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Research Article

Design and Development of Fractional Order Convolutional Neural Network Based Fractional Order Nonlinear Reactor Power Simulator for CANDU-PHWR

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Abstract: A highly complex nonlinear Reactor Regulating System (RRS) of Canadian Deuterium Uranium Pressurized Heavy Water Reactor (CANDU-PHWR) based Nuclear Power Plant (NPP) simulated in the present research. The internal design of RRS is secured and vendor controlled which is embedded in AC-132 Programmable Logic Controller (PLC). Therefore, the problem of the identification of the RRS controller model is addressed. A data-driven Fractional Order Nonlinear MIMO Hammerstein Model (FO-NC-MIMO-HM) of NPP is identified using an Adaptive Immune Algorithm (AIA) based on a Global Search Strategy (GSS) and Auxiliary Model Recursive Least Square Method (AMRLSM). Parameters of FO-MIMO-HM are identified using Innovative Real-Time Plant Operational Data (IRTPOD). The original PLC-based controller is replaced with a new Fractional Order Convolutional Neural Network (FO-CNN) based Fractional Order Nonlinear Controller (FO-NC). Therefore, a visual Simulator is developed for detailed modeling, control, simulation, and analysis of the proposed design scheme for RRS in Visual Basic (VB) Software. The performance of the proposed design scheme is tested and validated for different modes of RRS against benchmark data obtained from Plant Data Recorder (PDR) and found in close agreement well within the design bounds.

Keywords: Fractional Order, Convolutional Neural Network, Nonlinear Control, MIMO System, Visual Basic, Simulator, Reactor Regulating System, CANDU-PHWR.

1. INTRODUCTION

The reactor regulating system is a discrete logic base multivariable reactor power controller. This controller uses various inputs from primary and secondary side of CNADU-PHWR NPP. An auxiliary least squares identification method for Hammerstein model is discussed by Feng *et al.* [1]. ARX based LS algorithm is developed for multivariate output system by Qinyao *et al.* [2]. The concept of adaptive immune genetic algorithm is introduced for multivariable system using global optimization by Dai *et al.* [3]. Later an adaptive immune inspired multi-objective algorithm is designed using multiple DE strategies by Qiuzhen *et al.* [4]. An attempt is made using subspace identification for FO Hammerstein systems by Zeng *et al.* [5]. An iterative method is devised for online FO and parameter identification of system by Oliver *et al.* [6]. A parameter identification method for FO Hammerstein systems is formulated by Zhao *et al.* [7]. A FO Hammerstein state space model is developed for nonlinear dynamic system using input-output measurement data by Rahmani *et al.* [8]. A system identification method is suggested for hybrid fractional order Hammerstein-Wiener model in continuous time domain by Allafi *et al.* [9]. A recursive identification approach

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is chosen for FO Hammerstein model based on Adaptive Differential Evolution with the Local Search strategy by Jin *et al.* [10]. Later, a real time semantic segmentation network is introduced using the concept of Proportional Integral Derivative (PID) controller algorithm by Xu *et al.* [11]. A computer vision control based Convolutional Neural Network- Proportional Integral Derivative (CNN-PID) scheme is devised for mobile robot by Farkh *et al.* [12]. Research is further explored in which a PID controller approach is adopted for stochastic optimization of DNN based systems by An *et al.* [13]. Further research is addressed for CNN back propagation neural network optimized by a fractional order gradient method by Taresh *et al.* [14]. An investigation is performed for the realization and comparative analysis of fractional order controllers using different discretization techniques by Calderon [15]. A convolutional neural network based on FO order momentum term is trained and tuned by Kan *et al.* [16]. A fractional order integral sliding mode controller is designed for Pressurized Water Reactor (PWR) type NPP by Surjagade *et al.* [17].

In this research work, a new fractional order convolutional neural work based fractional order nonlinear sliding mode reactor power controller is designed for a nonlinear MIMO model of CANDU-PHWR NPP. The suggested methodology is the new algorithm which is synthesized for the first time in Visual Basic for the NPP with special emphasis on CANDU-PHWR type nuclear power with state-of-the-art Graphical User Interface (GUI) for modeling and controller design. The proposed scheme provides optimal solution with fast convergence and stability. The FO gradient method is chosen to enhance the dynamic significance of neural parameters for CNN. The fractional order nonlinear sliding mode controller is used for fast convergence and stability and is much better than conventional sliding mode controller because it offers minimum or smaller steady state error and the control law is more flexible due to the variable order of the fractional term with a great advantage of scalability of the fractional order to the sliding mode surface. The proposed design is a novel design with a coupled FO convolutional neural network and FO-SMC for a fractional order multivariable nonlinear model of CANDU-PHWR reactor regulating system optimized by AIA based on a GSS and AMRLSM.

2. MATERIALS AND METHODS

2.1. Reactor Regulating System

The reactor regulating system (RRS) uses three type reactivity mechanisms. One is fine reactivity insertion mechanism called moderator level variation method while two are coarse reactivity insertion mechanism called absorber rod method and booster rod method. Both coarse reactivity insertion method operates in a specific moderator level band. These all methods in turn are responsible for reactor power level change from 0% to 100%.

The reactor regulating system is designed on five control modes such as:

1. SD mode
2. ML mode
3. LL mode
4. NP mode
5. SP mode

These modes work in parallel as group of overrides. Thus, a mode controlling low power is always backed up by the modes ready to control high power levels. The automatic mode reductions provided in the event of loss of permissive for the activated mode. In addition, three overrides are present in all modes.

1. The high rate of log power override also called the rate log N override.
2. The Neutron power override also called the high linear N override.
3. The high moderator level override.

The reactor regulating system is made by CEGLEC ACEC Company of Belgium. This is a 186-machine consisting of bus driver, memory expander, Ethernet (LN1, LN2, and LN3) each of 256 Kbps. Its operating system is RNM-86 based on COGITO configuration.

2.2. CANDU-PHWR Modeling

The reactor regulating system is a multivariable CANDU power control system. It is the most important, critical and most complex control system of CANDU-PHWR type NPP. It is coupled with many other important systems of nuclear power plant. Various parameters/symbols and variables used hereafter in the process of RRS modeling are defined in Annexure I.

α_i are variable FO of differential $D_t^{\alpha_i}$ and integral $I_t^{\alpha_i}$ operators used for the model identification of the reactor regulating system. In system identification, the first step is to use AIA based on a GSS called AIAGS for initialization. Once the coefficients are calculated then second step is to use these model coefficients to identify the actual or true ones of FO-NC-MIMO-HM using AMRLSM. The AIAGS algorithm which is an intelligent optimization algorithm consists of stimulation function, mutation function and simulated annealing function [4].

$$f(x_i) = min\, f(y_k(t), \alpha, m, M, \Omega, \delta, \beta, \gamma) \quad (1)$$

Subject to the linear constraints:

$$g(y(t)^k) \geq 0$$
$$y(t)^k \leq y(t)^{k,max}$$

Where x_i, is i^{th} individual of population and $y(t)$ is a variable vector, $f(y(t)$ is the objective function or cost function, $y(t)^{k,\max}$ is the upper bound of variable $y(t)^k$ and $g(y(t)^k)$ is the inequality constraint of output variable in an intelligent optimization problem.

Fractional order HM is a nonlinear fractional order model consisted of cascaded fractional order static nonlinear model and fractional order dynamic linear model. The fractional order dynamic linear model can be defined as:

$$y_k(t) = G_{k,1}u_1^{NL} + G_{k,2}u_2^{NL} + \ldots + G_{k,p}u_p^{NL} \quad (2)$$

The static nonlinear model can be defined as [8]:

$$u_p^{NL} = a_{p,1}f_{p,1}(u_p(t)) + a_{p,2}f_{p,2}(u_p(t)) + \ldots\ldots\ldots + a_{p,p}f_{p,p}(u_p(t)) \quad (3)$$

The fractional order Hammerstein model can be modeled as:

$$y_k(t) = G'_{k,1}u_1 + G'_{k,2}u_2 + \ldots + G'_{k,p}u_p \quad (4)$$

The dynamic linear model with Gaussian White Noise can be defined as:

$$y_k^{GWN}(t) = y_k(t) + \varepsilon(t) \quad (5)$$

Now, with Gaussian White Noise, the auxiliary model is computed as:

$$y_k^{AM}(t) = G_{k,1}^{AM}u_1^{AMNL} + G_{k,2}^{AM}u_2^{AMNL} + \ldots + G_{k,p}^{AM}u_p^{AMNL} \quad (6)$$

The static nonlinear model can be modified as:

$$u_p^{AMNL} = a_{p,1}^{AM}f_{p,1}^{AM}(u_p^{AM}(t)) + a_{p,2}^{AM}f_{p,2}^{AM}(u_p^{AM}(t)) + \ldots\ldots + a_{p,p}^{AM}f_{p,p}^{AM}(u_p^{AM}(t)) \quad (7)$$

The fractional order Auxiliary Hammerstein model can be modeled as:

$$y_k(t) = G'^{AM}_{k,1}u_1^{AM} + G'^{AM}_{k,2}u_2^{AM} + \ldots + G'^{AM}_{k,p}u_p^{AM} \quad (8)$$

Now, by using the Recursive Least Square Method, the value of model parameter vector θ_k and the value of auxiliary model parameter vector θ_k^{AM} are estimated using input-output data and defining a cost function in terms of θ. Then, using the accurate values of coefficients, the value of fractional order of auxiliary model α is estimated by minimizing another cost function defined in terms of α [2]. The accuracy of the estimated model is computed using Mean Square Error (MSE).

2.3. Fractional Order Convolutional Neural Network Modeling

The fractional order deep convolutional neural network (FO-CNN) is a four-layer network. One is input layer, two convolution layers and one output layer. The convolution layer is an important part of FO-CNN and its main function is to extract dynamic modes of transient behavior. The two convolution layers have been chosen depending on the complexity of problem, size of dataset and specific architecture being used. However, there is no fixed number of layers that is optimal for all tasks. The output of FO-CNN is given as [14]:

$$\varepsilon = f_0(\varepsilon_2) = w_0\varepsilon_2 + b_0 \quad (9)$$

The weights and biases are optimized using fractional order gradient method [16].

2.4. Fractional Order Nonlinear Controller Modeling

Now, FO-SMC is modeled as fractional order nonlinear controller. The novel fractional order siding surface can be designed for fractional order nonlinear system as:

$$S = {}_{h_0}D_t^{1-\alpha} e + {}_{h_0}D_t^{-\alpha} He^{\frac{c}{d}} \quad (10)$$

Where,

$$H = diag(h_1, h_2, \ldots\ldots, h_n) \quad (11)$$

2.5. Coupling Between FO-CNN and FO-NC

Now, the weights and biases described in equation (9) are updated as:

$$w_{NEW} = w - \frac{1}{\eta_w} {}_{h_0}D_0^t w \quad (12)$$

$$b_{NEW} = b - \frac{1}{\eta_b} {}_{h_0}D_0^t b \quad (13)$$

Now, the weights and biases described in equation (9) are calculated as:

$$ {}_{h_0}D_t^{\alpha} w_0^{(i,q)} = S_i \varepsilon_2^q \quad (14)$$

$$b_0^i = {}_{h_0}I_t^{\alpha} S_i \quad (15)$$

The modeling error vector given as:

$$\Delta = [\Delta_1 \Delta_2 \Delta_3 \ldots\ldots \Delta_n]^T \quad (16)$$

Where Δ_n is the modeling error in each output variable affected by noise which is implemented using the concept of Gaussian White Noise. In the subsequent derivation, the dealing of modeling error in terms model uncertainties are described in detail.

The output of FO-CNN without any Gaussian White Noise is the ideal behavior which is given as:

$$\varepsilon^{Ideal} = w_0^{Ideal} \varepsilon_2 + b_0^{Ideal} \quad (17)$$

The uncertainty is addressed in terms of noise in the modeling which is responsible for uncertain dynamics in plant operation and control. Therefore, the lumped noisy parameters can be modeled as:

$$\varepsilon^{Lumped} = w_0^{Ideal} \varepsilon_2 + b_0^{Ideal} + \Delta \quad (18)$$

The estimated noise error function is given as:

$$\hat{\varepsilon} = \varepsilon^{Lumped} - \varepsilon$$
$$\hat{\varepsilon} = (w_0^{Ideal} - w_0)\varepsilon_2 + (b_0^{Ideal} - b_0) + \Delta \quad (19)$$

The error weights and biases matrices are given as:

$$\hat{w}_0 = w_0^{Ideal} - w_0 \quad (20)$$

$$\hat{b}_0 = b_0^{Ideal} - b_0 \quad (21)$$

Now, equation (19) becomes:

$$\hat{\varepsilon} = \hat{w}_0 \varepsilon_2 + \hat{b}_0 + \Delta \quad (22)$$

The Lyapunov function can be defined as:

$$V = \frac{1}{2} S^T S + \frac{1}{2} \eta_w \sum_{i,q} (\hat{w}_0^{(i,q)})^2 + \frac{1}{2} \eta_b \hat{b}_0^{\,T} \hat{b}_0 \quad (23)$$

The control law can be deduced from the following inequality as:

$$ {}_{h_0}D_t^{\alpha} V \leq S^T \left(\dot{e} + He^{\frac{c}{d}} \right) + \eta_w \sum_{i,q} (\hat{w}_0^{(i,q)})\, {}_{h_0}D_t^{\alpha} (\hat{w}_0^{(i,q)})$$
$$+ \eta_b \hat{b}_0^T \, {}_{h_0}D_t^{\alpha} \hat{b}_0 \quad (24)$$

The error dynamics of FO-NC is given as:

$$e = y_k^{AM} - y_k^{Reference}, \dot{e} = \dot{y}_k^{AM} - \dot{y}_k^{Reference} \quad (25)$$

On modifying equation (24) based on equation (22) and hence on simplifying using equation (25) with an assumption that Caputo fractional derivative for a constant is zero, the desired FO-CNN based FO-NC control law is given as:

$$u_{CNN}(t) = \left(G_{k,p}^{AM} \right)^{-1} \left[\left(\dot{y}_k^{Reference} - He^{\frac{c}{d}} \right) - \hat{\varepsilon} + \left(\eta s + K_{SMC} \frac{S}{\|S\|} \right) \right]$$
$$(26)$$

2.6. Controller Simulator Development

The controller simulator is developed in Visual Basic (VB) 6.0. VB supports well for event driven programming. In GUI various active X controls are designed dedicated to specific functions. For single and multiple graphs, tee chart active X control is used. As power Regulating system run on different sample time intervals, so timer control is used to show real time simulation of the transients scenarios. But for long time transients, fast simulation options are available with multipliers of 2, 5, 10, and 25.

3. RESULTS AND DISCUSSION

The entire synthesis of reactor regulating system is carried out in closed loop in the subsequent sections.

3.1. Design Analysis of Proposed Configuration and Simulator Development

The proposed designed scheme of FO-CNN-FO-NC based reactor regulating system is shown in Figure 1. The proposed framework is composed of CANDU-PHWR type nuclear power plant, structure of existing reactor regulating system, proposed modeling and controller synthesis scheme in testing and evaluation phases. The testing loop incorporates the estimated model and proposed controller while the validation loop incorporates the actual plant and the proposed controller. There are five set points for five different operational and control modes of nuclear power plant for RRS. Each control mode represents a sub-controller in RRS design. It takes several inputs from the plant and generates various control and output signals which are defined in detail in section 2.2. As reactor power increases from 0% to any desired power level or maximum up to 100%, the modes are configured sequentially, and signals are generated accordingly as the interlocks are met.

The proposed controller design scheme is shown in Figure 2 for neutron power mode as example for better understanding of problem formulation. Error and error rate signals are specially design to cater the requirements of proposed control design scheme.

The GUI for controller and simulation configuration is shown in Figure 3. Different GUI features such as mode selection, analysis selection, mode comparison, transient analysis, transient initialization schemes, online parameter adjustments and simulator administrative controls are provided in Figure 3. The transfer functions are solved using discrete factional order Tustin Approximation [15] as shown in Figure 4. Recursive solver uses previous value of input, output variables and previous value of output variable with sample time.

There are three different type of reactivity insertion mechanism. Booster rods method is one of the coarse power transient mechanisms as shown in Figure 5. More the booster rods inserted in the reactor core more will be power generated as introduces positive reactivity.

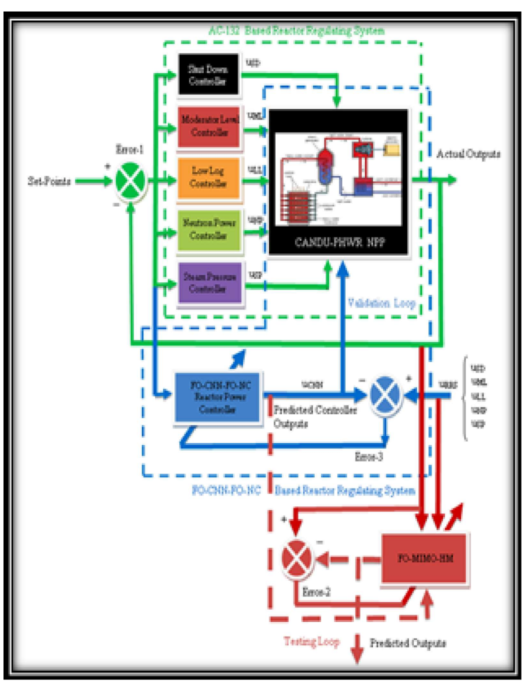

Fig. 1. Proposed configuration of FO-CNN-FO-NC based reactor regulating system.

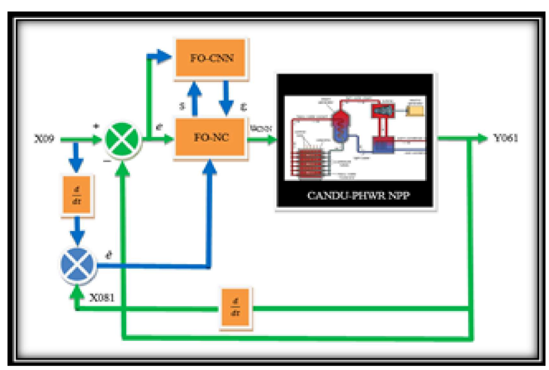

Fig. 2. Design configuration of FO-CNN-FO-NC in neutron power mode.

Fig. 3. GUI for controller and simulation selections.

Absorber rods method is another coarse power transient mechanism as shown in Figure 6. More the absorber rods inserted in the reactor core lesser will be power generated as introduces negative reactivity.

The GUI for the selection of transient is shown in Figure 7. Three transient mechanisms are provided for the insertion or withdrawal of reactivity depending on the type and direction of motion.

The GUI for the selection and design of standard and patent transients is shown in Figure 8. Reactivity transient selection menu is one of the unique features of the simulator. Once the type reactivity mechanism is chosen, the detailed menu will pop up for parametric adjustment and transient design.

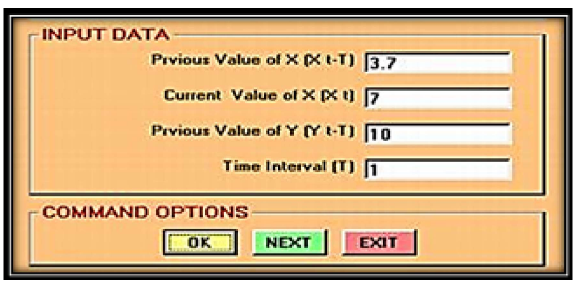

Fig. 4. GUI for discrete solvers.

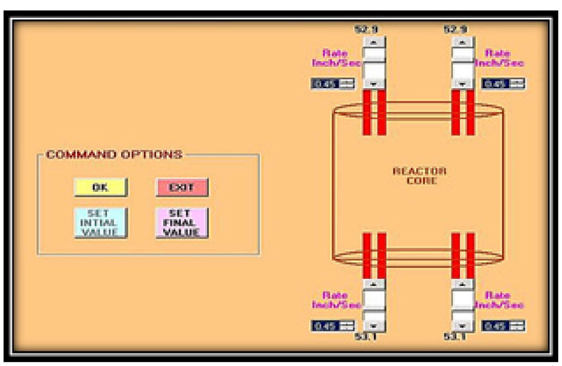

Fig. 5. GUI for booster rod transients.

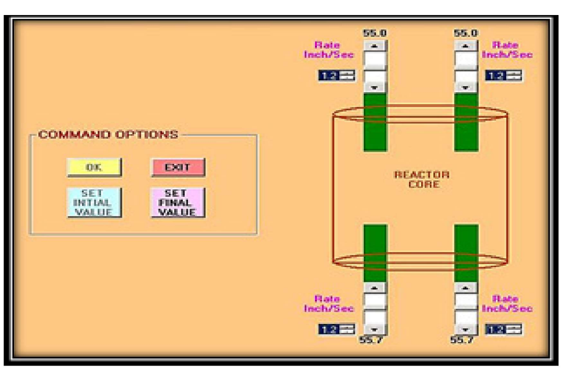

Fig. 6. GUI for absorber rod transients.

3.2. Evaluation of Proposed Controller Design for Moderator Level Controller

The proposed closed loop system is initialized using functions programmed using equation (1). The initialization of moderator level controller in reactor regulating system is shown in Figure 9.

The dynamics of existing and proposed RRS in the simulation framework is designated as Plant Data Recorder (PDR) and Simulator respectively and hence act like legends for entire simulator development and display system. Initialization is performed at 35 inches of moderator level and various parameters of interest are observed against it. New controller is initialized in moderator level mode as shown in Figure 9.

Now, the transient simulation of moderator level controller is shown in Figure 10. A special plant operational transient is configured in moderator level mode and various parameters of interest are visualized. There is a high level of fluctuations on parameters X04 and X05 but final control demand signal Y011 and X02 are tracking excellently. This proves the successful realization of proposed

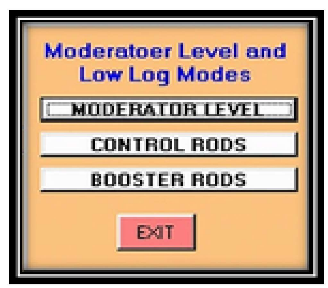

Fig. 7. GUI for reactivity transient selection of moderator level mode in low power operation.

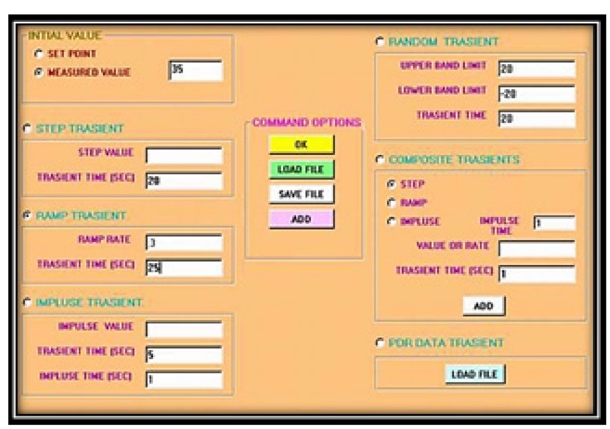

Fig. 8. GUI for selection and design of transients for moderator level controller.

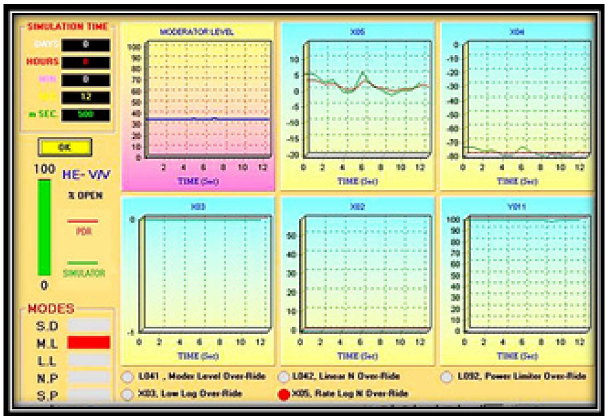

Fig. 9. Initialization of moderator level controllers.

moderator level controller and optimal design performance of parameters.

3.3. Evaluation of Proposed Controller Design for Neutron Power Controller

Now, the dialed reactor power is dropped from 70% to 30% via step change as shown in Figure 11. In this simulation scenario, a transient is configured in neutron power mode and various parameters of interest are visualized. In neutron power mode, under step down power transient, the dynamics of X08, Y061, Y083, Y112 and X12 with proposed scheme follows the benchmark transient data. This dynamic behavior proves the excellent trackability of proposed controller. This optimal performance is achieved due to a transient followed by step change in dialed reactor power. In this transient, the requirements or constraint imposed on the controller is that power ramp down for X08, Y061 and X12 must not exceed -0.25 % RP/sec. This proves the successful realization of proposed neutron power controller and design parameters are optimal in performance in high power operation of the plant.

3.4. Evaluation of Proposed Controller Design for Steam Pressure Controller

The front panel design for steam pressure mode is shown in Figure 12. The front panel design for steam pressure mode is meant for steam pressure, steam flow, primary system temperatures and primary system flows on representative channels.

A special plant operational transient is configured in steam pressure mode as shown in Figure 13 and various parameters of interest are observed. There is a very smooth tracking and very close performance of X08, Y061, X07, Y112 and X12 is achieved. This proves the successful realization of proposed steam pressure controller and optimal design performance of parameters.

The zoomed simulation comparison of X04 and X05 are shown in Figures 14 and 15 respectively.

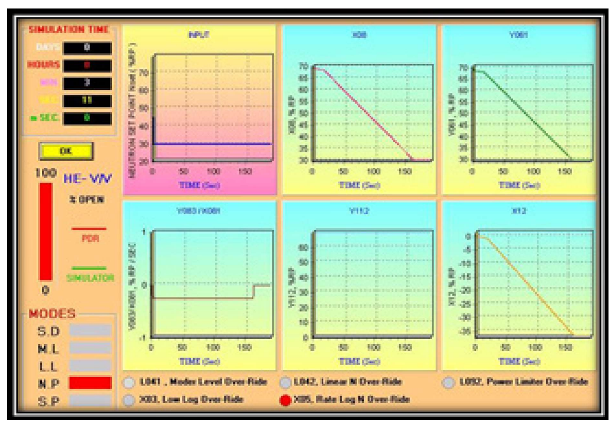

Fig. 11. Simulation of multiple parameters for neutron power controller.

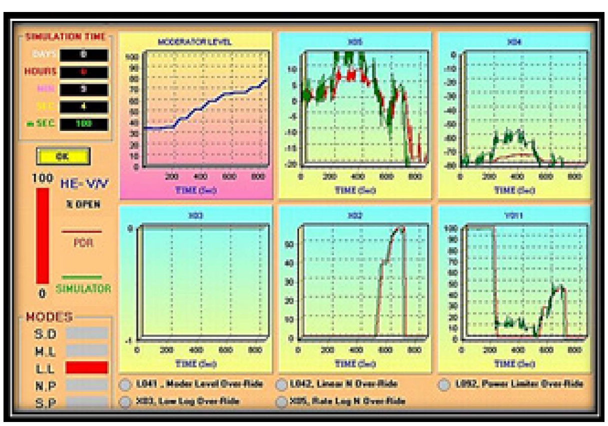

Fig. 10. Transient simulation of multiple parameters for moderator level controller.

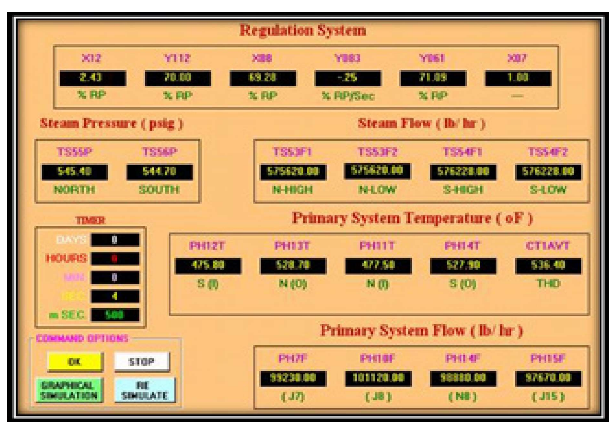

Fig. 12. Front panel design for steam pressure mode.

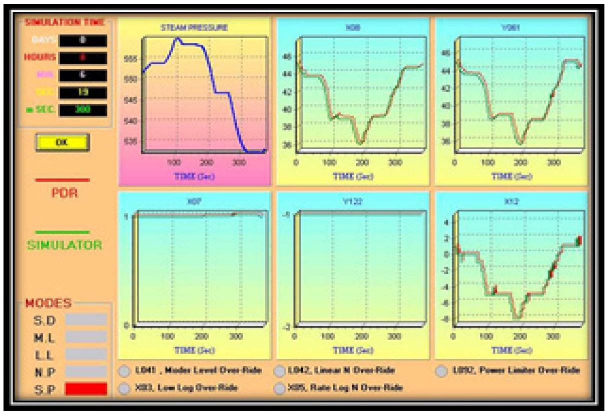

Fig. 13. Transient simulation of multiple parameters for steam pressure controller.

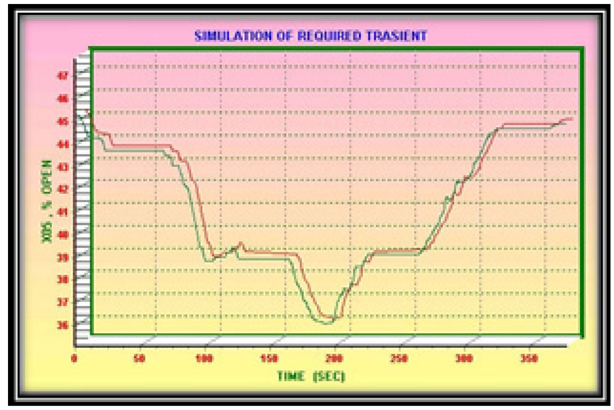

Fig. 15. Simulation of X05 in steam pressure mode.

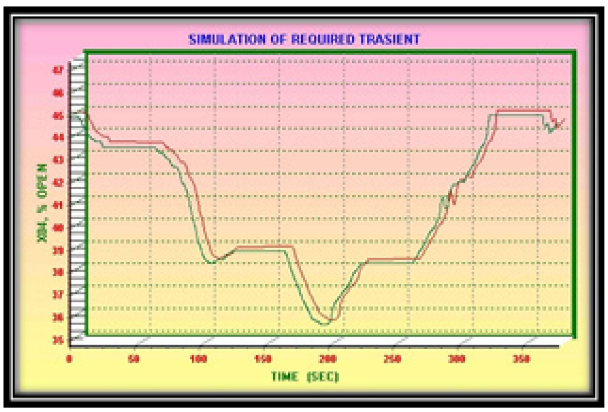

Fig. 14. Simulation of X04 in steam pressure mode.

The comparison is assessed based on the degree of relative errors in distribution of performance and found 0.43% and 0.42% respectively. The optimized design parameters of model and controllers' framework are obtained using proposed design modeled in equations (1) through (25). The optimized parameters are tabulated in Table 1.

Table 1. Optimized parameters of model and controllers.

Parameters	Values	Parameters	Values
Ω	1	A_2	20
δ	0.11	C	3
γ	0.21	D	7
β	0.64	A	0.333
MSE	0.012	η_w	14
P	2	η_b	16
A_1	10	K_{SMC}	7.7

4. CONCLUSIONS

The reactor regulating system of CANDU-PHWR is composite complex power controller of nuclear power generating station. A data driven nonlinear MIMO model of NPP is developed with desired parameters of interest. Model parameters are optimized using adaptive algorithms. Constrained fractional order CNN based FO-SMC is synthesized for RRS. Controller parameters are optimized for five modes of plant operation. Synthesized controller is evaluated and compared with permissives, interlocks, compensators and conventional controllers oriented RRS. A simulator is developed with visual environment for parametric analysis and simulation. Simulator is developed with advanced features of zooming, steady state analysis, transient analysis, customized transient design, fast simulation, multiple plots and online controller parameters adjustment. Therefore, the proposed control design scheme exhibits much robust performance against the model uncertainties and online controller parameters adjustments. The effectiveness and robustness of the proposed manifolds are proved by different configured modes of control to verify their efficacy. This simulator is a step towards other plant systems, controllers and new configuration schemes for advanced research and development in nuclear industry.

5. ACKNOWLEDGEMENTS

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6. CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Annexure I. Symbols/parameters of RRS.

Parameters	Definitions
X02	Moderator Level Controller Output
X03	Low Log Controller Output
X04	Dynamic Power Mismatch Compensator Output
X05	Transient Compensator Output corresponding to Reactivity Effects
X07	Compensator Power Correction Factor corresponding to Moderator Level and Power Mismatch of Thermal and Actual Reactor Power
X08	Turbine Power
NSETD /X09	Demanded Reactor Power
X081	Rate of Change of Reactor Power
X12	Reactor Power corresponding to Steam Pressure
Y011	Equilibrium Helium Valve Position
Y061	Actual Reactor Power
Y122	Compensated Rate corresponding to Steam Pressure
u_{SD}	Equilibrium Helium Valve Position for Shutdown Mode
u_{ML}	Equilibrium Helium Valve Position for Moderator Level Mode
u_{LL}	Equilibrium Helium Valve Position for Low Log Mode
u_{NP}	Equilibrium Helium Valve Position for Neutron Power Mode
u_{SP}	Equilibrium Helium Valve Position for Steam Pressure Mode
u_{RRS}	Control Signal of Reactor Regulating System
u_{CNN}	Control Signal of Fractional Order Convolutional Neural Network based Fractional Order Nonlinear Controller
S	Sliding Surface
E	Gaussian White Noise Compensation Vector
ε_2	Vector of Feature Map of Convolutional Kernel Layer 2
w_0	Weights of Output Layer
b_0	Biases of Output Layer
α_i	Variable Fraction Orders
m	Current Iterations
δ	Total Iterations
δ	Design Parameter for Current Population
δ	Parameter Estimation Error
β	Adaptive Operator
γ	Adaptive Variable for Mutation
P	Number of Inputs of FO-MIMO-HM
L	Number of Outputs of Static Nonlinear Model
K	Output Variables of FO-MIMO-HM

u_L^N	L-th Output of Nonlinear Model
u_L	L-th Output of Linear Model
$f_{L,n}$	Coefficients
$f_{L,n}$	Basic Functions
$G_{k,p}$	Fractional Order Transfer Function of Dynamic Linear Model
$G'_{k,p}$	Fractional Order Transfer Function of Hammerstein model
$G'^{M}_{k,p}$	Fractional Order Transfer Function of Auxiliary Hammerstein model
η	Positive Constant
η_w	Learning Rate associated with Weights
K_{SMC}	Learning Rate associated with Biases
K_{SMC}	Sliding Mode Controller Switching Gain
h_0	Design Positive Constant
c	First Positive Odd Number
d	Second Positive Odd Number
p	Number of Convolution Layers = 1, 2
q	Number of Feature Maps = 1,2, …, A_p
j	Number of Convolution Kernels in a Layer = 1, 2, …., n
A_p	Amount of Kernels in a Layer