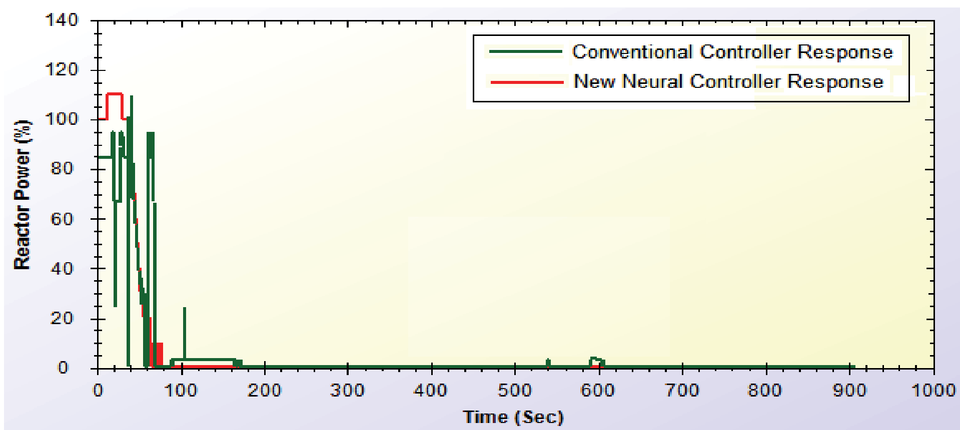

Fig. 11. Comparison of SIMO PID controller and new neural MISO AWNN-SBOS controller based response for reactor power.

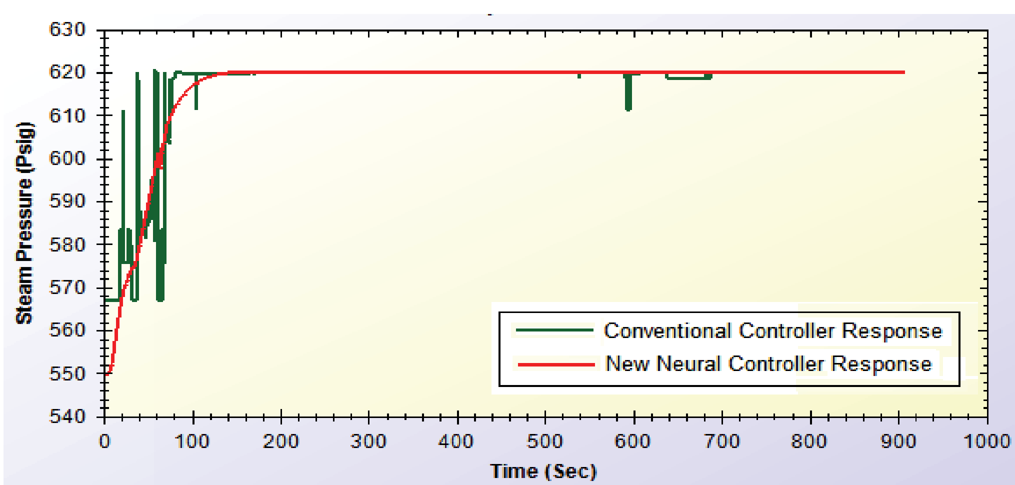

Fig. 12. Comparison of SIMO PID controller and new neural MISO AWNN-SBOS controller based response for steam pressure.

steam blow-off continued at the maximum rate and reaches a maximum attainable steam pressure of 620 psig which was exactly in accordance with the inherent design. Therefore, it stabilized at steam pressure error signal of -10 psig, which is simply the difference of 610 psig and 620 psig. The steam pressure signal and steam pressure rate took major fluctuations in first 150 seconds and 90 seconds, respectively. The comparison of conventional SIMO PID controller and proposed new MISO controller response for CV_1 is shown in Fig. 8. The response of MISO AWNN-SBOS controller was found lesser oscillatory, much smoother and with reduced overshoots in performance as compared to SIMO PID controller response. The comparison of conventional SIMO PID controller and MISO controller response for CV_2 is shown in Fig. 9. The response of MISO AWNN-SBOS controller was found lesser oscillatory, much smoother and much faster in initial phase of transient in performance as compared to SIMO PID controller response. The comparison of conventional SIMO PID controller and MISO controller response for CV_3 is shown in Fig. 10. The response of MISO AWNN-SBOS controller was found much lesser oscillatory, much smoother and much faster throughout the transient in performance as compared to SIMO PID controller response.

Now, CV_1 , CV_2 and CV_3 as three signals were applied at SBOS and P_S as output of SBOS was coupled to reactor core for reactor power signal while CV_{1N} , CV_{2N} and CV_{3N} were applied at MIMO AWNN-SBOS model for performance analysis purposes. The comparison of conventional SIMO PID controller and MISO controller response for P_R is shown in Fig. 11. The response of MISO AWNN-SBOS model for reactor power was found much lesser oscillatory and much smoother in performance as compared to SIMO PID controller based response. The reactor became 0% when steam blow-off transient was completed as shown in Fig. 11. The comparison of conventional SIMO PID controller and MISO AWNN-SBOS model for P_S is shown in Fig. 12. The response of MISO AWNN-SBOS model was found extremely smoother and critically damped in performance as compared to SIMO PID controller based response. When the steam blow-off transient settled down, the steam pressure signal attained a steady value of 620 Psig (Fig. 12). Hence, the proposed design methodology using artificial intelligence proved highly successful in robustness and performance.

4. CONCLUSIONS

A severe transient handling steam blow-off control system has been considered in this research work. A new multivariable MIMO adaptive wavelet neural controller has been proposed as new replacement of conventional SIMO PID controller of steam blow-off system. The proposed data-driven new controller has been utilized for capturing local fluctuations of multivariable adaptive wavelet neural dynamics of steam blow-off system. The training, testing and validation of proposed multivariable neural model has been carried out in cascaded neural environment. The proposed new closed loop control scheme has been proved a successful realization through simulation experiments.

5. ACKNOWLEDGEMENTS

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