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Original Article

Design of a Novel Multi-Objective Mixed Stochastic Optimization based Neuro-Controller for Reactor Coolant Pressure Control System

Arshad H. Malik[1*], Aftab A. Memon[2] and Feroza Arshad[3]

[1*]Department of Nuclear Instrumentation, Pakistan Atomic Energy Commission, A-104, Block-B, Kazimablad, Model Colony, Karachi, Pakistan

[2]Department of Telecommunication Engineering, Mehran University of Engineering and Technology, Jamshoro, Sindh, Pakistan

[3]Department of Management Information System, Pakistan Atomic Energy Commission, B-63, Block-B, Kazimablad, Model Colony, Karachi, Pakistan

Abstract: In this paper, a Novel Multi-Objective Mixed Stochastic Optimization (NMOMSO) based Neuro-Controller (NC) is synthesized for Multi-Input Multi-Output (MIMO) Reactor Coolant Pressure Control System (RCPCS) of Pressurized Heavy Water Reactor (PHWR)-type Nuclear Power Plant (NPP). In RCPCS, a new MIMO Modified Particle Swarm Optimization Algorithm (MPSOA) based nonlinear Adaptive Feedforward Neural Network (AFNN) model (MIMO MPSOA-AFNN) of the Reactor Coolant Pressure System (RCPS) is developed mapping five inputs and two outputs. A highly intelligent NMOMSO based NC is designed using AFNN and Mixed Stochastic Optimization Techniques (MSOT) in a MIMO framework. The NMOMSO is comprised of five Multi-Input Single-Output (MISO) AFNN optimized by MSOT. Three different stochastic techniques are used for the optimization of weight matrices of five MISO intelligent networks. A Modified Particle Swarm Optimization Algorithm (MPSOA) is used for the optimization of two intelligent MISO networks parameters for two feed valve positions. An Ant Colony Optimization Algorithm (ACOA) is implemented for the optimization of two intelligent MISO networks for two bleed valve positions and a Bee Colony Optimization Algorithm (BCOA) is used for the optimization of one intelligent MISO network for one spray valve position of RCPCS. In the proposed NMOMSO based NC, a multi-objective problem is formulated based on five parallel operating MISO intelligent networks using new configuration of reactor coolant and steam pressure signals. The proposed MIMO MPSOA-AFNN model and NMOMSO based neuro-controller of RCPS is designed in MATLAB and a Graphical User Interface (GUI) is developed for variables transfer and simulations in Visual C. The performance of model based novel neuro-controller is compared with Conventional Coupled Controller (CCC) using PID controlled reactor coolant pressure and ON-OFF controlled surge tank level and found remarkable.

Keywords: Nonlinear modeling, artificial intelligence, stochastic optimization, multi-objective control, reactor coolant pressure control system, nuclear power plant

1. INTRODUCTION

A Nuclear Power Plant (NPP) is basically a large scale system consisting of about 250 systems. Amongst various plant systems, Reactor Coolant Pressure System (RCPS) is one of the most important critical systems of a plant. The details of plant dynamics and control are available in [1, 2].

A system identification based linear model of Pressurized Heavy Water Reactor (PHWR) has been developed in [2]. The dynamics of Pressurized Water Reactor (PWR) and research reactor have been captured using recurrent neural network in [3]. A Multi-Input Multi-Output (MIMO) nonlinear model of PHWR has been identified in [4] using Adaptive Feedforward Neural Network (AFNN). A fuzzy logic controller has been designed for reactor coolant pressure control of PHWR in [5]. A MIMO adaptive neuro-fuzzy intelligent control system has been recently developed for reactor coolant pressure control system of PHWR in [6] using existing signals of

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

primary pressure control loop.

A neural network based predictive control has been devised for mobile robot [7] using particle swarm optimization (PSO). A fuzzy logic based reactor power controller has been designed for research reactor using PSO in [8]. A modified PSO based algorithm has been proposed in [9] using an adaptive inertial weight. A detailed design of steel frames has been proposed in [10] using ant colony optimization. A preliminary design concept using bee optimization algorithm has been introduced in [11]. A detailed application has been proposed for control chart pattern recognition using bee optimization algorithm in [12].

In this research, a new highly nonlinear MIMO neural model of RCPS is developed using hybrid modified particle swarm optimization algorithm and an adaptive feedforward neural network. A new signal configuration is proposed based on both primary and secondary loops of PHWR-type nuclear power plant for better control of reactor coolant pressure. Based on new signal configuration, a novel MIMO neuro-controller is proposed using multi-objective mixed stochastic optimization design approach. The proposed MIMO neuro-controller is a highly complex design configured with one thousand fifty three controller design parameters using hybrid modified particle swarm optimization algorithm and an adaptive feedforward neural network for two feed valves position control, hybrid ant colony optimization algorithm and an adaptive feedforward neural network for two bleed valves position control, and hybrid bee colony optimization algorithm and an adaptive feedforward neural network for spray valve position control. This mixed stochastic multi-objective control problem is solved using hybrid global and local optimization techniques.

2. MATERIALS AND METHODS

2.1. Reactor Coolant Pressure System

The purpose of reactor coolant pressure system (RCPS) is to maintain 1500 psig coolant pressure in order to avoid boiling in reactor coolant. Therefore, high coolant temperature can be attained by maintaining this pressure. The RCPS consists of a feed-bleed system and a surge tank. The feed-bleed system consists of two feed valves (FV_1, FV_2), two bleed valves (BV_1, BV_2) and one spray valve (SV). The surge tank consists of three heaters. The detail of RCPS is available in [6].

2.2. Conventional Coupled Controller for RCPS

The reactor coolant pressure is controlled by a conventional coupled controller consisting of a PID controller for feed-bleed system and ON-OFF controller for surge tank system. The PID controller works on e_P which is a reactor pressure control error signal using P_{Pset} and P as the reactor coolant pressure set-point and the measured reactor coolant pressure respectively. Similarly, the ON-OFF controller works on e_L which is a surge tank level control error signal using L_{set} and L as surge tank level set-point and measured surge tank level signal respectively. The closed loop architecture of conventional coupled controller based reactor coolant pressure control system (RCPCS) is shown in Fig. 1.

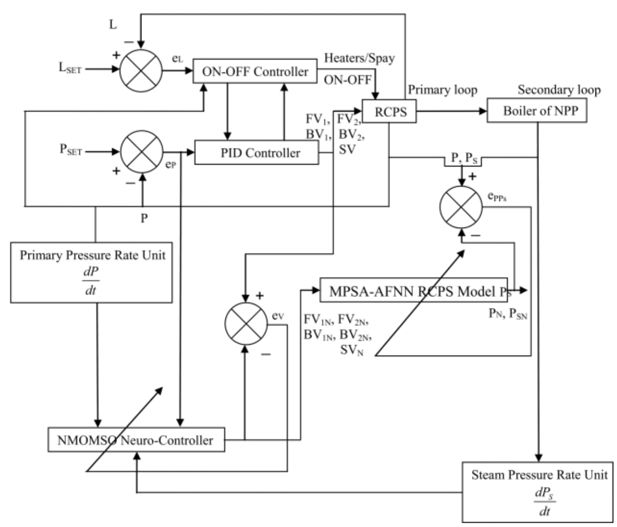

Fig. 1. Closed loop architecture of CCC and NMOMSO based RCPCS.

2.3. Adaptive Feedforward Neural Network (AFNN)

Both RCPS model and its neuro-controller are basically intelligent nonlinear structures consisting of weights and biases matrices. These weights and biases are known neural parameters. The basic architecture of both neural RCPS model and its neuro-controller is an adaptive feedforward neural network (AFNN). Therefore, using the algorithm of AFNN [4], the objective function of AFNN can be generalized for *n* number of patterns at *k*-th iteration as:

$$J(k)=\frac{1}{2}\sum_{k=1}^{n}[f(\bar{W}_H(k),\bar{W}_I(k),\bar{U}_M(k),\bar{B}_I(k),\bar{B}_H(k))-\bar{Y}_M(k)]^2 \quad (1)$$

where *f*(.) is a nonlinear function and $\bar{U}_M$, $\bar{Y}_M$, $\bar{W}_H$, $\bar{W}_I$, $\bar{B}_H$ and $\bar{B}_I$ are measured input vector, measured output vector, weights matrix associated with hidden layer, weights matrix associated with input layer, biases vector associated with hidden layer and biases vector associated with input layer respectively. $\bar{U}_M$ is an input vector of five inputs as two feed valve positions, two bleed valve positions and one spray valve position respectively while $\bar{Y}_M$ is an output vector of two outputs as reactor coolant pressure signal and steam pressure signal respectively for neural RCPS modeling. Similarly, $\bar{U}_M$ is an input vector of three inputs as reactor coolant pressure error signal, reactor coolant pressure rate signal and steam pressure rate signal while $\bar{Y}_M$ is an output vector of five outputs as two feed valve positions, two bleed valve positions and one spray valve position respectively for neural RCPS controller model.

2.4. Mixed Stochastic Optimization Methodology

2.4.1. *Stochastic Optimization Techniques*

Now, the objective is to optimize parameters of neuro-controller using stochastic techniques. In this research work, a mixed stochastic optimization approach has been adopted for the computation of neuro-controller parameters. The combination of three most recent and popular stochastic optimization techniques are selected for this design work. These stochastic techniques are modified particle swarm optimization, ant colony optimization and bee colony optimization.

2.4.2. *Modified Particle Swarm Optimization Algorithm (MPSOA)*

In particle swarm optimization algorithm, each solution is called a particle. In stochastic search, a population size is defined which determines the number of particles in a solution space. Each particle acts like a point in *N*-dimensional search space. All particles communicate with one another. Each particle has its current position, previous position, best attained previous position and moving velocity designated as X_{Ci}, X_{Pi}, X_{Bi} and V_{Mi} respectively. In discrete domain, the new velocity of each particle seeking for best particle with dynamic adaptation can be formulated using algorithm [9] as:

$$V_{Mi_{NEW}}=I_W V_{Mi_{CURRENT}}+\mu_1(X_{Pi}-X_{Ci})R_1+\mu_2(X_{Bi}-X_{Ci})R_2 \quad (2)$$

where I_W, μ_1, μ_2, R_1 and R_2 are adaptive inertial weight, stochastic learning rate for cognitive coefficient, stochastic learning rate for social coefficient, random number sequence for cognitive term and random number sequence for social term respectively.

The new position of particle is given by:

$$X_{i_{NEW}}=X_{i_{CURRENT}}+V_{Mi_{NEW}} \quad (3)$$

2.4.3. Ant Colony Optimization Algorithm (ACOA)

In ant colony optimization algorithm, each solution is called an ant. In stochastic search, a population size is defined which determines the number of ants in a solution space. Each ant moves greedily in an *N*-dimensional search space for food point. All ants communicate with one another so as to find the shortest distance between nest and food point by depositing pheromone trials. Each ant has n_i (i= 1,2,…,N) paths to travel with α_i pheromone concentrations. In discrete domain, the deposition of pheromone concentration associated with each path can be formulated using algorithm [10] as:

$$\alpha_{i_{CURRENT}}=\chi\alpha_{i_{PREVIOUS}}+\Delta\alpha_i \quad (4)$$

where χ is a pheromone evaporation rate.

The change in pheromone concentration is given by [10]:

$$\Delta\alpha_i = \sum_{i=1}^{N} \begin{cases} \dfrac{\beta}{g_i(.)} & \text{if an ant chooses new path} \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where β is called pheromone reward factor and g_i (.) is called a performance index.

The stochastic model of ant (A_{ant}) is given by [10]:

$$A_{anti} = \frac{[\alpha_i]^a [h_i]^b}{\sum_{i=1}^{N} [\alpha_i]^a [h_i]^b n_i} \quad (6)$$

where a and b are nonlinear parameters and h_i is called preferred path selection factor.

2.4.4. *Bee Colony Optimization Algorithm (BCOA)*

In bee colony optimization algorithm, bees are classified into three classes called scout bees, employed bees and onlooker bees respectively. In stochastic search, a population size is defined which determines the number of scout bees in a solution space. Each scout bee moves greedily in an N_{scout}-dimensional search space for food point. All scout bees communicate with one another so as to find food sources close to their hive. The scout bees search for food sources randomly. The total search space for all bees is N-dimensional. Food sources are basically the good solutions in search space. The employed bees are associated with specific food sources while onlooker bees are closely watching the movement of employed bees within the hive for choosing food source. The locations of food sources are basically the possible solutions while amount of nectar is basically a fitness function of an optimization problem. Details of an algorithm are available in [11, 12]. If x_F is the location of food source and x_{FNEW} is the new location of food source searched by employed bees then neighbour food source x_{FNEWi} is given by using algorithm [12] as:

$$x_{F_{NEWi}} = x_{Fi} + R_3(x_{Fi} - x_{Ri}) \quad (7)$$

where R_3 and x_{Ri} are random sequence for employed bees and randomly selected food sources respectively.

The fitness function of neighbour food source is given by [12]:

$$\text{Fitness} = \begin{cases} \dfrac{1}{1+\Psi(x_F)} & \text{if } \Psi(x_F) \geq 0 \\ 1+\text{abs}(\Psi(x_F)) & \text{if } \Psi(x_F) < 0 \end{cases} \quad (8)$$

where $\psi(.)$ is an objective function value of solution x_F.

The stochastic model with which x_F is selected by

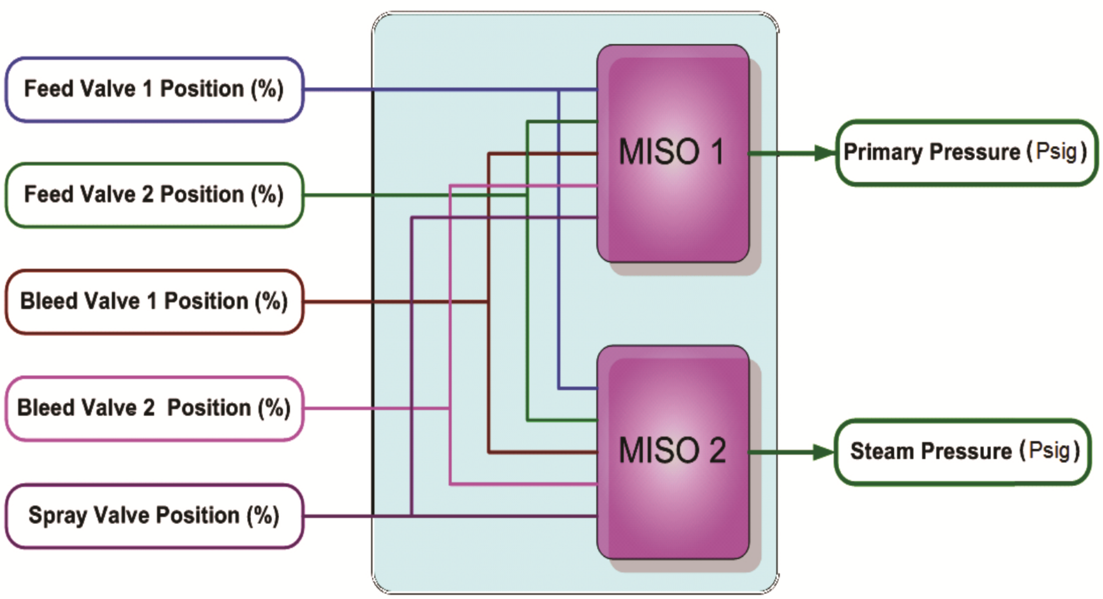

Fig. 2. Structure of inputs and outputs of MIMO MPSOA-AFNN model of RCPS.

an onlooker bee ($O_{onlookerbee}$) is given by [12]:

$$O_{onlookerbee_i} = \frac{Fitness_i}{\sum_{i=1}^{N} Fitness_i} \quad (9)$$

2.5. Development of MIMO Nerual Reactor Pressure Coolant System Model

2.5.1. *Selection of Inputs and Outputs for Neural Model of RCPS*

The inputs and outputs of conventional RCPCS are shown in Fig. 1. There are five inputs and two outputs of RCPS. The five inputs are two feed valve positions, two bleed valve positions and one spray valve position while the two outputs are reactor coolant pressure signal and steam pressure signal respectively. These inputs and outputs are selected in such a way that the design, testing and validation of MIMO neural model based MIMO neuro-controller of RCPCS can be made.

2.5.2. *Architecture of MIMO Neural Model of RCPS*

The MIMO neural model of RCPS is designed based on two parallel operating MISO neural models. These two MISO neural models, MISO1 and MISO2 are designed for predicting reactor coolant pressure signal and steam pressure signal respectively. The structure of inputs and outputs of MIMO MPSOA-AFNN model of RCPS is shown in Fig. 2. The parameters of MIMO neural model of RCPS are optimized by MPSOA. The MPSOA-AFNN model optimization setup for RCPS is shown in Fig. 3.

2.6. Novel Multi-Objective Mixed Stochastic Optimization Based Neuro-Controller

2.6.1. *Selection of New Inputs for Novel MIMO Neuro-Controller for RCPS*

The inputs of conventional coupled controller of RCPCS are e_P and e_L that are dependent on P_{Pset}, P, L_{set} and L. Both these signals are acquired from primary loop of PHWR-type nuclear power plant. In this research work, a new configuration of signals is devised for the design of novel multi-objective mixed stochastic optimization (NMOMSO) based neruo-controller (NC). One old signal and one new signal are acquired from primary loop and one new signal is acquired from secondary loop of plant. Thus, the new input signals for NMOMSO based NC are reactor coolant pressure error signal (e_P), reactor coolant pressure rate signal ($\frac{dP}{dt}$) and steam pressure rate signal ($\frac{dP_S}{dt}$). The steam pressure rate signal is acting like a feed forward signal for this controller because this controller is meant for primary side but one steam pressure rate signal is being fed from secondary side of plant. This new combination of signals is more powerful because now it is an integration of primary and secondary sides and thus more information is being utilized in a better way.

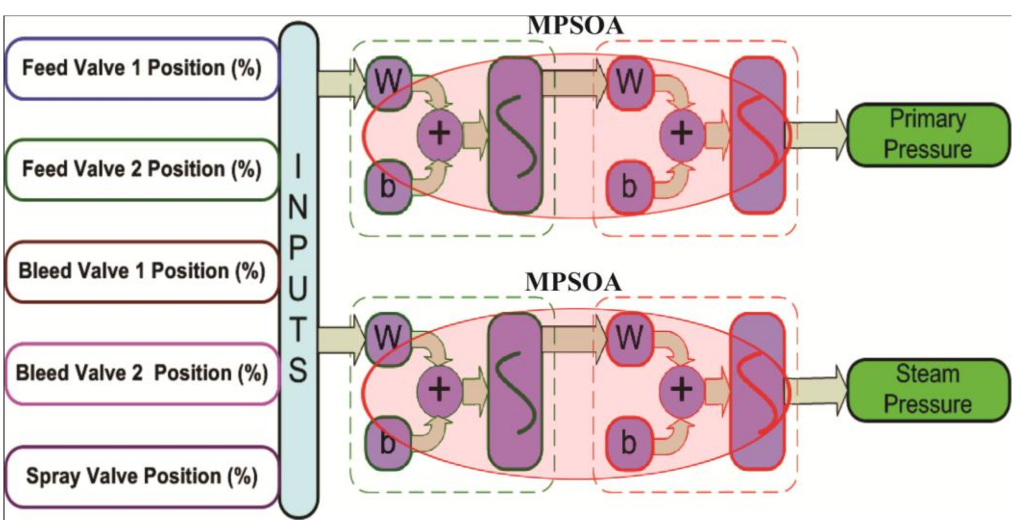

Fig. 3. MPSOA-AFNN model optimization setup for RCPS model.

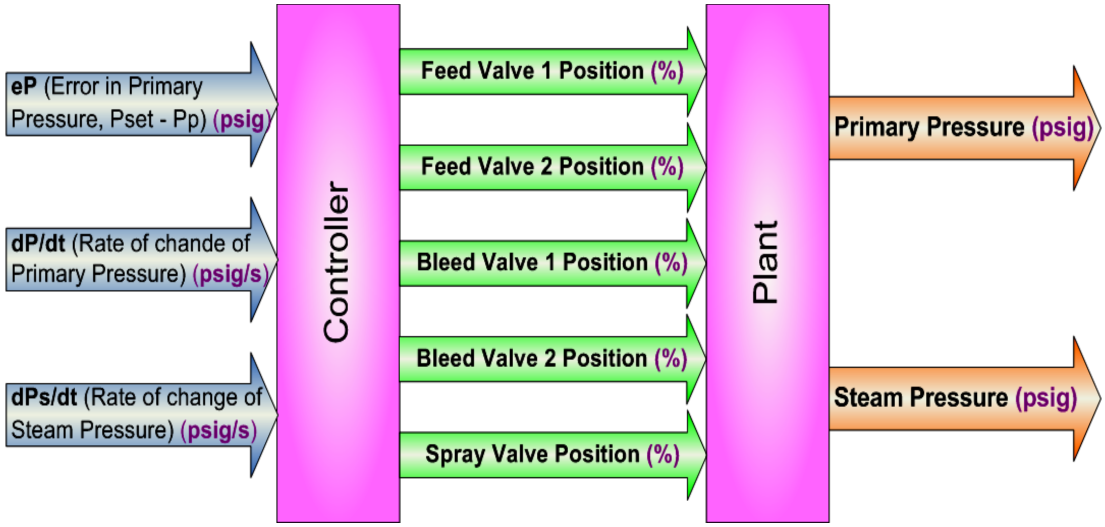

Fig. 4. Structure of inputs and outputs for NMOMSO based RCPCS.

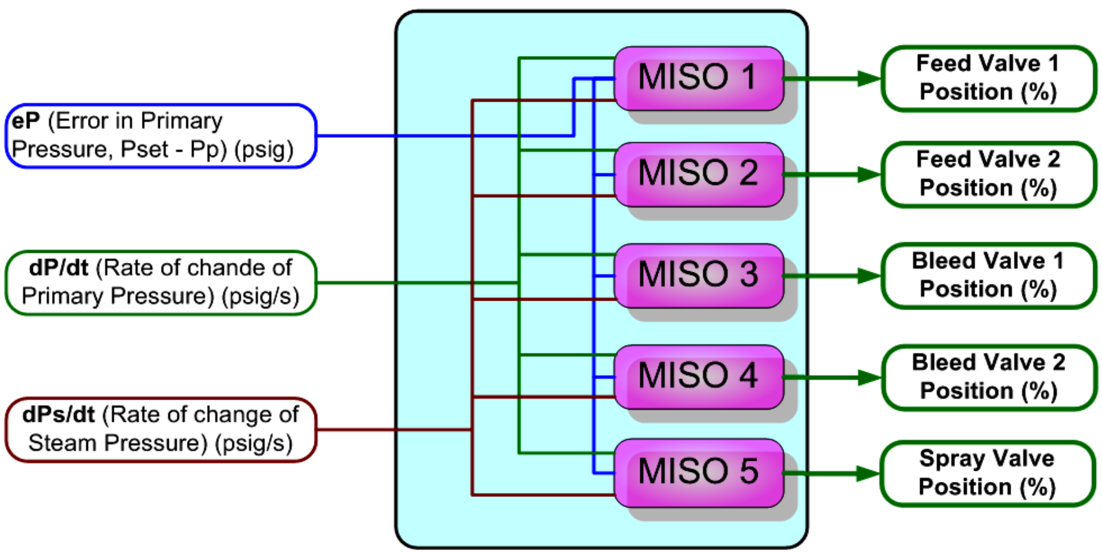

Fig. 5. Decoupling of MIMO NMOMSO based NC into MISO sub neuro-controllers.

2.6.2. *Architecture of Novel MIMO Neuro-Controller for RCPCS*

The structure of inputs and outputs for NMOMSO based RCPCS is shown in Fig. 4. NMOMSO based RCPCS is a MIMO neuro-controller. The MIMO NMOMSO based RCPCS is designed by decomposing it into five parallel operating MISO sub neuro-controllers. Five MISO sub neuro-controllers are designed for predicting two feed valve positions, two bleed valve positions and one spray valve position respectively. All five MISO sub neuro-controllers are designed using hybrid configuration of stochastic optimization techniques and AFNN. The parameters of five MISO sub neuro-controllers are optimized using MPSOA, ACOA and BCOA. Based on optimal solutions obtained through each combination for each control valve, the optimal hybrid combinations of MPSOA-AFNN, ACOA-AFNN and BCOA-AFNN are found best suited for predicting two feed valve positions, two bleed valve positions and one spray valve position respectively. The decoupling of MIMO NMOMSO based NC into five MISO sub neuro-controllers is shown in Fig. 5. The mixed stochastic optimization based setup for the selection of parameters of NC is shown in Fig. 6.

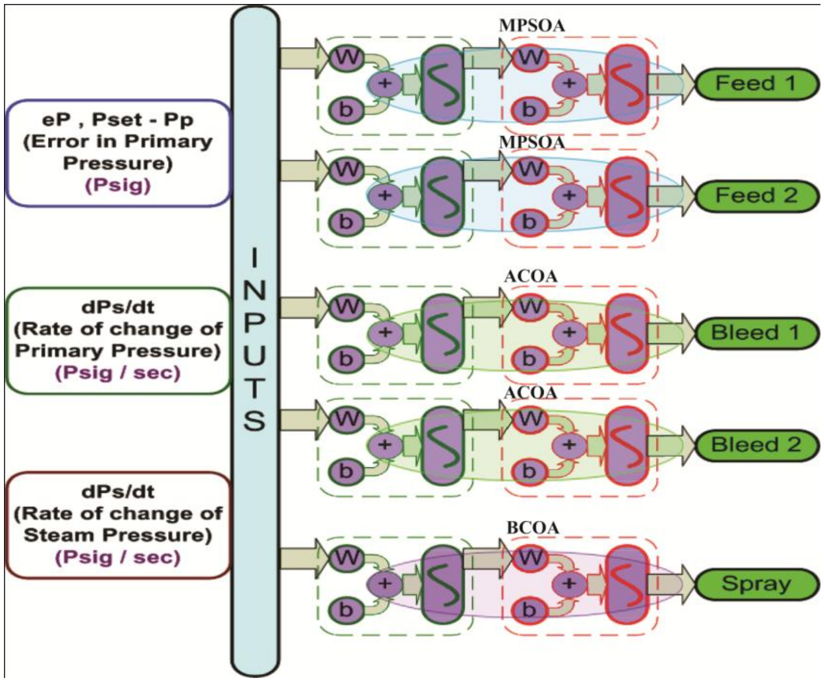

Fig. 6. Mixed stochastic optimization for parameters of MIMO NC.

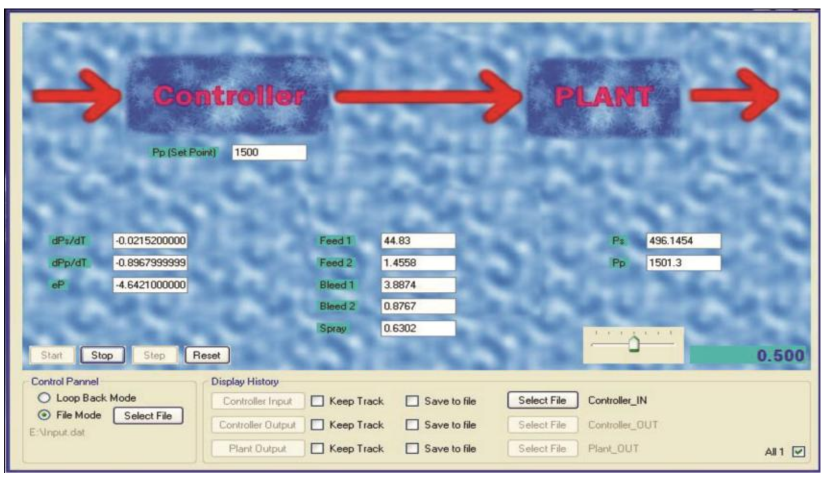

Fig. 7. GUI for variables transfer and simulation in Visual C environment.

3. RESULTS AND DISCUSSION

The process of optimization of MIMO neural model and MIMO neuro-controller parameters is carried out in MATLAB. A graphical user interface (GUI) is developed for variable transfer and simulation of inputs and outputs of model and controller in Visual C environment as shown in Fig. 7.

3.1. Nonlinear Identification of MIMO MPSO Based RCPS

Total 32766 patterns are acquired from an operating PHWR-type nuclear power plant [1]. These patterns are acquired under plant transient conditions. These patterns are classified into three sets of data called training, testing and validation datasets. The parameters of MIMO MPSOA-AFNN RCPS model are set using equation (1) and are optimized using equation (2) and equation (3). The design parameters of MISO1 MPSOA-AFNN and MISO2 MPSOA-AFNN for RCPS model are presented in Table 1 and Table 2 respectively.

Table 1. Design parameters for MISO1 MPSOA-AFNN model of RCPS.

Network Parameter	Value
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO1 MPSOA-AFNN	5
Number of Neurons in Hidden Layer of MISO1 MPSOA-AFNN	39
Number of Neurons in Output Layer of MISO1 MPSOA-AFNN	1
Number of Particles for MISO1MPSOA-AFNN	274
Number of Runs for MISO1 MPSOA-AFNN	40
Stochastic Learning Rate for Cognitive Coefficient of MISO1 MPSOA-AFNN	1.8
Stochastic Learning Rate for Social Coefficient of MISO1 MPSOA-AFNN	1.5
First Value of Adaptive Inertial Weight of MISO1 MPSOA-AFNN	1.3
Last Value of Adaptive Inertial Weight of MISO1 MPSOA-AFNN	0.5
Maximum Particle Velocity for MISO1 MPSOA-AFNN	18
Number of Generation Cycles of MISO1 MPSOA-AFNN	3900
MSE of MISO1 MPSOA-AFNN	2.7321×10^{-4}

Table 2. Design parameters for MISO2 MPSOA-AFNN model of RCPS.

Network Parameter	Value
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO2 MPSOA-AFNN	5
Number of Neurons in Hidden Layer of MISO2 MPSOA-AFNN	39
Number of Neurons in Output Layer of MISO2 MPSOA-AFNN	1
Number of Particles for MISO2 MPSOA-AFNN	274
Number of Runs for MISO2 MPSOA-AFNN	40
Stochastic Learning Rate for Social Coefficient of MISO2 MPSOA-AFNN	1.6
First Value of Adaptive Inertial Weight of MISO2 MPSOA-AFNN	1.4
Last Value of Adaptive Inertial Weight of MISO2 MPSOA-AFNN	0.4
Maximum Particle Velocity for MISO2 MPSOA-AFNN	18
Number of Generation Cycles of MISO2 MPSOA-AFNN	3967
MSE of MISO2 MPSOA-AFNN	1.4589×10^{-4}

3.2. Nonlinear Identification of NMOMSO Based Neuro-Controller for RCPCS

Similarly, same number of patterns is obtained for feed valve 1 and feed valve 2 positions and is classified into datasets. The parameters of MISO1 and MISO2 MPSOA-AFNN sub neuro-controllers for predicting feed valve 1 and feed valve 2 positions are set using equation (1) and are optimized using equation (2) and equation (3). The design parameters of MISO1 and MISO 2 MPSOA-AFNN sub neuro-controllers are presented in Table 3 and Table 4, respectively.

Table 3. Design parameters of MISO1 MPSOA-AFNN sub neuro-controller for feed valve 1.

Network Parameter	Value
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO1 MPSOA-AFNN	3
Number of Neurons in Hidden Layer of MISO1 MPSOA-AFNN	20
Number of Neurons in Output Layer of MISO1 MPSOA-AFNN	1
Number of Particles of MISO1 MPSOA-AFNN	101
Number of Runs for MISO1 MPSOA-AFNN	40
Stochastic Learning Rate for Cognitive Coefficient of MISO1 MPSOA-AFNN	1.9
Stochastic Learning Rate for Social Coefficient of MISO1 MPSOA-AFNN	1.5
First Value of Adaptive Inertial Weight of MISO1 MPSOA-AFNN	1.7
Last Value of Adaptive Inertial Weight of MISO1 MPSOA-AFNN	0.6
Maximum Particle Velocity for MISO1 MPSOA-AFNN	5
Number of Generation Cycles of MISO1 MPSOA-AFNN	3500
MSE of MISO1 MPSOA-AFNN	2.8891×10^{-4}

Table 4. Design parameters of MISO2 MPSOA-AFNN sub neuro-controller for feed valve 2.

Network Parameter	Value
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO2 MPSOA-AFNN	3
Number of Neurons in Hidden Layer of MISO2 MPSOA-AFNN	20
Number of Neurons in Output Layer of MISO2 MPSOA-AFNN	1
Number of Particles of MISO2 MPSOA-AFNN	101
Number of Runs for MISO2 MPSOA-AFNN	40
Stochastic Learning Rate for Cognitive Coefficient of MISO2 MPSOA-AFNN	2.0
Stochastic Learning Rate for Social Coefficient of MISO2 MPSOA-AFNN	1.6
First Value of Adaptive Inertial Weight of MISO2 MPSOA-AFNN	1.6
Last Value of Adaptive Inertial Weight of MISO2 MPSOA-AFNN	0.7
Maximum Particle Velocity for MISO2 MPSOA-AFNN	5
Number of Generation Cycles of MISO2 MPSOA-AFNN	3530
MSE of MISO2 MPSOA-AFNN	3.7754×10^{-4}

The parameters of MISO3 and MISO4 ACOA-AFNN sub neuro-controllers for predicting bleed valve 1 and bleed valve 2 positions are set using equation (1) and are optimized using equation (4) to equation (6). The design parameters of MISO3 and MISO 4 ACOA-AFNN sub neuro-controllers are presented in Table 5 and Table 6 respectively.

The parameters of MISO5 BCOA-AFNN sub neuro-controller for predicting spray valve position are set using equation (1) and are optimized using equation (7) to equation (9). The design parameters of MISO1 and MISO 2 MPSOA-AFNN sub neuro-controllers are presented in Table 7.

Table 5. Design parameters of MISO3 ACOA-AFNN sub neuro-controller for bleed valve 1.

Network Parameters	Values
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO3 ACOA-AFNN	3
Number of Neurons in Hidden Layer of MISO3 ACOA-AFNN	20
Number of Neurons in Output Layer of MISO3 ACOA-AFNN	1
Number of Ants for MISO2 ACOA-AFNN	101
Nonlinear Parameter1 for MISO3 ACOA-AFNN	1.5
Nonlinear Parameter2 for MISO3 ACOA-AFNN	2.7
Pheromone Evaporation Rate for MISO3 ACOA-AFNN	0.3
Pheromone Reward Factor for MISO3 ACOA-AFNN	12
Number of Generation Cycles of MISO3 ACOA-AFNN	205
MSE of MISO3 ACOA-AFNN	1.2×10^{-5}

Table 6. Design parameters of MISO4 ACOA-AFNN sub neuro-controller for bleed valve 2.

Network Parameters	Values
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Ants for MISO4 ACOA-AFNN	101
Number of Neurons in Input Layer of MISO4 ACOA-AFNN	3
Number of Neurons in Hidden Layer of MISO4 ACOA-AFNN	20
Number of Neurons in Output Layer of MISO4 ACOA-AFNN	1
Nonlinear Parameter1 for MISO4 ACOA-AFNN	1.3
Nonlinear Parameter2 for MISO4 ACOA-AFNN	2.9
Pheromone Evaporation Rate for MISO4 ACOA-AFNN	0.4
Pheromone Reward Factor for MISO4 ACOA-AFNN	11
Number of Generation Cycles of MISO4 ACOA-AFNN	231
MSE of MISO4 ACOA-AFNN	1.5×10^{-5}

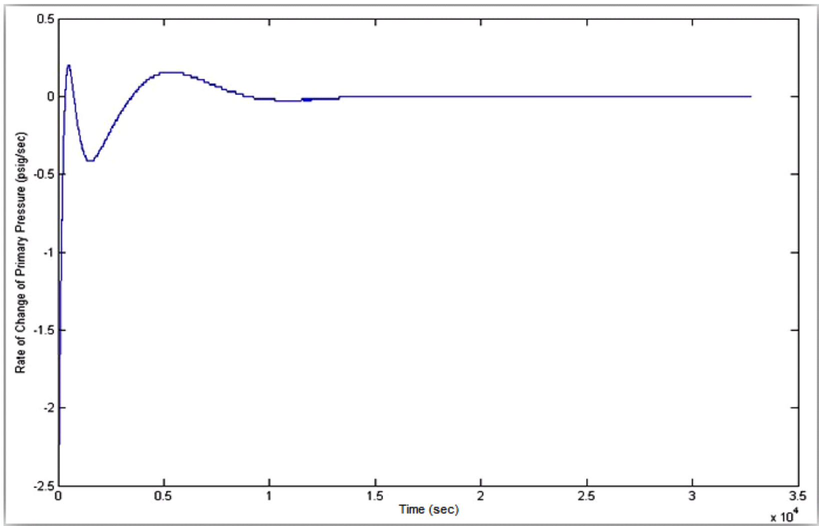

Fig. 8. Simulation of measured primary pressure rate signal for NMOMSO based NC.

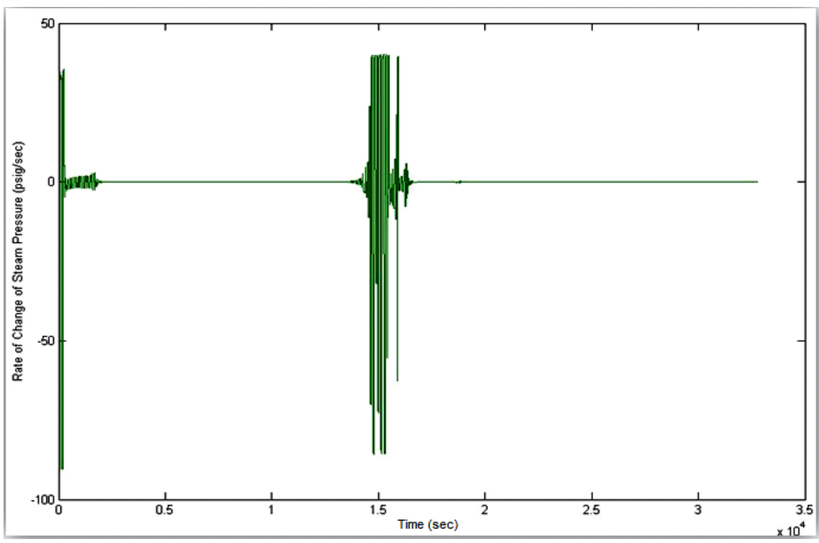

Fig. 9. Simulation of measured steam pressure rate signal for NMOMSO based NC.

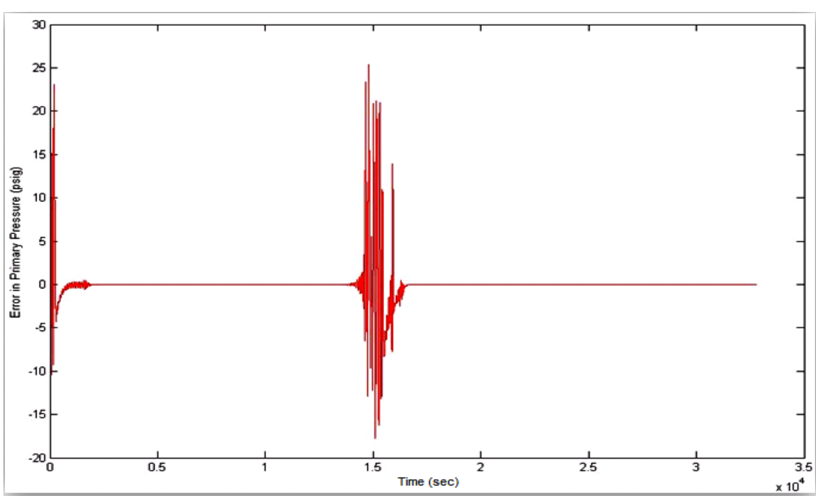

Fig. 10. Simulation of primary pressure error signal for NMOMSO based NC.

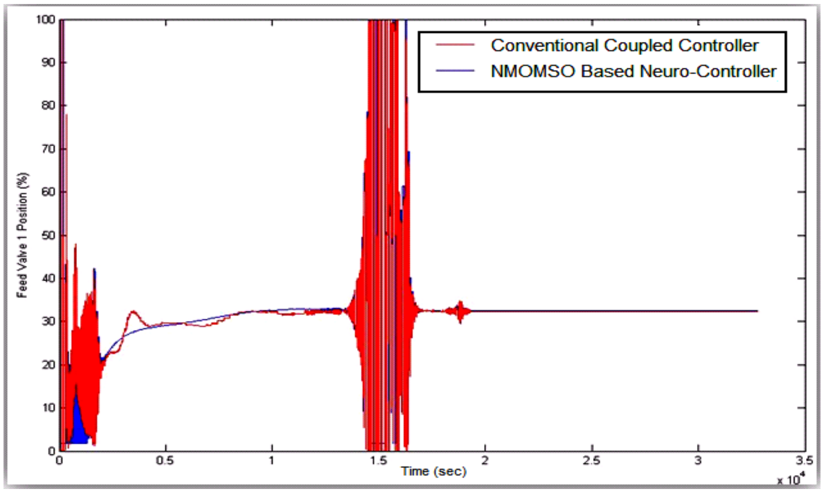

Fig. 11. Comparison of conventional coupled and NMOMSO controllers for predicting feed valve 1 position.

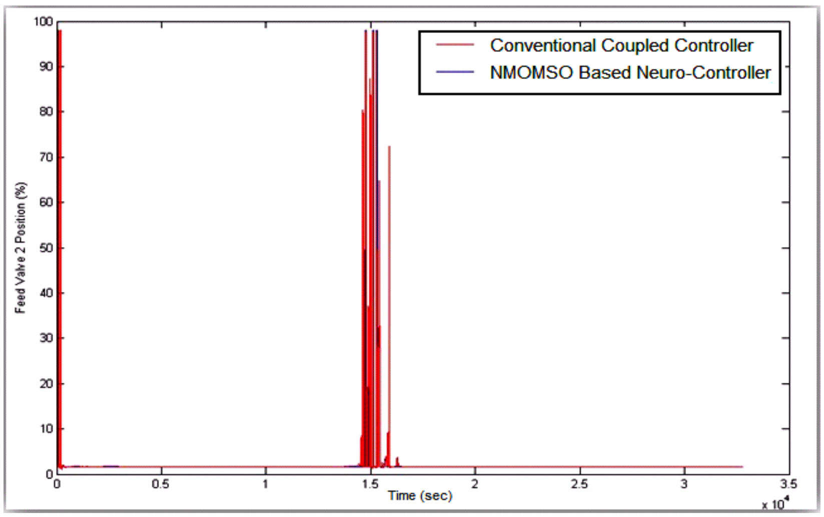

Fig. 12. Comparison of conventional coupled and NMOMSO controllers for predicting feed valve 2 position.

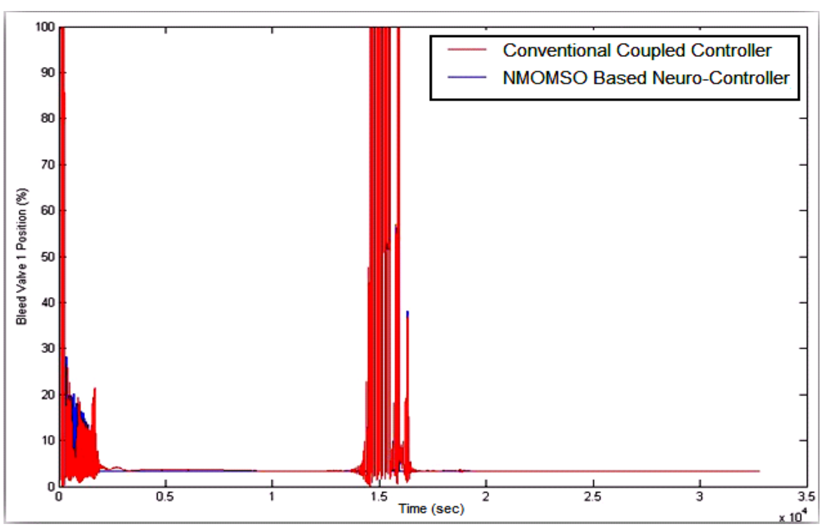

Fig. 13. Comparison of conventional coupled and NMOMSO controllers for predicting bleed valve 1 position.

Table 7. Design parameters of MISO5 BCOA-AFNN sub neuro-controller for spray valve.

Network Parameter	Value
Total Patterns (100%)	32766
Number of Training Patterns (60%)	16659
Number of Testing Patterns (20%)	6553
Number of Validation Patterns (20%)	6553
Number of Neurons in Input Layer of MISO5 BCOA-AFNN	3
Number of Neurons in Hidden Layer of MISO5 BCOA-AFNN	20
Number of Neurons in Output Layer of MISO5 BCOA-AFNN	1
Total Number of Bees for MISO5 BCOA-AFNN	101
Number of Groups of Bees for MISO5 BCOA-AFNN	3
Number of Selected Sites for MISO5 BCOA-AFNN	12
Number of Best Selected Sites for MISO5 BCOA-AFNN	4
Number of Scout Bees for MISO5 BCOA-AFNN	56
Number of Employed Bees for Best Selected Sites for MISO5 BCOA-AFNN	30
Number of Onlooker Bees for Remaining Selected Sites for MISO5 BCOA-AFNN	15
Dimension of Weight Set for MISO5 BCOA-AFNN	101
Limit Value for MISO5 BACOA-AFNN	10201
Number of Generation Cycles of MISO5 BCOA-AFNN	2800
MSE of MISO5 BCOA-AFNN	5.5×10^{-6}

3.3. Validation of Proposed NMOMSO Based Closed Loop Neuro-Control System for RCPCS

The closed loop architecture of NMOMSO based neuro-controller for RCPCS is shown in Fig. 1. For closed loop performance analysis, three input signals reactor coolant pressure (primary pressure) rate signal, steam pressure rate signal and primary pressure error signal are applied at the input of proposed NMOMSO neuro-controller. The simulation responses of these signals are shown in Fig. 8-10. The comparison of conventional coupled and NMOMSO based controllers output for feed valve 1 is shown in Fig. 11. The performance of MISO1 MPSOA-AFNN sub neuro-controller is excellent both in transient and steady state phases. The response of feed valve 1 controller is found much smooth as compared to that of conventional controller in early phase of transient and much lesser level of amplitude is observed in highly fluctuating region. The comparison of conventional coupled and NMOMSO based controllers output for feed valve 2 is shown in Fig. 12. The response of MISO2 MPSOA-AFNN sub neuro-controller is perfectly depicting the conventional controller throughout the transient and much lesser level of amplitude is observed in highly fluctuating region. The comparison of conventional coupled and NMOMSO based controllers output for bleed 1 is shown in Fig. 13. The performance of MISO3 ACOA-AFNN sub neuro-controller is excellent throughout the transient and found bit smoother as compared to that of conventional controller and much lesser level of amplitude is observed in highly fluctuating region. The comparison of conventional coupled and NMOMSO based controllers output for bleed valve 2 is shown in Fig. 14. The response of MISO4 ACOA-AFNN sub neuro-controller is perfectly depicting the conventional controller throughout the transient and much lesser level of amplitude is observed in highly fluctuating region. The comparison of conventional coupled and NMOMSO based controllers output for spray valve is shown in Fig. 15. The performance of MISO5 BCOA-AFNN sub neuro-controller is excellent and much lesser level of amplitude is observed in highly fluctuating region. The robustness of MIMO MPSOA-AFNN RCPS model is also validated through simulation experiments. The comparison of conventional coupled controller and NMOMSO based neuro-controller for predicting primary pressure is shown in Fig. 16. The proposed model predicts real dynamics of primary pressure and model predicts bit faster output. The comparison of conventional coupled and NMOMSO based neuro-controller for predicting steam pressure is shown in Fig. 17. The proposed model predicts real dynamics of steam pressure and shown much smooth and faster output. Hence, a successful neural realization has been established for RCPCS.

4. CONCLUSIONS

A nonlinear MIMO neural model of reactor coolant pressure system of PHWR-type nuclear power has been developed using MPSOA-AFNN technique. A robust NMOMSO neuro-controller

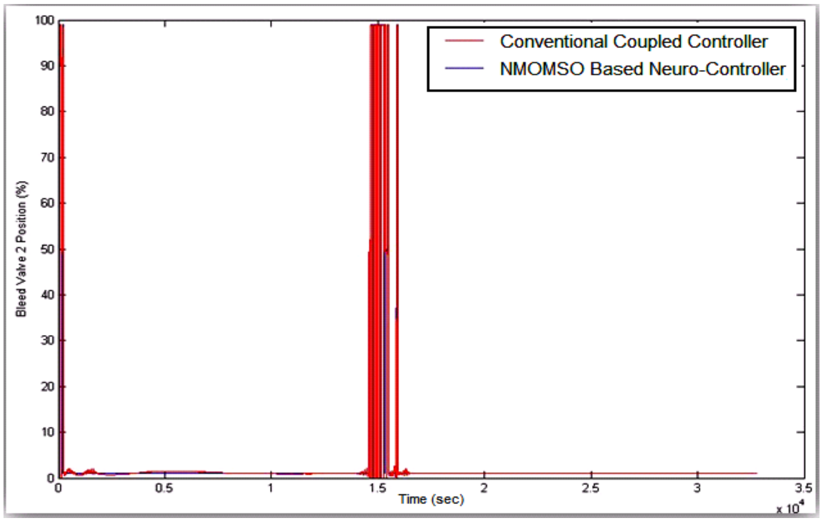

Fig. 14. Comparison of conventional coupled and NMOMSO controllers for predicting bleed valve 2 position.

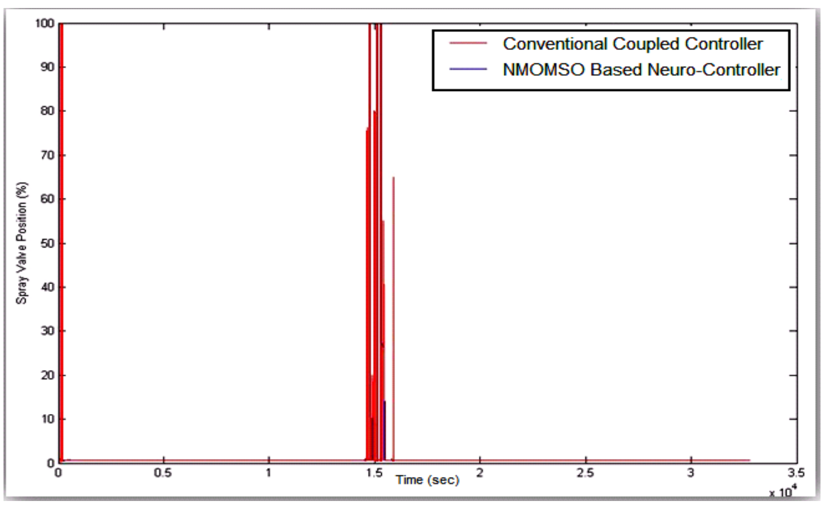

Fig. 15. Comparison of conventional coupled and NMOMSO controllers for predicting spray valve position.

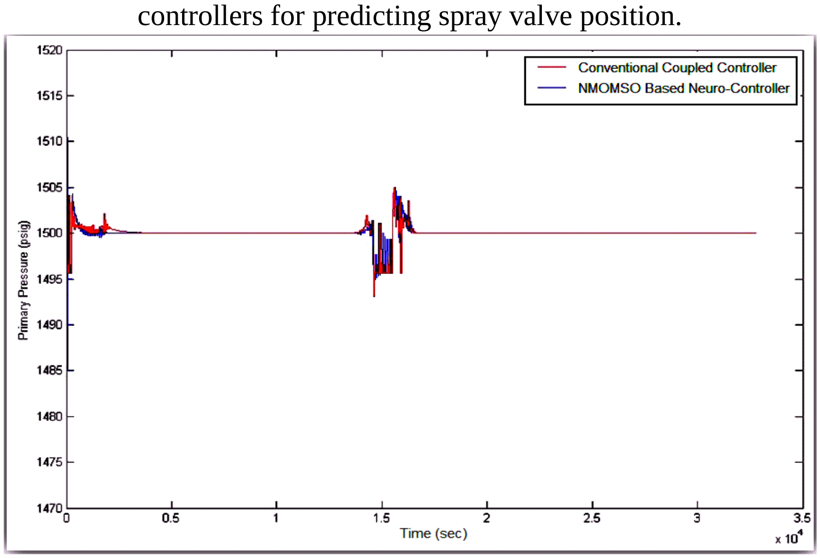

Fig. 16. Comparison of conventional coupled and NMOMSO based controllers response for predicting primary pressure.

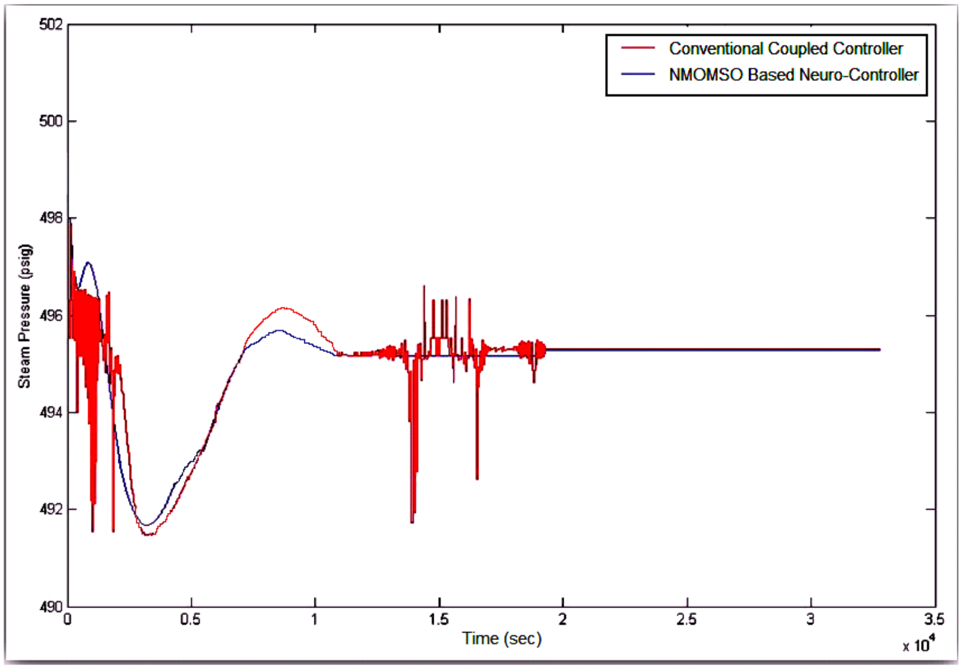

Fig. 17. Comparison of conventional coupled and NMOMSO based controllers response for predicting steam pressure.

has been designed using mixed stochastic techniques. A robust NMOMSO neuro-controller has been integrated using five MISO intelligent sub controllers. Three stochastic techniques have been attempted for reactor coolant pressure control system. Amongst three techniques, modified particle swarm optimization algorithm has been found suitable for two feed valves positions, ant colony optimization algorithm has been found best for two bleed valves positions and bee algorithm has been found excellent for spray valve position. All training, testing and validation of proposed nonlinear neural model and NMOMSO based NC has been carried out in MATLAB. The performance of proposed NMOMSO based NC is validated by comparing it with conventional coupled controller and found excellent in transient and steady state conditions.

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