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Original Article

Subspace Modeling, Neural Decoupling and Robust Nonlinear Controller Design for Two-Time-Scale Nuclear Power Plant

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Abstract: In this paper, a novel Hybrid Linear and Nonlinear (HLN) technique of modeling and control design for two-time-scale nuclear power plant has been devised in LabVIEW environment. A higher order linear model for two-time-scale nuclear power plant power control is developed based on Deterministic-Stochastic Subspace Identification via Principal Component Analysis (DSSIPCA) technique. The eighth order linear model is identified using innovative time domain plant data. The eighth order model is decoupled into two modes of dynamics using Nonlinear Recurrent Artificial Neural Network (NRANN). The first reduced order model is a second order model capturing slow dynamics of plant while second reduced order model is a sixth order model capturing fast dynamics of plant. The slow dynamics model is so decoupled that it mimics the original higher order model of nuclear power plant. A sliding surface is designed in state space for slow dynamics model and full order model. Based on sliding surface, a Robust Discrete Nonlinear Controller (RDNC) is designed for decoupled two-time-scale nuclear power plant model in Triangular Block Structure (TBS) form using Sliding Mode Control (SMC) technique. The design, optimization, testing, validation and analysis work is carried out in most modern graphical programming environment LabVIEW 7.0. The performance of proposed of HLN technique is tested in reference tracking mode for an operating unit of pressurized heavy water reactor based nuclear power plant in Pakistan and found satisfactory and within design limits.

Keywords: System identification, principal component analysis, recurrent neural network, sliding mode control, nuclear power plant

1. INTRODUCTION

The Nuclear Power Plant (NPP) has a very complex dynamics and control. The nuclear power plant considered in this paper is a Pressurized Heavy Water Reactor (PHWR) type which uses compensator based complex hardwired distributed control system. The reactor power is controlled by manipulating the moderator control valve position in a nuclear power plant which in turn changes the moderator level in reactor core. So it approximates to a Single Input Single Output (SISO) system. Therefore, this SISO system uses Moderator Level Control (MLC). The details of nuclear power plant under consideration are available in [1, 2].

The nuclear power plant has many states. Some of them are slowly varying and some are fastly varying states. Hence, it posses two-time-scale dynamics which is identified using system identification tool based on ARX modeling approach [2]. The dynamics of a research reactor is modeled using Monte Carlo method in [3]. The dynamics of primary side of Russian power reactor is modeled based on first principle method in [4]. The nonlinear dynamics of research and power reactors have been identified by different researchers using feedforward and recurrent neural networks in [5, 6]. Different algorithms are

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proposed in [7] for subspace system identification. In this research work, a Deterministic-Stochastic Subspace Identification via Principle Component Analysis (DSSIPCA) has been adopted for modeling the two-time-scale nuclear power plant dynamics in state space form.

A singular perturbation theory based model decomposition strategy has been adopted in [2] for a nuclear power plant. Another quick and efficient model decoupling strategy based on matrix reducibility is presented in [8] for non-nuclear applications. Therefore, in this research work, a higher order model decoupling using Nonlinear Recurrent Artificial Neural Network (NRANN) has been attempted.

A fast output sampling and periodic output feedback controllers have been designed for special control of PHWR in [9, 10]. Different linear optimal controllers have been designed for nuclear power plant in LabVIEW environment in [11]. A model predictive composite reactor power controller and H_∞ power controller are designed for an operating nuclear power plant in Pakistan [1] in [12, 13]. An output tracking sliding mode controller is designed for thermionic converters of space nuclear reactor in [14].

A sliding mode controller has been proposed for rod control system for research reactor in Pakistan using supper twisting algorithm in [15]. A recursive sliding mode and fuzzy adapted sliding mode controllers have been designed for turbine throttle pressure regulation for advanced boiling water reactor in [16, 17]. A sliding mode observer has been designed for spatial control of PHWR in [18]. A discrete time output feedback sliding mode controller has been proposed for spatial control of PHWR in [19].

All these sliding mode controllers have been designed based on single-time-scale consideration while modeling and controller design for research reactor, advanced boiling water reactor and PHWR. Also, the concept of Liquid Zone Controller (LZC) for spatial xenon control in PHWR type nuclear power plant has been considered in [9, 10]. But in this research work, an attempt has been made to design a Novel Robust Discrete Nonlinear Controller (NRDNC) based on Discrete Sliding Mode for Two-Time-Scale Model Decoupling (DSMTTSMD) in Triangular Block Structure (TBS) form using Matrix Reducibility Concept (MRC) optimized by NRANN. This controller has been designed based on MLC design concept which is different from LZC design concept.

Hence in this research work, a new hybrid technique is proposed based on mixed linear and nonlinear technologies. This new closed loop configuration is composed of DSSIPCA, NRANN and NRDNC based on DSMTTSMD using MRC for a different PHWR [1] with MLC design concept.

2. MATERIALS AND METHODS

2.1. Moderator Level Control System (MLCS)

Basically the reactor power control in PHWR is accomplished by moderator level controller, rod controller and chemical shim controller. The main controller for large power excursions in an operating PHWR in Pakistan is a moderator level controller while rod controller is a regulating controller for fine tuning of power. The shim controller is used at the time of reactor start-up only. In this research work, only moderator level controller is considered for coarse power control in PHWR. The change in moderator level is accomplished by manipulating the moderator control valve. This moderator level controller is known as reactor power controller. The existing controller is a compensator based controller with hundreds of permissive and interlocks implemented on seven programmable controllers forming a distributed control system. This controller is interfaced with real nuclear power plant. Therefore, the main objective of this research work is to formulate the dynamics of plant in state space and synthesize a controller based on identified model.

2.2. Deterministic-Stochastic Subspace Modeling

2.2.1. Model Structure

In the safety analysis report of PHWR [1], different data sets are reported with and without measurement noise. In this research work, a huge data set is considered with measurement noise. Therefore, the deterministic-stochastic subspace model structure is selected for the identification of plant model. Subspace method uses Principle Component Analysis (PCA) to estimate the model parameters based on important modes of plant dynamics. This method does not require a zero correlation between the input signal and output noise. If a measured moderator level control valve position is used as stimulus signal $u(k)$ and measured reactor power is used as response signal $y(k)$ then a recursive subspace identification framework can be developed which is shown in Fig. 1.

The subspace model structure can be described as:

$$x(k+1) = A_d\, x(k) + B_d\, u(k) + G\, e_i \quad (1)$$

$$y(k) = C_d\, x(k) + D_d\, u(k) + e_i \quad (2)$$

where A_d, B_d, C_d and D_d are matrices of appropriate dimensions of the identified system in discrete time and G is the Kalman gain.

If $y_P(k)$ is the predicted reactor power output signal and $e_P(k)$ is the prediction error between $y_P(k)$ and $y(k)$ then the prediction error is given by:

$$e_P(k) = \frac{1}{k}\sum_{i=1}^{k} e_i^{\,2} \quad (3)$$

where $e_i = y_i(k) - y_{P_i}(k)$

A Virtual Instrument (VI) is designed in LabVIEW 7.0 to identify the subspace model using plant time domain data. The block diagram design of this VI is shown in Fig. 2.

2.2.2. Optimization Algorithm

2.2.2.1. Computation of State Space Matrices: All state space matrices are computed based on least square algorithm using parameter matrix, past and future Hankel matrices and Sigular Value Decomposition (SVD) as reported in [7].

The front panel design for the identification of subspace model is shown in Fig. 3.

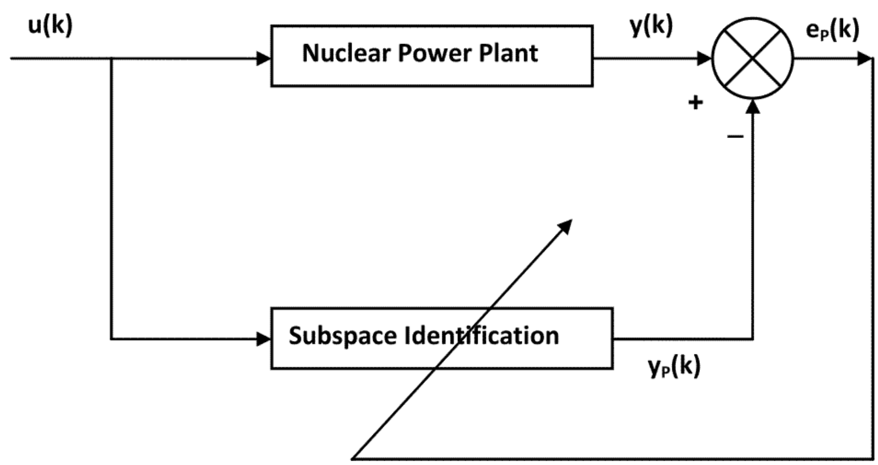

Fig. 1. Block diagram for deterministic-stochastic subspace identification of plant.

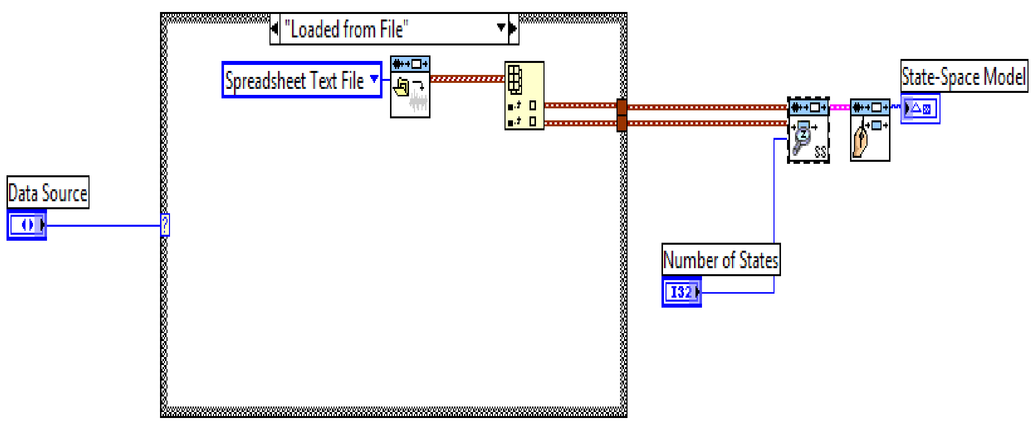

Fig. 2. Block diagram design for state space model from time domain plant data.

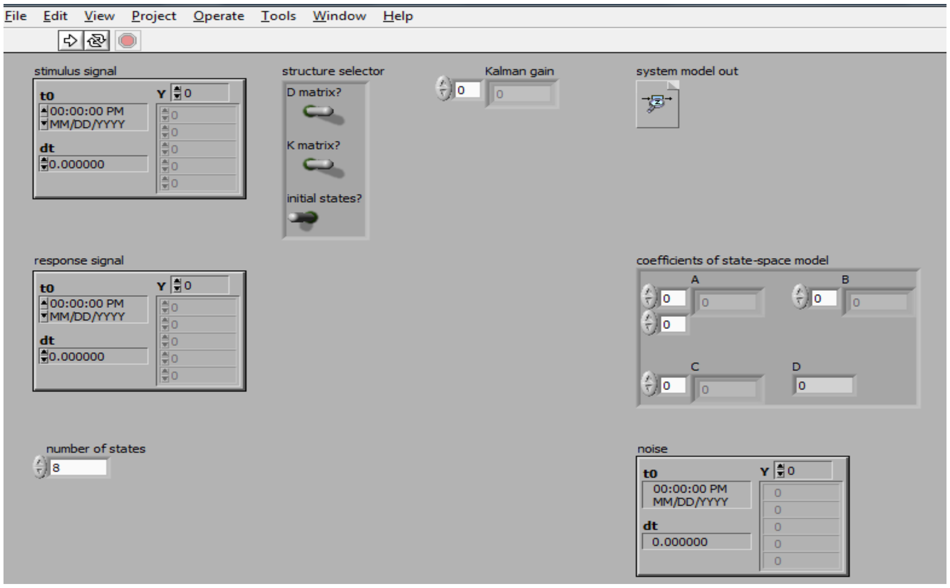

Fig. 3. Front panel design for estimation algorithm using state space model.

2.2.2.2. Computation of Kalman Gain: Kalman gain is computed based on least square algorithm using first block column optimization [7].

2.2.2.3. Computation of Initial States: Initial states of system are estimated based on least square algorithm using Kalman gain, extended model matrices composed of extended observability matrix and Hankel matrices [7].

2.3. Neural Decoupling

2.3.1. Recurrent Artificial Neural Network

The recurrent neural network uses the concept of multidirectional information flow. It incorporates the sense of time and memory of previous states [5]. In this research work, a delta learning algorithm is used for supervised learning of recurrent artificial neural network. This neural network is a globally recurrent neural network utilizing the concept of time delay structure.

2.3.2. Decoupled Model Structure

If T is the similarity transformation matrix then the transformed model can be represented as:

$$x_t(k+1) = A_{td}\, x_t(k) + B_{td}\, u(k) \tag{4}$$

$$y_t(k) = C_{td}\, x_t(k) + D_{td}\, u(k) \tag{5}$$

where A_{td}, B_{td}, C_{td} and D_{td} are matrices of appropriate dimensions of the transformed plant model in discrete time. The subscript *td* stands for "transformed, discrete-time".

The transformed discrete time state space model can be modeled as:

$$x_t(k+1) = T^{-1}AT\, x_t(k) + T^{-1}Bu(k) \tag{6}$$

$$y_t(k) = CT\, x_t(k) + Du(k) \tag{7}$$

Now, the problem is to compute the similarity transformation matrix based on matrix reducibility technique which is to be computed using recurrent ANN.

The purpose is to decouple the higher order plant model into slow and fast dynamics models. Using matrix reducibility technique [8], the decoupled transformed slow and fast dynamics models of two-time-scale nuclear power plant model can be obtained.

The transformed slow dynamics model coupled with fast dynamics model of two-time-scale nuclear power plant model can be obtained as:

$$x_{ts}(k+1) = A_s\, x_{ts}(k) + A_{sf}\, x_{tf}(k) + B_s\, u(k) \tag{8}$$

$$y_{ts}(k) = C_s\, x_{ts}(k) + C_f\, x_{tf}(k) + D_s\, u(k) \tag{9}$$

where A_s, A_{sf}, B_s, C_s , C_f and D_s are slow subsystem, coupled slow-fast subsystem, slow input subsystem, slow output subsystem, fast output subsystem and slow direct transmission data matrices of the transformed slow plant model in discrete time. The subscripts *ts* and *tf* stands for "transformed, slow" and "transformed, fast" respectively.

Since the slow-fast mode does not appear in transformed discrete time state space model due to decoupling. Therefore, the transformed fast dynamics model coupled with slow dynamics model of two-time-scale nuclear power plant model can be obtained as:

$$x_{tf}(k+1) = A_f\, x_{tf}(k) + B_f\, u(k) \tag{10}$$

$$y_{tf}(k) = C_f\, x_{tf}(k) + D_f\, u(k) \tag{11}$$

where A_f, B_f, C_f and D_f are fast subsystem, fast input subsystem, fast output subsystem and fast direct transmission data matrices of the transformed fast plant model in discrete time.

After some change in state variables, manipulations and simplifications, the purely slow dynamics of two-time-scale nuclear power plant model can be arrived at [2]:

$$x_s(k+1) = A_s\, x_s(k) + [A_{sf}(I_f - A_f)^{-1} B_f + B_s] u_s(k) \tag{12}$$

$$y_s(k) = C_s\, x_s(k) + [C_f(I_f - A_f)^{-1} B_f + D_s] u_s(k) \tag{13}$$

where I_f is a fast identity matrix of the transformed decoupled plant model in discrete time.

If $y_s(k)$ is the predicted slow dynamics model and $e_s(k)$ is the predicted mean square error (MSE) between $y_P(k)$ and $y_s(k)$ then the MSE is given by:

$$e_s(k) = \frac{1}{k}\sum_{j=1}^{k} e_j^{\,2} \tag{14}$$

where $e_j = y_{P_j}(k) - y_{s_j}(k)$

The framework of obtaining decoupled two-time-scale system using globally recurrent neural optimization is shown in Fig. 4.

2.3.3 Neural Optimization Algorithm

Now, the objective is to compute the values of A_s, A_{sf}, B_s, C_s and D_s using similarity transformation matrix (T). This similarity transformation matrix (T) is estimated using recurrent ANN which results in triangular block structure.

If Q is the external input and N is the number of neurons then $u(k)$ and $y_s(k)$ are $Q \times 1$ input vector applied to recurrent ANN and $N \times 1$ output vector at discrete instant k respectively. The input vector $u(k)$ and one step delayed output vector $y_s(k)$ forms an input layer of recurrent ANN. If W is the recurrent ANN weight matrix then it can be defined as the product of transformed triangular block matrix and transformed slow-fast plant input matrix:

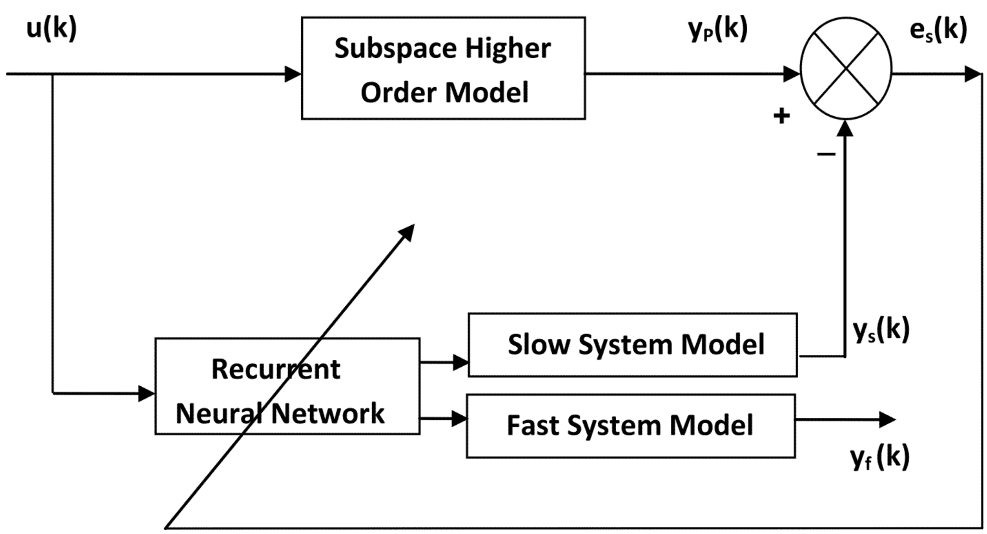

Fig. 4. Block diagram for system decoupling using recurrent neural network.

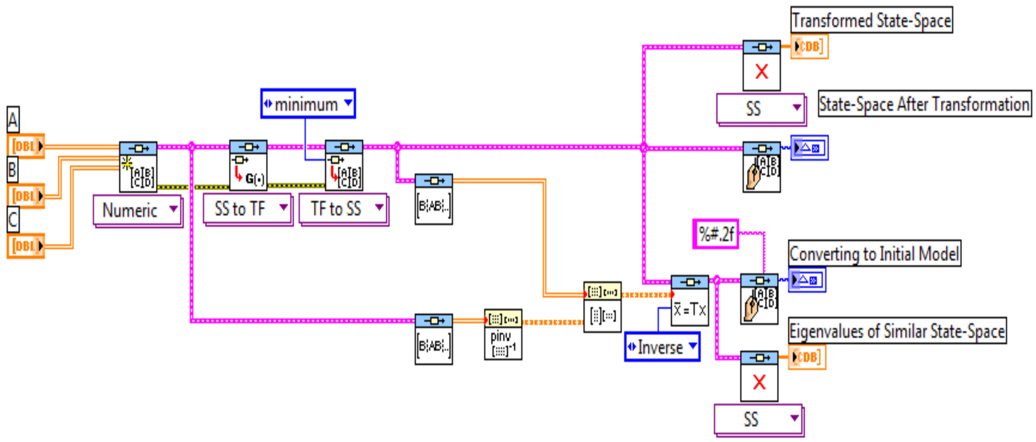

Fig. 5. Block diagram design for transformation matrix computation.

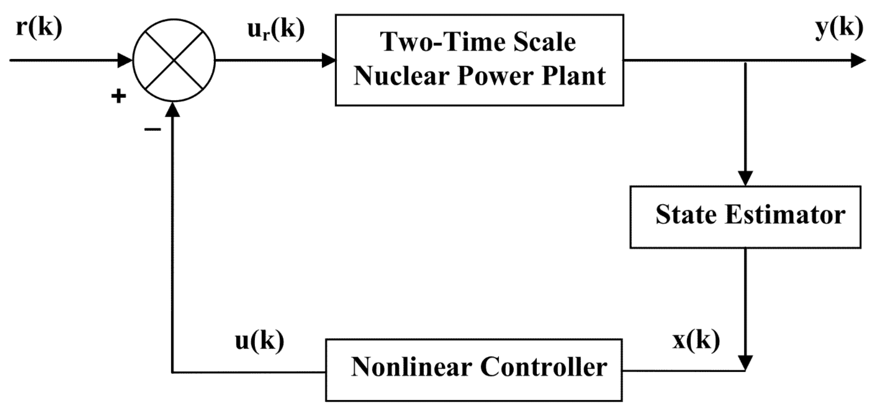

Fig. 6. Closed loop configuration of nonlinear control system.

$$W = \begin{bmatrix} A_s & A_{sf} \\ 0 & A_f \end{bmatrix} \begin{bmatrix} B_s \\ B_f \end{bmatrix} \tag{15}$$

The weight change and weight update logics are devised and computed successively using delta learning algorithm [7].

Once the similarity transformation matrix is obtained using recurrent ANN, transformed state space model is obtained using a specially designed new virtual instrument in LabVIEW 7.0 as shown in Fig. 5.

2.4. Synthesis of Robust Discrete Nonlinear Controller

2.4.1. Concept of Sliding Mode Control

Now-a-days sliding mode control has gained a great popularity in nonlinear control design. The sliding mode control utilizes attaining prescribed plant dynamics by defining sliding surface on which sliding mode occurs. The control system so obtained becomes robust, insensitive to uncertainties and disturbances. Since modern control systems are implemented on digital Programmable Logic Control (PLC) systems, so the design of nonlinear sliding mode controller in discrete domain is genuine. The closed loop configuration of nonlinear control system design is shown in Fig. 6.

2.4.1.1. Formulation of sliding surface for decoupled Two-Time-Scale NPP Model: If n is the order of original higher system model then the sliding surface parameters for original higher order can be defined as [18]:

Sliding surface parameters for original higher order system model =

$$S_{ch} = [s_{c_1} \quad s_{c_2} \quad s_{c_3} \cdots s_{c_n}] = \begin{bmatrix} K_n \\ I_n \end{bmatrix}$$

Similarly, if *tn* is the order of transformed higher system model and r_s is the order of slow system model then sliding surface parameters for transformed higher order and purely slow dynamics models can be formulated as:

Sliding surface parameters for transformed higher order model = $S_{cth} = [s_{tc_1} \quad s_{tc_2} \quad s_{tc_3} \cdots s_{tc_n}] = \begin{bmatrix} K_{tn} \\ I_{tn} \end{bmatrix}$

Sliding surface parameters for purely slow system model = $S_{cps} = [s_{sc_1} \quad s_{sc_2} \quad s_{sc_3} \cdots ss_{c_{rs}}] = \begin{bmatrix} K_{srs} \\ I_{rs} \end{bmatrix}$

where K_n, K_{tn} and K_{srs} are nonlinear sliding mode controllers optimal gains for original higher order, transformed higher order and purely slow subsystem models respectively.

Now, the sliding surface for original higher order system model can be defined as [16]:

$$s_h(k) = S_{ch}^T\, x(k) \tag{16}$$

Similarly, the sliding surface for transformed higher order model can be defined as:

$$s_{th}(k) = S_{cth}^T\, x_t(k) \qquad 17)$$

And, the sliding surface for purely slow dynamics system model can be defined as:

$$s_s(k) = S_{cs}^T\, x_s(k) \tag{18}$$

The S_{ch} and S_{cth} can be linked with following relationship [19]:

$$S_{cth} = [I_{rs} : 0] T^{-1} S_{ch} \tag{19}$$

2.4.1.2. Formulation of discrete nonlinear controller for Purely Slow NPP Model: For the given problem using equation (1), equation (12) and equation (18), the discrete time sliding mode control law described in [16] can be reformulated for purely slow dynamics system model as:

$$\begin{aligned} u_s(k) &= -[(S_{cs}^T B_d)^{-1}\{S_{cs}^T A_{sf}(I_f - A_f)^{-1} B_f + B_s\}]x_s(k) = \\ &-[K_{S_1} \quad K_{S_2} \quad K_{S_3} \cdots K_{S_{nr}}]x_s(k) \end{aligned} \tag{20}$$

2.4.1.3. Formulation of discrete nonlinear controller for Higher Order NPP Model: Similarly, for the given problem using equation (1), equation (6) and equation (17), the discrete time sliding mode control law described in [16] can be reformulated in terms of states of original higher order system model as:

$$\begin{aligned} u_h(k) &= -[(S_{cth}^T B_d)^{-1}(S_{cth}^T T^{-1} B_d)]x(k) = \\ &-[K_1 \quad K_2 \quad K_3 \cdots K_n]x(k) \end{aligned} \tag{21}$$

2.4.1.4 Formulation of closed loop reference tracking nonlinear control system: If $r(k)$ is the reference signal then the closed loop reference tracking control system based on slow controller can be represented as:

$$u_s(k) = -[(S_{cth}^T B_d)^{-1}(S_{cth}^T T^{-1} B)]x(k) + r(k) \tag{22}$$

Similarly, the closed loop reference tracking control system based on higher order controller can be represented as:

$$\begin{aligned} u_h(k) &= -[(S_{cs}^T B_d)^{-1}\{S_{cs}^T A_{sf} \\ &(I_f - A_f)^{-1} B_f + B_s\}]x_s(k) + r(k) \end{aligned} \tag{23}$$

Since, after change of state variables and some manipulations, we arrive at that the closed loop dynamics of slow dynamics system model with equation (20) depicts the similar closed loop dynamics of original higher order system model with equation (21). Therefore, ultimately, we arrive at the following approximation without loss of generalization:

$$u_s(k) = u_h(k) = u(k) = -K\, x(k) + r(k) \tag{24}$$

3. RESULTS AND DISCUSSION

In this section, all important results related to subspace modeling, neural decoupling and nonlinear controller design are presented and discussed.

3.1 Parameter Estimation of Subspace NPP Model

The subspace model of nuclear power plant is developed based on real time domain data. The time domain data is fetched from an operating unit of PHWR type nuclear power plant in Pakistan at a sample time of 0.01 sec. This dataset is a noisy measurement data. The dataset is divided into two subsets, one containing 63900 patterns for the identification while second containing 1000 patterns for the validation purposes. The state space model of nuclear power plant is identified

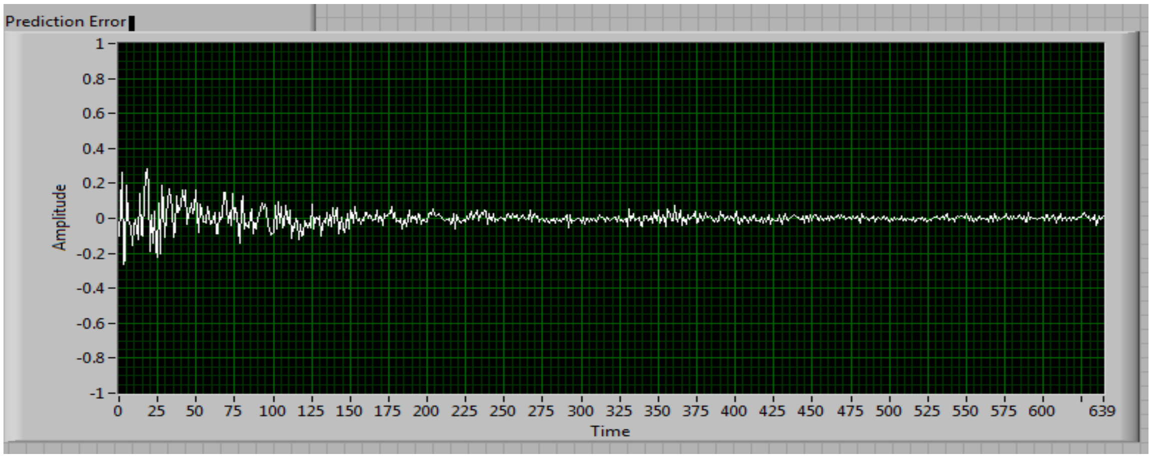

Fig. 7. Optimization of state space model prediction error.

using equations (1) through (3). The design parameters for the identification and validation of model are presented in Table 1. The optimization of model prediction error is shown in Fig. 7. The optimized prediction error is found to be 0.02.

Table 1. Design parameters for subspace model identification and validation.

Design Parameter	Value
Sample Time for Fetching Real Time Plant Data	0.01 sec
Number of Time Domain Patterns for Identification	63900
Number of Time Domain Patterns for Validation	1000
Optimal Prediction Error	0.02

The optimized Kalman gain matrix is given as:

$$G = \begin{bmatrix} 1.0139 \\ 0.3541 \\ 0.0774 \\ 0.0411 \\ 0.1995 \\ 1.2558 \\ 0.0022 \\ 0.7337 \end{bmatrix}$$

The identified discrete time state space model can be put in partitioned form as:

$$x(k+1) = \begin{bmatrix} A_{d11} & A_{d12} \\ A_{d21} & A_{d22} \end{bmatrix} x(k) + \begin{bmatrix} B_{d1} \\ B_{d2} \end{bmatrix} u(k)$$

$$y(k) = \begin{bmatrix} C_{d1} & C_{d2} \end{bmatrix} x(k)$$

where

$$A_{d11} = \begin{bmatrix} 0.6620 & -0.1935 & 0.0411 & -0.0107 \\ 0.1935 & 0.6922 & 0.0664 & -0.0318 \\ -0.0411 & 0.0664 & -0.5804 & -0.2069 \\ -0.0240 & 0.0318 & 0.2069 & -0.2262 \end{bmatrix},$$

$$A_{d12} = \begin{bmatrix} -0.0279 & 0.0015 & -0.0012 & 0.0003 \\ -0.0279 & 0.0014 & -0.0014 & 0.0002 \\ -0.1265 & 0.0264 & -0.0200 & 0.0009 \\ 0.5416 & 0.0624 & -0.0453 & 0.0010 \end{bmatrix},$$

$$A_{d21} = \begin{bmatrix} 0.0200 & -0.0279 & -0.1265 & -0.5416 \\ 0.0015 & -0.0015 & -0.0264 & 0.0624 \\ 0.0011 & -0.0011 & -0.0200 & 0.0453 \\ 0.0003 & -0.0004 & -0.0009 & 0.0010 \end{bmatrix},$$

$$A_{d22} = \begin{bmatrix} 0.2147 & -0.0850 & 0.0626 & -0.0019 \\ 0.0850 & -0.4186 & -0.3573 & 0.1125 \\ 0.0626 & 0.3573 & 0.3821 & 0.1653 \\ 0.0019 & 0.1125 & -0.1653 & -0.2401 \end{bmatrix},$$

$$B_{d1} = \begin{bmatrix} 0.4047 \\ -0.1694 \\ 0.1067 \\ 0.0568 \end{bmatrix}, \quad B_{d2} = \begin{bmatrix} -0.0486 \\ -0.0032 \\ -0.0026 \\ -0.0002 \end{bmatrix},$$

$$C_{d1} = \begin{bmatrix} 0.4047 & 0.1694 & -0.1067 & 0.0568 \end{bmatrix},$$

$$C_{d2} = \begin{bmatrix} 0.0486 & -0.0032 & 0.0001 & -0.0002 \end{bmatrix}$$

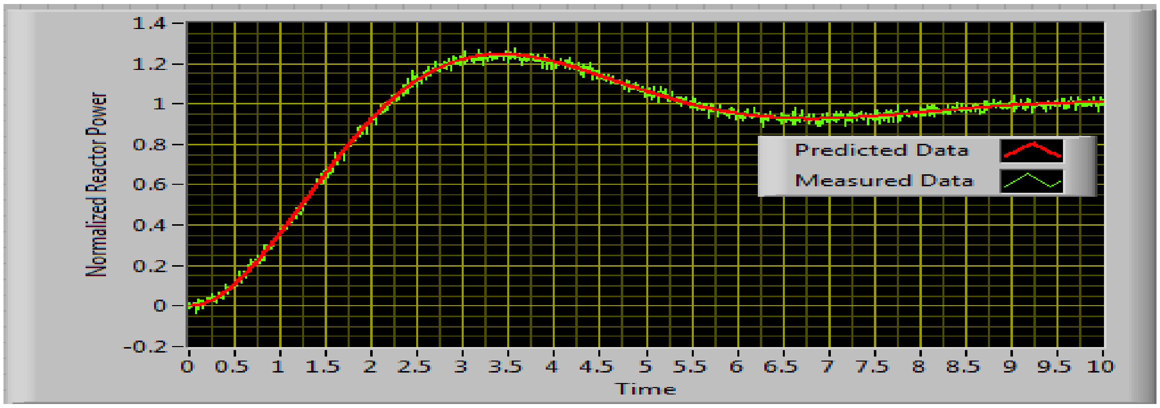

Fig. 8. Comparison of measured and model predicted data.

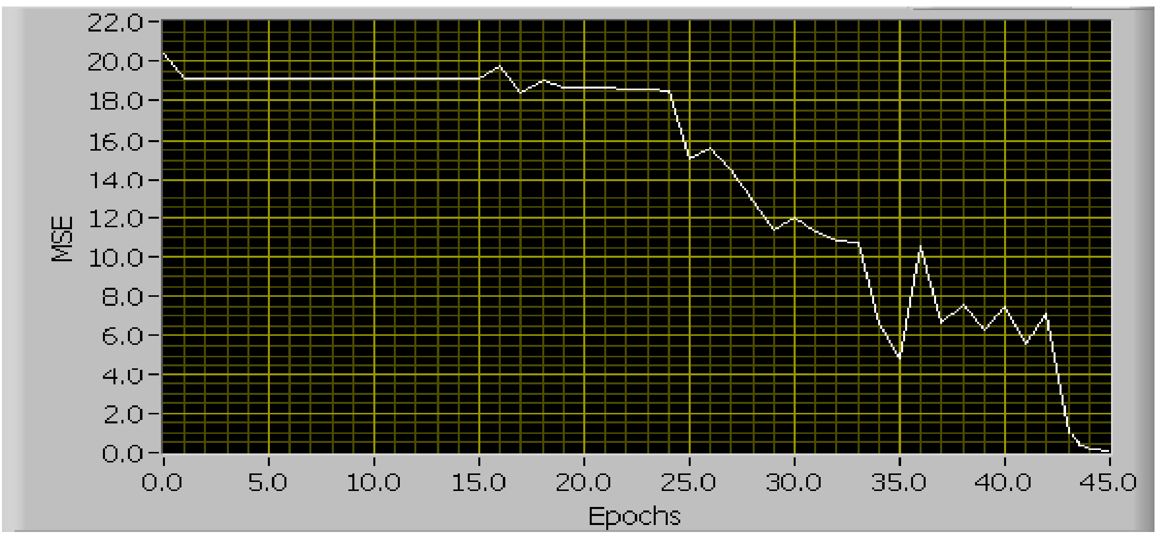

Fig. 9. MSE optimization of recurrent neural network for decoupling.

3.2 Validation of Subspace NPP Model

In validation phase, 1000 patterns are used for validation purpose. The reactor power can vary from 0% to 100% under normal conditions while it can vary from 0% to 120% under large power excursions. But it can vary from 0% to 125% under large power excursion with measurement noise. Therefore, this reactor power varying from 0% to 125% is normalized between 0 1nd 1.25. The comparison of measured and model predicted normalized reactor power is shown in Fig. 8 which shows excellent agreement between measured and predicted results.

3.3. Training of Recurrent ANN for Decoupled Subspace NPP Model

In the design of recurrent ANN, one external input and 2 neurons are used. A (1×1) input vector applied is to recurrent ANN and as a result a (2 ×1) output vector progresses at each discrete instant of time in 0.01 sec. The input vector $u(k)$ and one step delayed output vector $y_s(k)$ forms an input layer of recurrent ANN. The starting order of the original system model is n = 8 while the target of order slow dynamics and fast dynamics models are r_s = 2 and r_f = 6 respectively. The recurrent ANN is trained using delta learning algorithm and the optimized network is obtained at a learning rate of η = 0.019 against 45 epochs. The optimal MSE value is found to be 0.005 which proves that a highly efficient and fast recurrent ANN has been designed. The designed recurrent ANN parameters are presented in Table 2. The MSE optimization of recurrent ANN for decoupling is shown in Fig. 9.

Table 2. Design parameters for recurrent ANN.

Design Parameters	Values
Discrete Time Step (k) for Recurrent ANN	0.01 sec
Order of Original Higher Order System (n)	8
Order of Target Slow System (r_s)	2
Order of Target Fast System (r_f)	6
Number of Neurons (N)	2
Number of External Inputs (Q)	1
Learning Rate (η)	0.019
Number of Epochs	45
Optimal MSE for Recurrent ANN Design	0.005

3.4 Decoupled Slow NPP Model

After training the recurrent ANN, the decoupled slow dynamics model is obtained using equations (12-13) as follows:

$$x_s(k+1) = \begin{bmatrix} 0.06971 & -0.3107 \\ 0 & 0.5312 \end{bmatrix} x_s(k) + \begin{bmatrix} 0.2813 \\ -0.1557 \end{bmatrix} u_s(k)$$

$$y_s(k) = \begin{bmatrix} 0.4144 & 0.01173 \end{bmatrix} x_s(k) + \begin{bmatrix} -0.0168 \end{bmatrix} u_s(k)$$

The comparison of open loop response of original higher order model and decoupled slow dynamics model is shown in Fig. 10 which proves that a successful realization has been made.

3.5 Synthesis of Robust Discrete Nonlinear Controller for NPP Model

The values of designed sliding surface parameters are shown in Table 3. The values of optimal gain sequence for slow discrete nonlinear controller are computed using sliding surface and equation (20) and are shown in Table 4. Similarly, the values of optimal gain sequence for original higher system is computed using equation (21) and are shown in Table 5. The performance of closed loop nonlinear control system is tested under step signal which is introduced in the system through a reference signal $r(k)$. The variation of control signal $u(k)$ is shown in Fig. 11 which starts appearing in 1.6 sec and completes its control action quickly in next 1 sec. The variation of reference signal $r(k)$ and normalized reactor power $y(k)$ is shown in Fig. 12. Since it is required that control system for nuclear power plant should be so designed that it must not take any overshoot and oscillations. Therefore, from the response shown in Fig. 12, it is proved that a critically damped control system is designed without any overshoot which tracks the reference signal in excellent fashion.

Table 3. Sliding function parameters for slow plant model.

Design Parameter	Value
ssc_1	- 0.3271
ssc_2	- 5.2861

Table 4. Optimal gains sequence for slow nonlinear controller design.

Design Parameter	Value
Ks_1	0.9713
Ks_2	2.249

Table 5. Optimal gains sequence for full order nonlinear controller design.

Design Parameter	Value
K_1	0.97136
K_2	2.28215
K_3	0.77214
K_4	0.43983
K_5	0.05331
K_6	0.01198
K_7	0.00309
K_8	0.00072

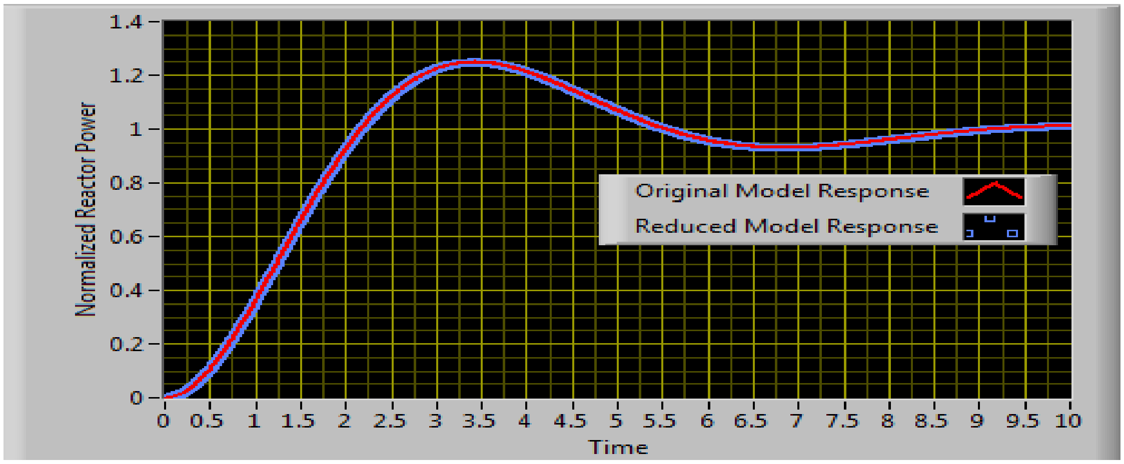

Fig. 10. Comparison of open loop original and reduced order system response.

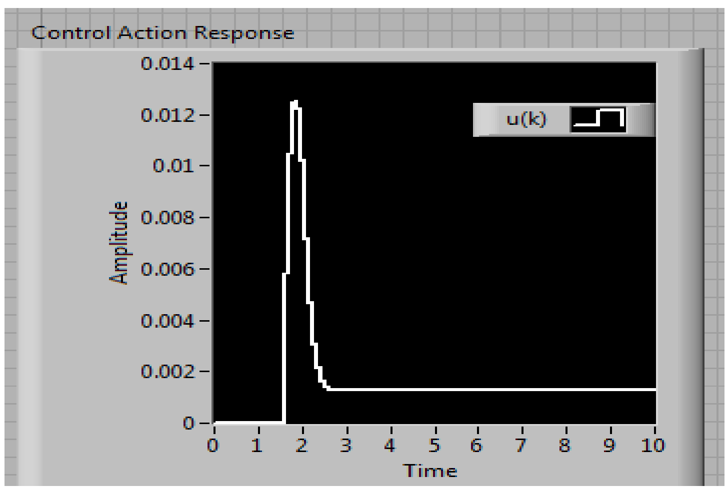

Fig. 11. Variation of control signal.

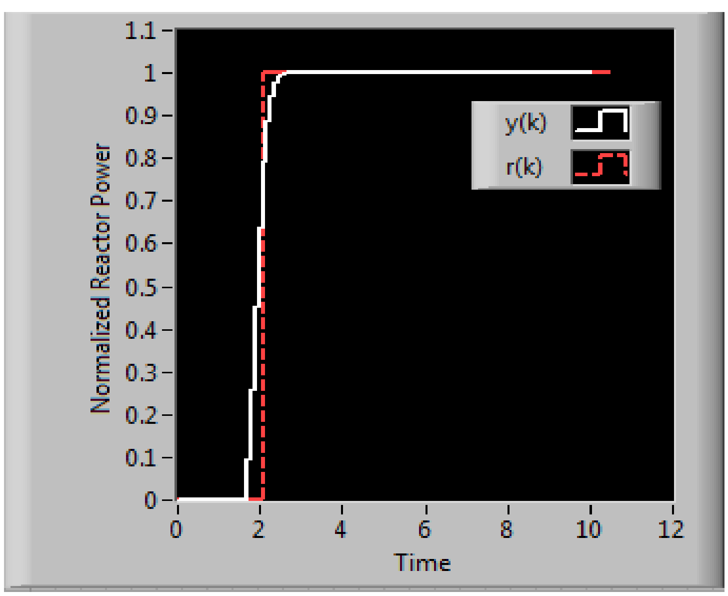

Fig. 12. Variation of normalized closed loop plant power output.

4. CONCLUSION

A hybrid technique based on linear and nonlinear technologies has been proposed for two-time-scale nuclear power plant modeling and control synthesis purposes. A subspace higher order model has been identified for two-time-scale nuclear power plant using deterministic-stochastic method via Principal Component Analysis. The higher order model is decomposed into two slow and fast subsystems. The decoupling process is optimized using recurrent neural network. A robust discrete nonlinear controller is proposed for decomposed two-time-scale nuclear power plant model in triangular block structure form based on sliding mode control design methodology. The proposed hybrid design produces fast control without any overshoot.

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