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Adaptive Neuro-Fuzzy Self-Tuned-PID Controller for Stabilization of Core Power in a Pressurized Water Reactor

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ABSTRACT

There has been a lot of interest in generating electricity using nuclear energy recently. This interest is due to the features of such a source of energy. The main part of the nuclear energy system is the reactor core, especially the most widely used Pressurized Water Reactor (PWR). This reactor is the hottest part of the nuclear system; security risks and economic possibilities must be considered. Controlling this reactor can increase the security and efficiency of nuclear power systems. This study presents a dynamic model of the (PWR), including the reactor's core, the plenums of the upper and lower, and the connecting piping between the reactor core and steam generator. In addition, an adaptive neuro-fuzzy (ANFIS) self-tuning PID Controller for the nuclear core reactor is presented. This adaptive controller is used to enhance the performance characteristics of PWR by supporting the profile of the reactor power, the coolant fuel, and hot leg temperatures. The suggested proposed ANFIS self-tuning controller is estimated through a comparison with the conventional PID, neural network, and fuzzy self-tuning controllers. The results showed that the proposed controller is best over traditional PID, neural network, and fuzzy self-tuning controllers. All simulations are throughout by using MATLAB/SIMULINK.

Nomenclature

A	Area of heat transference between fuel and coolant	M_{lp}	The lower plenum of water mass
An	Neutrons of generation time	M_{hl}	water mass of hot leg
C	Precursor concentration	M_{mo}	Coolant node lump
C_{PC}	heat coolant capacity	M_{up}	water mass of the Upper plenum
C_{PF}	capacity heat of fuel	Nl	negative of large
$e(t)$	signal of error	Nm	medium for negative
FLC	Fuzzy logic control	Ns	low negative
Fr	power from the fuel component	Pl	large of a positive number
h	Average total heat transference coefficient	Pm	The medium of positive
k_P	Proportional gain	Ps	small positive
k_I	Integral gain	$Pd(t)$	Desired Power

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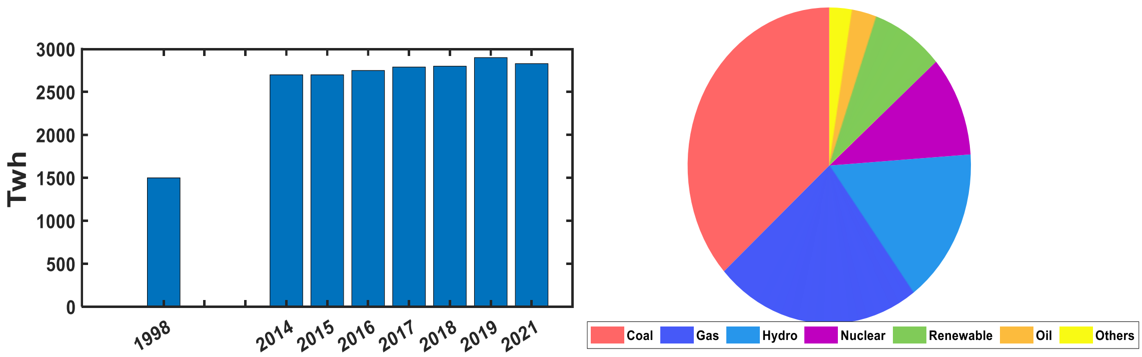
k_D	Derivative gain	$Pa(t)$	Output Power
k_{p1}	Proportional fuzzy gain	P	power in the reactor core in each node
k_{i1}	Integral fuzzy gain	T_{f1-3}	Temperatures of Fuel in nodes (1-3)
k_{d1}	Derivative fuzzy gain	T_{hl}	Temperature of hot-leg
M_C	The flow rate of Coolant mass	T_{lp}	The temperature of the fluid in the lower plenum
M	Coolant mass for two fluid nodes	$T_{m\,1-6}$	Temperatures of moderator in nodes
M_{Cl}	water mass of cold leg	T_{up}	The temperature of fluid in the Upper plenum
M_F	Fuel mass for each node	T_{po}	Outlet temperature in primary water
u(t)	Control activity of PID controller	τ_{lp}	lower plenum time constant
Z	zero gain	τ_C	moderator nodes time constant
α_c	Coolant coefficient of reactivity	γ	Average of six group decay constant
α_f	Fuel coefficient of reactivity	ρ	Total reactivity
β_t	Totally delayed neutron group fraction	ρ_{ex}	External reactivity
T_{cl}	The temperature of the cold leg	τ_{hl}	The time constant of hot leg
τ_{up}	The time constant of the upper plenum		

1. Introduction

Due to the rapid multiplying of the world's population and modernization, the electrical energy demand is enormously increasing. Thus, new untraditional techniques for generating power should be implemented to cover the gap between the generated and demanded power from which nuclear power plants. Nuclear energy is the energy generated by controlling the fission reactions or fusion of an atom [1]. This energy is harnessed in nuclear power plants, where some water reactors heat water to produce water vapor. This water vapor is then used for spinning the turbines to produce electricity [2-3]. Nuclear power plants have been implemented in the power system generation to cover the gap and reduce the adverse impact of using fossil fuels. Nuclear energy is characterized by huge production, increased safety rates, a very reliable energy source, and clean energy. It is not like wind or wave energy that depends on the seasons or the vicissitudes of nature [2-3]. Also, nuclear energy can be provided anywhere as long as the raw materials can be found. Consequently, there is an increased interest in generating electric power from nuclear energy. From 1990 to 2021, the production of electric power from nuclear is nearly doubled, as in Fig. 1(a). The net global production of electric power from nuclear is 10.3% that beyond all renewable energy sources, as in Fig. 1(b) [4].



(a) (b)

Fig. 1. Global growth of nuclear energy (a) Nuclear electricity production (b) World electricity production by source, 2020

Control systems within nuclear reactors provide vital functions in terms of safety and efficiency. One of the most used reactors in nuclear power plants is the pressurized water reactor [5]. The design and control of pressurized water reactors is a significant issue in nuclear power stations. Steady pressure is maintained via pressurization systems, which can be utilized to keep water from boiling. Control rods and the coolant system work together to act as moderators and control the reactivity of the core, with the coolant system also preventing the core from overheating and transferring the heat to be used elsewhere. Control systems are found throughout the entire plant, and these systems must be appropriately implemented, used correctly, and not ignored when they raise an alert.

Most of the research over decades worked on improving the reactor core's performance. Classical proportional-integrated-derivative (PID) controllers are widely used [6-7]. Different methods of PID gains regulation have been advanced in controlling nuclear power plants, like genetic algorithm (GA) [8]. Halim and Bakhri [9] aimed to obtain a safety control system using the fractional-order PID (FOPID) control system and prove that using the control system will provide better results than other existing system applications based-PID controllers. Also, with these good results, it is difficult to control nuclear power plant systems using these classical controllers as of those complex, time-varying and parameters that are not well-known. Some other modern intelligent controllers were applied to nuclear power systems.

Implementing intelligent systems to control large-scale complex nonlinear systems such as nuclear power plants is an up-and-coming issue. Al Fayiz and Masri [10] used an adaptive neural network algorithm to control the power in nuclear power plants. Based on a Dynamic Neural Network System, Identification uses nuclear reactor data to train and validate the structure. The simulation results suggest that the neural network-identified model is capable of adequately capturing nuclear reactor dynamics and of approximating the complicated nuclear reactor system [11]. Using the neural network's nonlinear mapping capabilities, the overall reactivity of the nuclear reactor is estimated using a combination of artificial neural networks and mechanism models by Fan, Lixia, and Liangyu [12].

Reactivity in the nuclear power plant was controlled using fuzzy logic control by Narrendar and Tilak et al. [13]. The development of a PID controller based on fuzzy logic to operate in a pressurizer of a nuclear-pressurized water reactor by Thiago, Lira, and Wagner [14]. The fuzzy logic tuning of the proportional-integral-derivative was applied as a controller used in the Genetic Algorithm (GA) for power control in a nuclear power plant by Liu et al. [15]. The designed fuzzy logic controller has been compared with some conventional PID controllers tuned by different rules for controlling the movement of control rods [16-17]. Thus, it can be concluded that the designed fuzzy logic controller (FLC) is best suitable for both servo and regulatory operations within the operating region. The fuzzy self-tuning control system is applied to breathing air control systems in nuclear power plants whose control succeeded at improving the performance and was proposed to keep the system pressure within design bounds by Harsh, Hossam, and Gabbar [18]. Both classical and intelligent systems presented for nuclear power reactors succeed at improving the system's performance. However, these methods were not able to update the control parameters adaptively [19-25].

From the literature review about the controllers presented for core power in a pressurized water reactor, it can be concluded that:

- Development from classical control was started by applying neural network control as in [10].
- Converting the neural network into an adaptive one as in [11, 13, 21] for dynamic neural networks and for neural network's nonlinear mapping as in [12].
- Using FLC as in [13].
- Updating the PID controllers based FLC as in [14-17].
- Convert the FLC into fuzzy self-tuning control [18].
- Dynamic modeling control [19].
- State feedback controller [22].

All these aforementioned controllers for the pressurized water reactor were trying to improve the performance by updating and making some modifications in the controllers. To the authors, the Adaptive Neuro-Fuzzy Self Tuned-PID controller is not applied for this application of controller. However, the superiority of these controllers [23-26].

This article introduces an ANFIS self-tuning controller to adjust the power level, fuel, and hot leg temperatures of nuclear power reactor-based pressurized water reactor (PWR) system in a nuclear power plant under desired constant and variable power input levels. The proposed controller introduced in this work has been compared with three control types, PID, neural network, and Fuzzy-PID controllers. The ANFIS self-tuning controller proved higher achievement than the three other controllers by comparing various control points through maximum overshoot and settling of time.

This paper is organized as follows: Section 2 presents a description of the nuclear reactor model. The fuzzy logic self-tuning-based PID controller is discussed in Section 3. The concept of the ANFIS self-tuning-based PID control system is discussed in section 4. Section 5 presents the results and discussions. Finally, the conclusion of this research is presented in Section 6.

2. Nuclear Reactor Model

The dynamic model of a nuclear reactor used in this study includes the core of the reactor, the upper and lower plenums, and the piping between the steam generator and the core of the reactor. The lumped parameter paths are used to improve the model of the reactor from the first principles. The heat transfer model in this process is identical to Mann's model for heat exchangers [19]. The fuel element has been divided into three nodes and the coolant into six nodes. The model is normalized according to Fig. 2. The upper plenum, lower plenum, hot leg, and cold leg are the remaining reactor coolant system nodes applied in this model. To predict the average fission power in the reactor core using six delayed neutron models of point kinetics with average precursor groups. For along the axial direction in the reactor core, assuming the power is stable and constant [19].

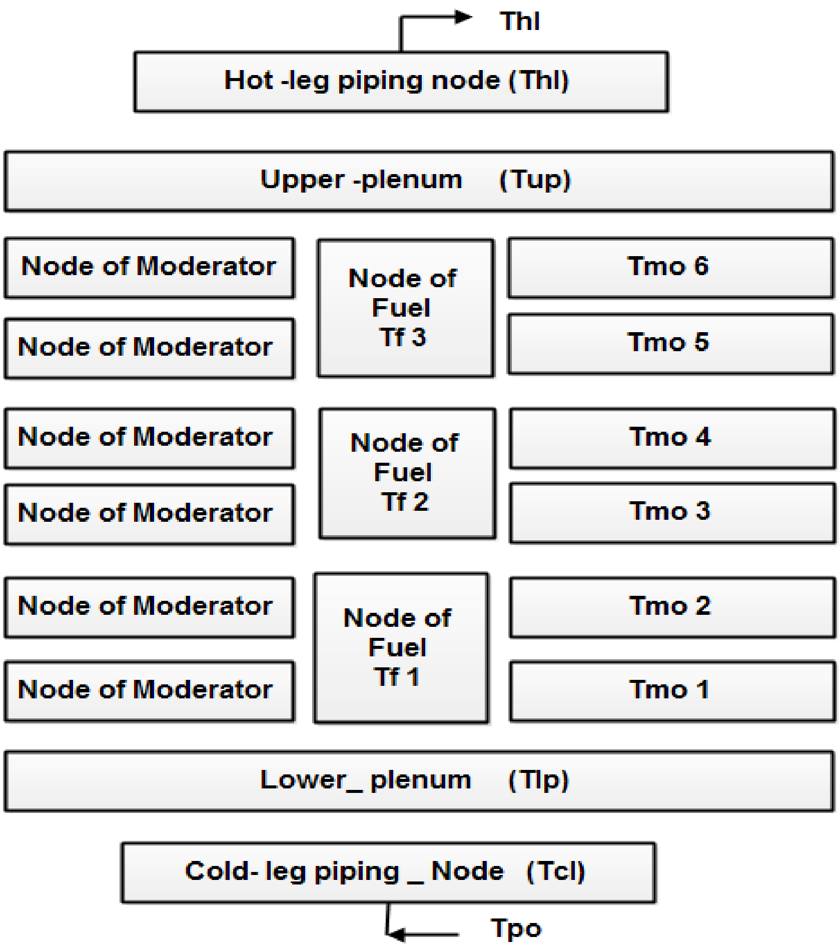


Fig. 2. node of moderator model of the reactor diagram (with the piping of primary)

The mathematical model of the nuclear reactor core makes up the fifteenth differential equation. These mathematical models are defined as follows [19]. Equations of point kinetics of the reactor are

$$\frac{d(P/P_o)}{dt} = \frac{\rho - \beta_t}{\Lambda}\frac{P}{P_o} + \lambda c \tag{1}$$

$$\frac{dC}{dt} = \frac{\beta}{\Lambda}\frac{p}{p_o} - \lambda c \tag{2}$$

Heat Transfer Equations of the reactor core for the first node is

$$\frac{dT_{f1}}{dt} = \frac{F_r P_o}{(MC_p)_F}\frac{P}{P_o} + \frac{hA}{(MC_p)_F}(T_{mo1} - T_{f1}) \tag{3}$$

$$\frac{dT_{mo1}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_p)_C}(T_{f1} - T_{mo1}) + \frac{(T_{lp} - T_{mo1})}{\tau_C} \tag{4}$$

$$\frac{dT_{mo2}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_P)_C}(T_{f1} - T_{mo1}) + \frac{(T_{mo1} - T_{mo2})}{\tau_C} \tag{5}$$

The second node is

$$\frac{dT_{f2}}{dt} = \frac{F_r P_o}{(MC_P)_F}\frac{P}{P_o} + \frac{hA}{(MC_P)_F}(T_{mo3} - T_{f2}) \tag{6}$$

$$\frac{dT_{mo3}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_p)_C}(T_{f2} - T_{mo3}) + \frac{(T_{mo2} - T_{mo3})}{\tau_C} \tag{7}$$

$$\frac{dT_{mo4}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_p)_C}(T_{f2} - T_{mo3}) + \frac{(T_{mo3} - T_{mo4})}{\tau_C} \tag{8}$$

The third node is

$$\frac{dT_{f3}}{dt} = \frac{F_r P_o}{(MC_p)_F}\frac{P}{P_O} + \frac{hA}{(MC_p)_F}(T_{mo5} - T_{f3}) \tag{9}$$

$$\frac{dT_{mo5}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_p)_C}(T_{f3} - T_{mo5}) + \frac{(T_{mo4} - T_{mo5})}{\tau C} \tag{10}$$

$$\frac{dT_{mo6}}{dt} = \frac{(1 - F_r)\,P_o}{(MC_p)_C}\frac{P}{P_o} + \frac{hA}{(MC_p)_C}(T_{f3} - T_{mo5}) + \frac{(T_{mo5} - T_{mo6})}{\tau C} \tag{11}$$

Cold Leg Temperature is

$$\frac{dT_{cl}}{dt} = \frac{(T_{po} - T_{cl})}{\tau_{cl}} \tag{12}$$

The lower and upper plenum temperatures can be defined as

$$\frac{dT_{lp}}{dt} = \frac{(T_{cl} - T_{lp})}{\tau_{lp}} \tag{13}$$

$$\frac{dT_{up}}{dt} = \frac{(T_{mo6} - T_{up})}{\tau_{up}} \tag{14}$$

Hot Leg Temperature is

$$\frac{dT_{hl}}{dt} = \frac{(T_{up} - T_{hl})}{\tau_{hl}} \tag{15}$$

Constitutive equations is

$$\rho = \rho_{ex} + \frac{\alpha_f}{3}\left[(T_{f1} + \cdots + T_{f3}) - (T_{f1_0} + \cdots + T_{f3_0})\right] + \frac{\alpha_c}{6}\left[(T_{mo1} + \cdots + T_{mo6}) - (T_{mo1_0} + \cdots + T_{mo6_0})\right] \tag{16}$$

Where

$$\lambda = \frac{\beta_t}{\sum_{i=1}^{6}\frac{\beta_i}{\lambda_i}} \tag{17}$$

$$\tau_C = \frac{M_C}{2\dot{M}} \tag{18}$$

$$\tau_{cl} = \frac{M_{cl}}{\dot{M}} \tag{19}$$

$$\tau_{lp} = \frac{M_{lp}}{\dot{M}} \tag{20}$$

$$\tau_{up} = \frac{M_{up}}{\dot{M}} \tag{21}$$

$$\tau_{hl} = \frac{M_{hl}}{\dot{M}} \tag{22}$$

3. Nuclear Reactor Control Algorithms

In this section, the proposed control algorithm (ANFIS self-tuning), along with the other three algorithms used for comparison (PID, NN, and Fuzzy self-tuning), will be introduced.

3.1. PID Controller

PID controller is the most commonly used algorithm for controller design, and it has many industrial applications [26-27]. In this paper, the PID controller is presented as a benchmark for comparison with the proposed controller. The error between the reference power ($P_d(t)$) and the output power from the nuclear reactor ($P_a(t)$) is compared. The difference between this power represents the input to the PID controller. The output signal from the controller is used for driving the reactor to adjust the power and try to decrease the error.

The error signal is calculated as

$$e(t) = P_d(t) - P_a(t) \tag{23}$$

This error signal drives the PID controller to generate the control signal ($u(t)$) given by

$$u(t) = k_P e(t) + k_I \int_0^t e(t)d(t) + k_D \frac{de(t)}{dt} \tag{24}$$

and consequently, regulates the output power from the reactor. Fig. 3 shows the nuclear reactor control block diagram using the PID controller.

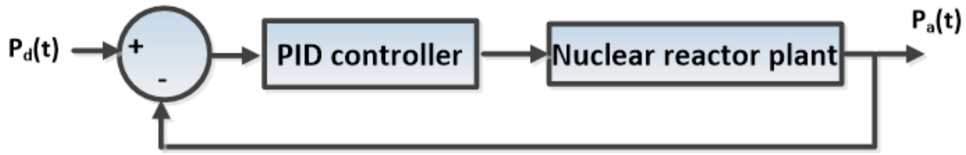


Fig. 3. PID controller

3.2. Neural Network

A neural network (NN) controller is designed such give an ensured closed-loop performance in terms of minor tracking errors and limited controls. In this paper, the input (error signal) of the NN controller is the difference between the reference power ($P_d(t)$) and the actual output power ($P_a(t)$). The output of the NN is the control signal ($u(t)$), which stabilizes the output power of the nuclear reactor plant, as shown in Fig. 4.

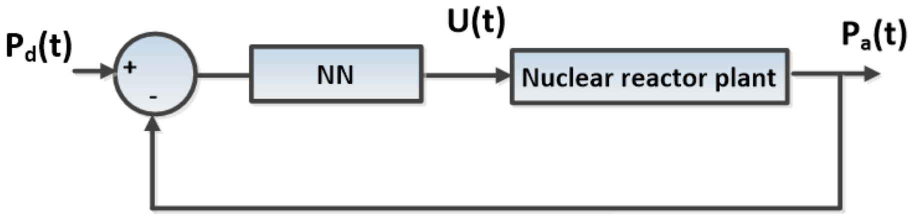


Fig. 4. Neural Network Controller

3.3. Fuzzy Self-Tunning PID Controller

The knowledge base, fuzzification, inference engine, and defuzzification are the core components of fuzzy logic. The fuzziness of additional data in the FLC is named fuzzification. Fuzzy linguistic definitions are modal equipment representations made by fuzzy rules for IF-THEN. To keep the power level is updated the fuzzy controller. The block diagram of a Fuzzy controller is shown in Fig. 5.

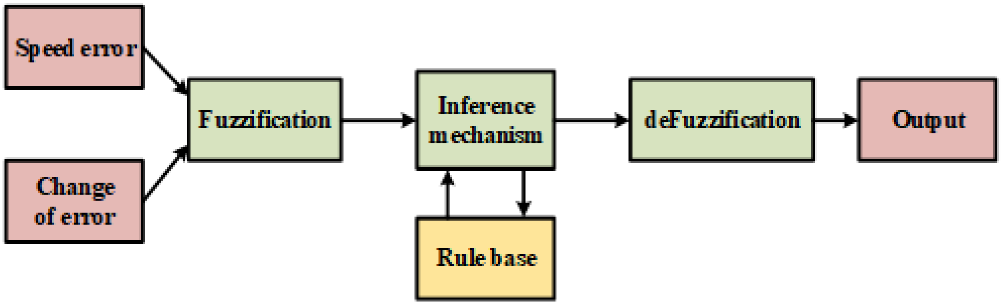


Fig. 5. The fuzzy controller block diagram

The fuzzy logic controller design used the error and variation of error as inputs to the self-tuning, and the gains (k_{p1}, k_{i1}, k_{d1}) are outputs. The FLC is inserted into the conventional PID controller to update the parameters of the PID controller online based on the change of the error and the change of the error. The controller suggested also contains scaling gains inputs (k_e, k_{de}) to satisfy the operational ranges making them more comprehensive, as shown in Fig. 6 [28-29].

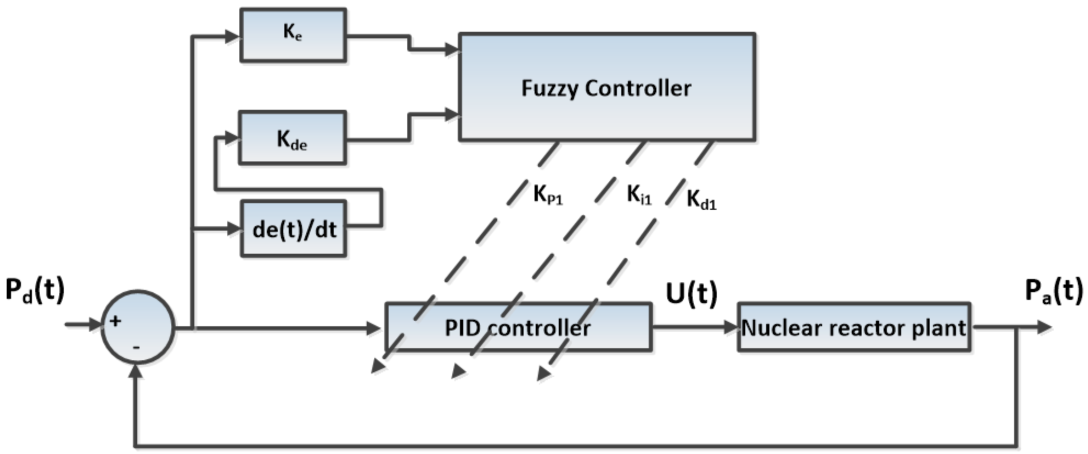


Fig. 6. Fuzzy self-tuning controller.

After self-tuning of the PID controller by FLC, the control action can be described as:

$$u(t) = k_{p2}e(t) + k_{i2}\int_0^t e(t)d(t) + k_{d2}\frac{de(t)}{dt} \tag{25}$$

So, the new gain of the PID controller are k_{p2} , k_{i2} , k_{d2} equals to

$$k_{p2} = k_{p1} * k_p, \quad k_{i2} = k_{i1} * k_i, \quad k_{d2} = k_{d1} * k_d$$

where the outputs of the fuzzy controller gain are k_{p1}, k_{i1} and k_{d1} which are adjusted online with the system output controlled.

3.4. Neuro-Fuzzy Self-Tunning PID Controller

This paper proposed an adaptive neuro-fuzzy self-tuning PID control of nuclear power reactors. The structure of the neuro-fuzzy self-tuning PID controller is shown in Fig. 7. The neuro-fuzzy controller has two inputs (error and variation of error) and three outputs (k_{p1}, k_{i1}, k_{d1}). The outputs of the neuro-fuzzy controller are used to adapt the parameters for the PID controller [22]. The output control signal of the PID controller is applied as an input signal to the nuclear reactor to force the power level to reach the desired value (in a short time with minimum overshoot).

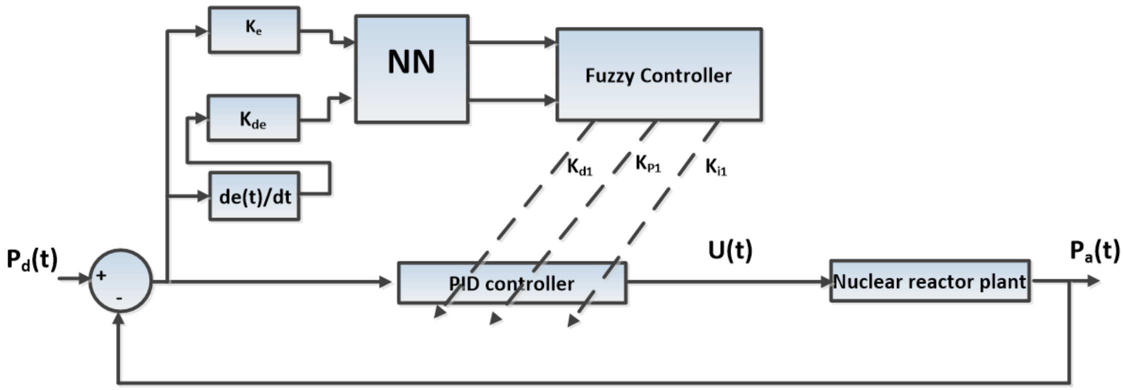


Fig. 7. ANFIS self-tuning block diagram.

The proposed neuro-fuzzy network combined a fuzzy logic algorithm with a five-layer artificial neural network (ANN) structure. The proposed scheme uses the Sugeno fuzzy model with a five-layer ANN structure. The first layer provides inputs, the second layer represents fuzzification, the third and fourth layers represent fuzzy rule valuation, and the fifth layer represents defuzzification in this five-layer ANN structure [26]. Fig. 8 describes the adaptive Neuro-Fuzzy Inference System (ANFIS) architecture of two inputs first-order Sugeno fuzzy model with two rules:

Rule 1: If (x is $A1$) and (y is $B1$), then $f_1 = p_1 * x + q_1 * y + r_1$

Rule 2: If (x is $A2$) and (y is $B2$), then $f_2 = p_2 * x + q_2 * y + r_2$

The determined parameters designed for during the period of the training phase are r_i, p_i, and q_i [7].

All the adjustable parameters (membership functions and weights) are replaced via ANFIS' learning and training algorithm to compare ANFIS output to the data trained.

$$\begin{aligned} z = \frac{w_1}{w_2 + w_1}z_1 + \frac{w_2}{w_1 + w_2}z_2 &= \overline{w_1}(p_1x + q_1y + r_1) + \overline{w_2}(p_2x + q_1y + r_2) \\ &= (\overline{w_1}x)p_1 + (\overline{w_1}y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}y)q_2 + (\overline{w_2})r_2 \end{aligned} \tag{26}$$

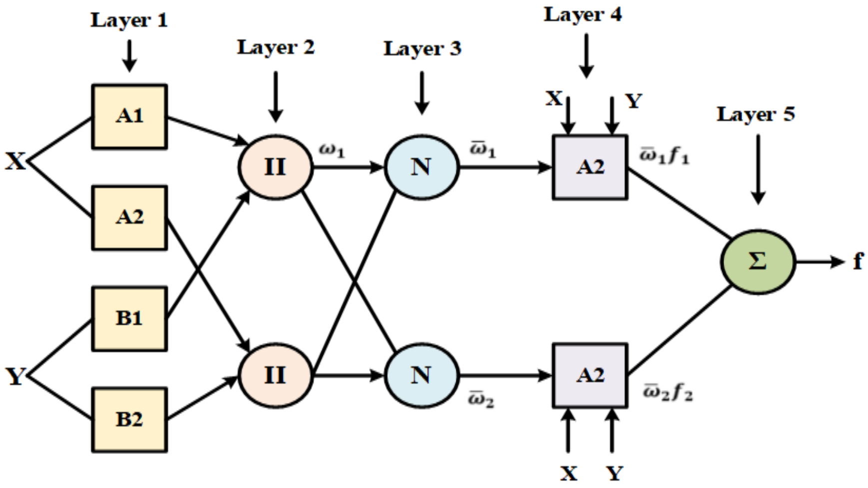


Fig. 8. The adaptive neuro-fuzzy inference system architecture (ANFIS)

4. Results and discussions

In this paper, the ANFIS self-tuning PID controller is used to regulate the reactor core power in a pressurized water reactor used in nuclear power plant. The Neuro-fuzzy controller is a mix of a fuzzy logic controller and neural network that makes the fuzzy controller self-tuning and adaptive. Two test cases will be presented to study the effectiveness of the proposed controller. The first case is performed at constant reference power, while the second is performed at variable reference power. A comparison with three different controllers is presented to assess the proposed Neuro-fuzzy self-tuning PID. These three controllers are the PID controller, NN controller, and Fuzzy self-tuning controller. In this work, the reactor core of the PWR system is used together with the controllers were modeled using MATLAB/SIMULINK. The data used for simulation are given in the [19].

The behavior of the system with the presented controllers would be evaluated by the profile of core power, fuel temperature, moderator temperature, and hot leg temperature in terms of some dynamic performance characteristics. These characteristics include steady-state error, maximum overshoot, and settling time.

PID controller is presented in this paper with the coefficients $K_p = 0.0017$, $K_i = 027$, and $K_d = 0.1$. These coefficients were obtained after many trials using the Ziegler-Nichols method [20].

The NN controller design is performed by a three-layer artificial neural network. The first and third layers are the input (error in the power $e(t)$) nad trhe output layes (control signal $u(t)$). The second layer (hidden layer) has 10 nodes. Each node in the hidden layer is a weighted sum of the input node value. Before being transmitted to the weighted sums of the output layer, each node's value is transformed using a nonlinear sigmoid function. The output node is the weighted sum of the hidden node values. The value of the output node is transformed by a linear function, which is considered the control signal to stabilize the power of the nuclear reactor plant, as shown in Fig. 9.

For the Fuzzy self-tuning PID controller, the error and derivative of the error power represent the two inputs, while the control signal from the PID controller represents the output. The base rules of the obtained fuzzy self-tuning system consist of 25 rules for the three PID controller parameters, as given in Table 1.

ANFIS self-tuning controller design has used the data of inputs and output acquired from the optimal PID controller. The hybrid learning algorithm has been used to modify the trainable parameters of the neuro-fuzzy controller. The control rules used for the neuro-fuzzy self-tuning of the PID controller are shown in Table 2. Fig. 10 shows the simulation modeling of an adaptive neuro-fuzzy self-tuning system.

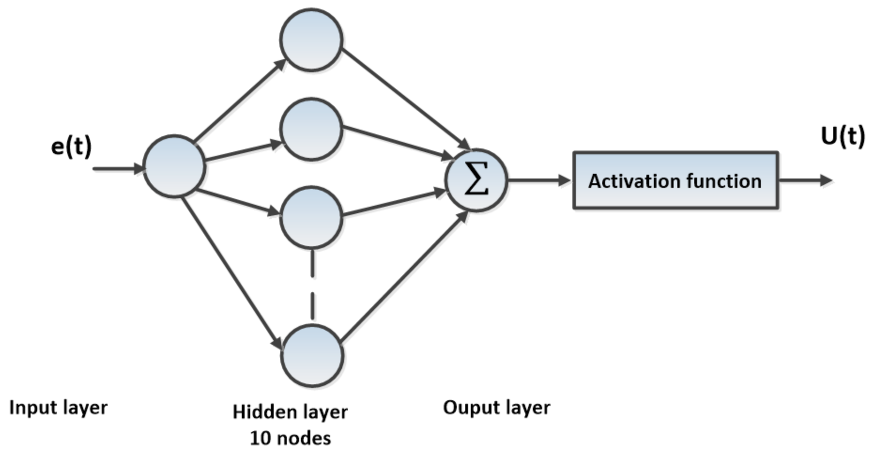


Fig. 9. NN architecture

Table 1. Fuzzy self-tuning Rules for tuning PID control parameters x

	K_p					K_i					K_d				
	Nl	**Ns**	**Z**	**Ps**	**Pl**	**Nl**	**Ns**	**Z**	**Ps**	**Pl**	**Nl**	**Ns**	**Z**	**Ps**	**Pl**
Nl	VP	VP	VP	VP	VP	M	M	M	M	M	Z	S	M	MP	VP
Ns	P	P	P	MP	VP	S	S	S	S	S	S	P	MP	VP	VP
Z	Z	Z	MS	S	S	MS	MS	MS	MS	MS	M	MP	MP	VP	VP
Ps	P	P	P	MP	VP	S	S	S	S	S	P	VP	VP	VP	VP
Pl	VP	VP	VP	VP	VP	M	M	M	M	M	VP	VP	VP	VP	VP

Table 2. Neuro Fuzzy self-tuning rules matrix

E / **dE**	**Nl**	**Nm**	**Ns**	**Z**	**Ps**	**Pm**
Nl	Nl	Nl	Nl	Nl	Nl	Nl
Nm	Nm	Nm	Nm	Nm	Nm	Nm
Ns	Ns	Ns	Ns	Ns	Ns	Ns
Z	Z	Z	Z	Z	Z	Z
Ps	Ps	Ps	Ps	Ps	Ps	Ps
Pm	Pm	Pm	Pm	Pm	Pm	Pm
Pl	Pl	Pl	Pl	Pl	Pl	Pl

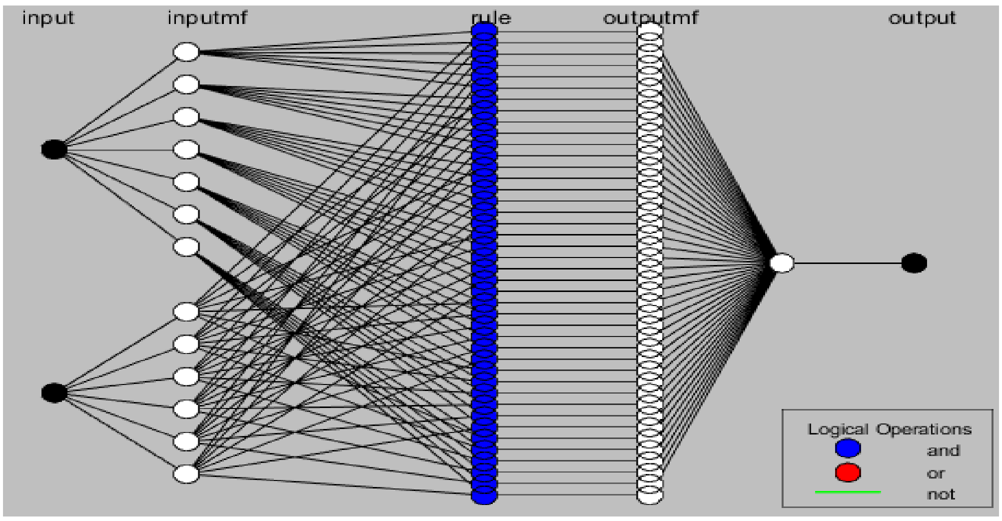


Fig. 10. ANFIS self-tuning structure for power control of the nuclear core reactor.

4.1. Test Case 1: Constant Power

In this case, the reference power is kept constant at 1.2pu, and the proposed ANFIS self-tuning PID controller and the other three controllers used for comparison will be applied to the system. The profile of the nuclear reactor core is improved when the proposed ANFIS self-tuning controller is implemented rather than using the other three controllers. The ANFIS self-adjusting controller successfully reduced the overshoot and reached the steady-state value of 1.2pu faster when compared to the three controllers, as shown in Fig. 11.

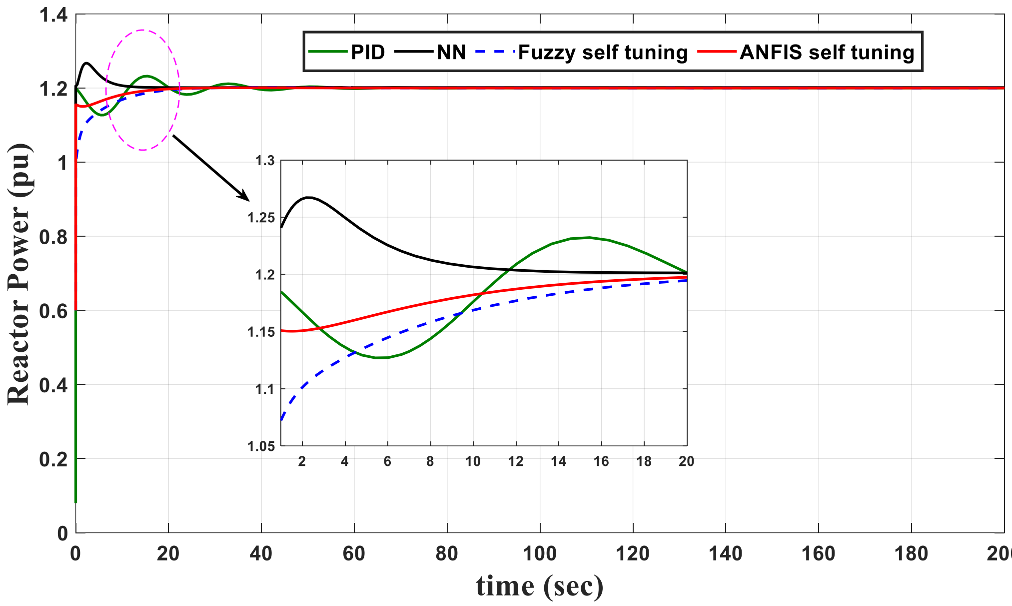
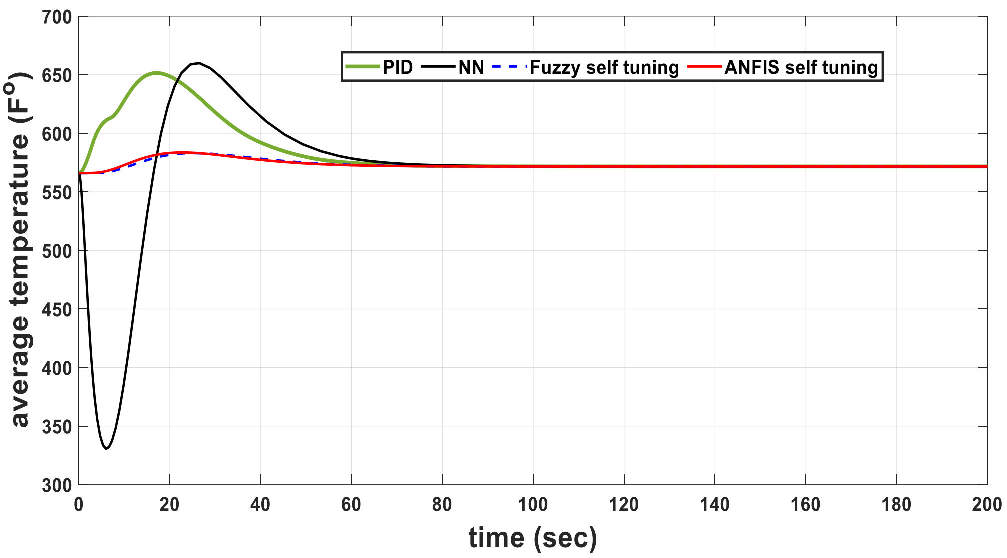
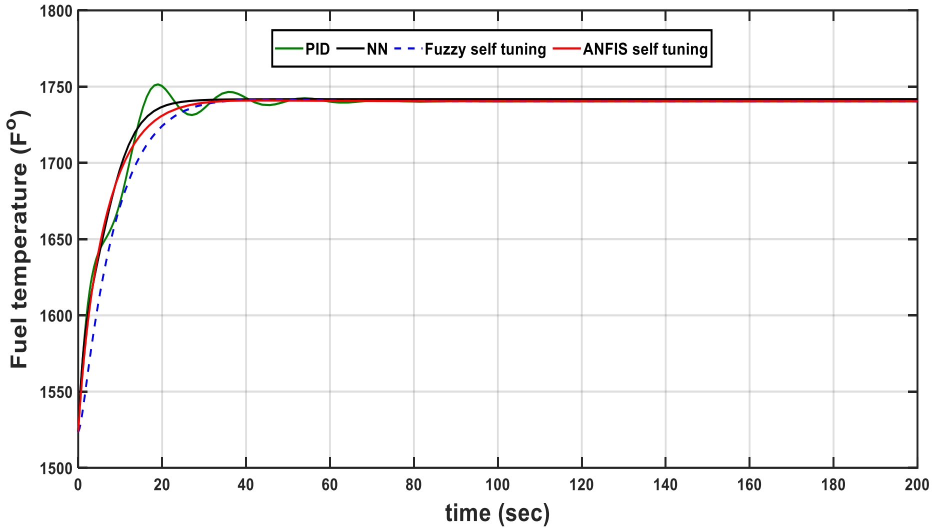


Fig. 11. Power response of nuclear reactor using PID, NN, Fuzzy, and ANFIS self-tuning controllers

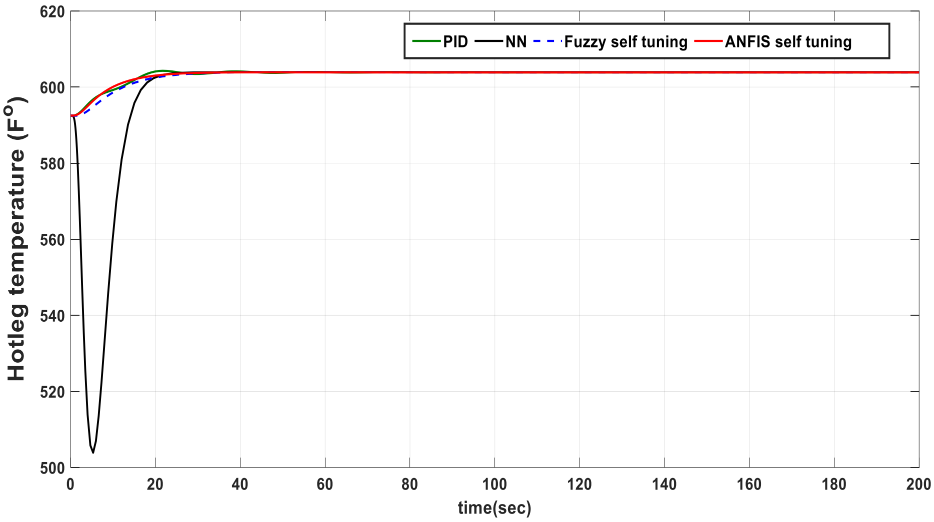
The average, fuel, hotleg, and moderate temperatures in this normal operation using the four controllers are depicted in Fig. 12. The proposed ANFIS self-tuning controller has the best response in terms of maximum overshoot and settling time. The average temperature reached the maximum value of about 670 °F by PID and NN controllers, while it reached 575 °F and 572 °F when applying Fuzzy and ANFIS self-tuning techniques, respectively.



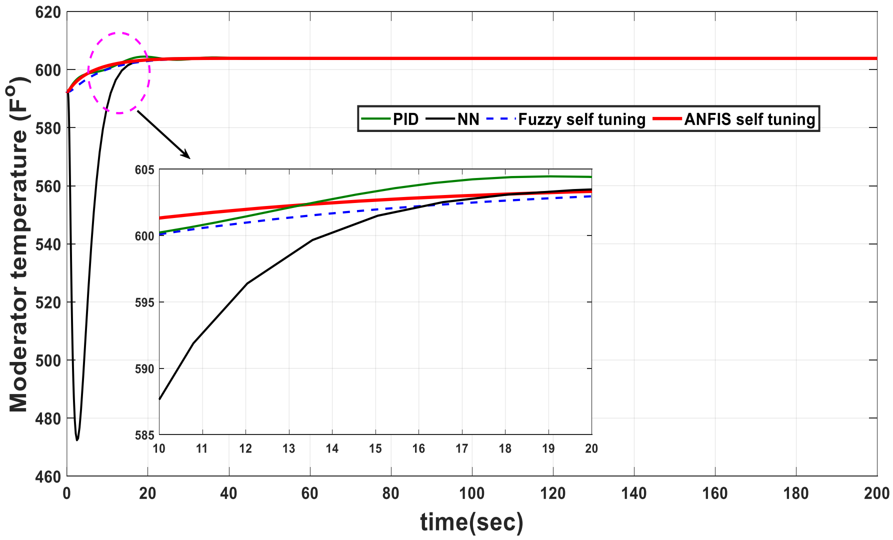
(a) Average temperature response



(b) Fuel temperature response



(c) Hotleg temperature response



(d) Moderator temperature response

Fig. 12. Temperature profile using PID, NN, Fuzzy self-tuning, and ANFIS self-tuning controllers

4.2. Test Case 2: Variable Power

Another test case is applied to the system to test the efficiency of the proposed controller to regulate the reactor power. In this case, a sudden decrease in the reference power from 1.2 to 0.2pu between 60 and 140s is introduced. The proposed ANFIS self-tuning PID controller is used in and also compared to the three other controllers to regulate the power. The proposed self-tuning method of ANFIS has the best performance compared to the other three methods. The response of the power of the system due to ANFIS has nearly no overshoot and less settling time compared with PID, NN, and fuzzy self-tuning methods, as depicted in Fig. 13.

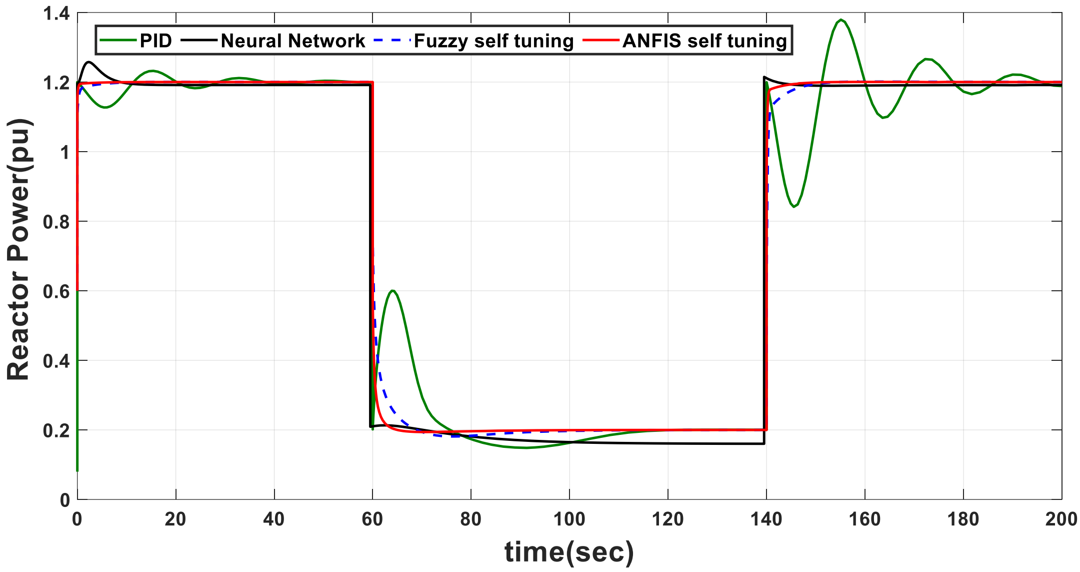
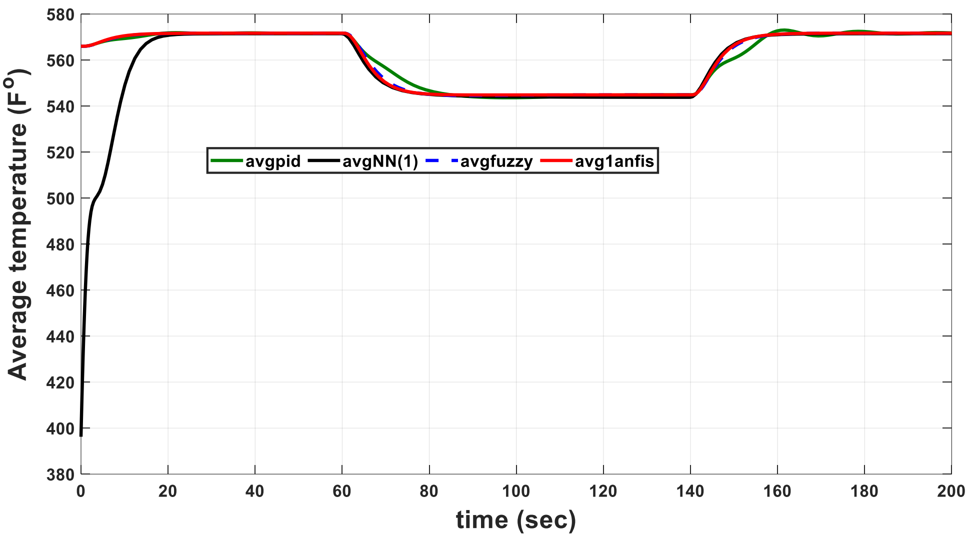
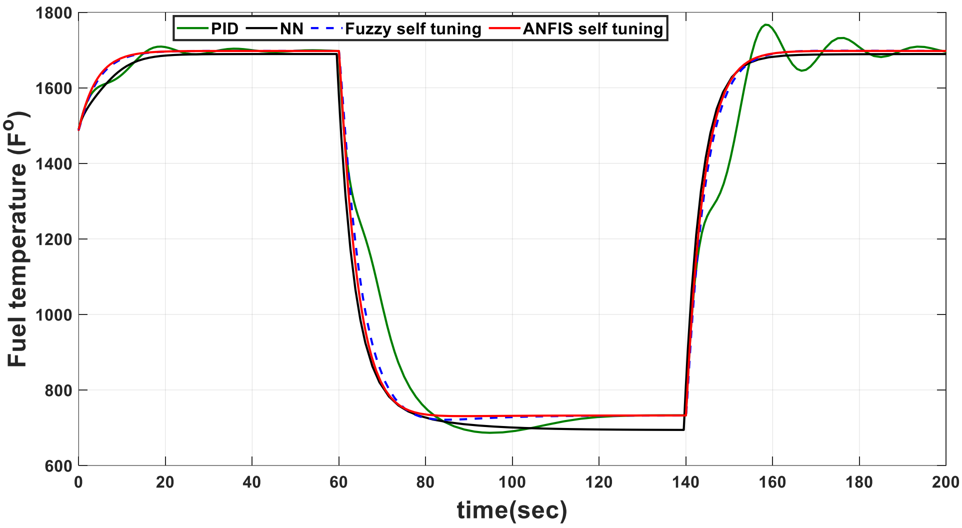


Fig. 13. Reactor power profile using PID, NN, Fuzzy, and ANFIS self-tuning controllers.

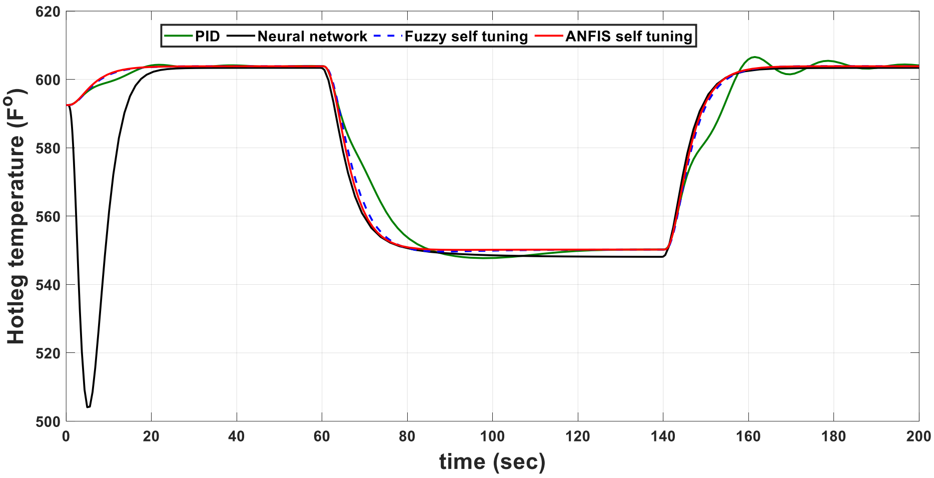
With this sudden change in the power, there will be a sudden decrease in the average, fuel, hot leg, and moderate temperatures, as in Fig. 14(a), Fig. 14(b), Fig. 14(c), and Fig. 14(d). The proposed ANFIS-self-tuning controller succeeded in improving the profiles of the average, fuel, hotleg, and moderate temperatures rather than the three controllers. The temperature profile when applying the proposed controller is without maximum overshoot nearly and with the lees setting time, as shown in Fig. 14.



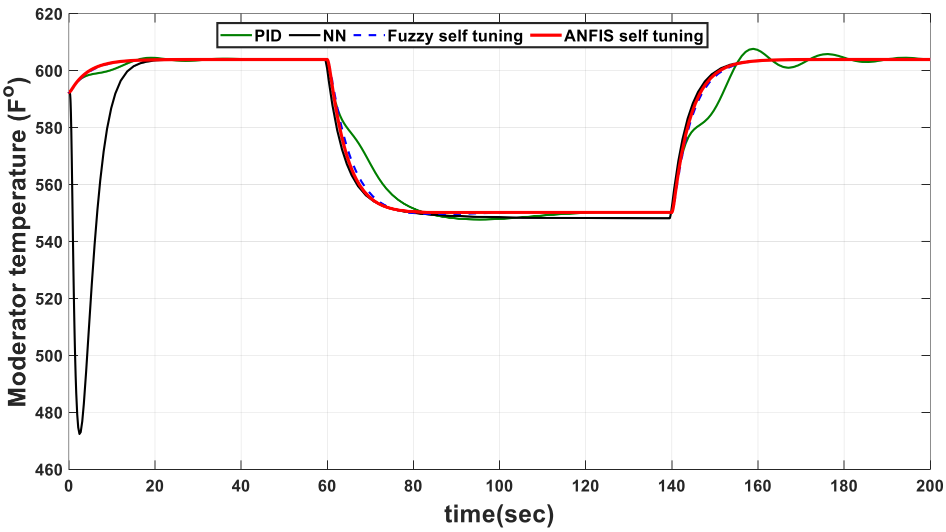
(a) Average temperature response



(b) Fuel temperature



(c) Hotleg temperature response



(d) Moderate temperature

Fig. 14. Temperature's profile using PID, NN, Fuzzy and ANFIS self-tuning controllers

The results discussed in the second case show that the best performance is obtained when applying the proposed ANFIS self-tuning controller when the power is changed. A quantitative comparison between the system performance in terms of some control indices for the reactor power, fuel, hot leg, and moderate temperatures when applying the four controllers is given in Table 3. It has been concluded that the ANFIS self-tuning controller has high effectiveness compared with PID, NN, and Fuzzy self-tuning controllers.

Table 3. Comparative study for four controllers

State variable	PID		NN		Fuzzy self-tuning		ANFIS self-tuning	
	% Max overshoot	Settling time(s)	% Max overshoot	Settling time (s)	% Max overshoot	Settling time(s)	% Max overshoot	Settling time (s)
Power	0.0266	64.12	1.2925	38.57	0	26.34	0	19.58
Fuel temperature	0.0063	114.21	0.0011	99.10	0.0005	81.19	0.0005	65.22
Hotleg temperature	0.0008	64.01	0.1654	48.67	0.0002	36.11	0.0001	31.21
Moderator temperature	0.0012	76.86	0.0001	68.13	0.0001	52.15	0.0001	41.14

5. Conclusion

An adaptive controller, which is called ANFIS self-tuning, is used for tuning and updating the parameters of PID controller gains and is introduced in this paper. This adaptive controller is presented to control a nuclear core reactor with type PWR. This adaptive controller improved the nuclear system's performance in terms of some control indices. These indices are maximum overshoot and settling time for nuclear power, fuel, hotleg, and moderate temperatures. The suggested proposed ANFIS self-tuning controller and three other controllers (conventional PID, neural network, and fuzzy self-tuning controllers) are presented and compared. The results proved the superiority of the proposed adaptive controller over the other three controllers in enhancing the dynamic performance of the power level, fuel, hot leg, and moderator temperature profiles. The proposed controller succeeded at nearly canceling the overshoot of the nuclear power greeted, fuel, hotleg, and moderate temperatures. In addition, the proposed controller could reduce the settling time g for the nuclear power generated to 19s compared to 64, 38, and 26 s when using PID, NN, and fuzzy-self-tuning controllers, respectively.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix

Table A. Reactor Design Parameters

Parameter	Value
Core Diameter (inches)	119.7
Core Height (inches)	144
First Delay Neutron Group Fraction	0.000209
Second Delay Neutron Group Fraction	0.001414
Third Delay Neutron Group Fraction	0.001309
Fourth Delay Neutron Group Fraction	0.002727
Fifth Delay Neutron Group Fraction	0.000925
Sixth Delay Neutron Group Fraction	0.006898

Parameter	Value
Total Delayed Neutron Group Fraction	0.006898
First Group Decay Constant (1/sec)	0.0125
Second Group Decay Constant (1/sec)	0.0308
Third Group Decay Constant (1/sec)	0.1140
Fourth Group Decay Constant (1/sec)	0.307
Fifth Group Decay Constant (1/sec)	1. 19
Sixth Group Decay Constant (1/sec)	3.1 9
Moderator Coefficient of Reactivity (1/oF)	-2.0$\times 10^{-4}$
Fuel Coefficient of Reactivity (1/oF)	-1.1$\times 10^{-5}$
Prompt Neutron Generation Time (sec)	1.79$\times 10^{-5}$
Nominal Power Output (mwt)	3436
Fraction of Total Power Generated in Fuel	0.974
Coolant Volume in Upper Plenum (ft^3)	1376
Coolant Volume in Lower Plenum (ft^3)	1791
Coolant Volume in Hot Leg Pipings (ft^3)	1000
Coolant Volume in Cold Leg Pipings (ft^3)	2000
Coolant Volume in Core (ft^3)	540
Mass of Fuel (lbm)	222739
Total Coolant Mass Flow Rate (lbm/hr)	1.5108
Effective Heat Transfer Area (Jt2)	59900
Specific Heat Capacity of Fuel (btu\1bm-oF)	0.059
Specific Heat Capacity of Moderator (btu/1bm-oF)	1.39
Average Overall Heat Transfer Coefficient (btuflbm -ft^2)	200

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