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Implementation and Performance Evaluation of Intelligent Techniques for Controlling a Pressurized Water Reactor

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Abstract:
Pressurized water reactors (PWRs) are the most common and widely used type of reactor, and ensuring the stability of the reactor is of utmost importance. The challenges lie in effectively managing power fluctuations and sudden changes in reactivity that could result in unsafe situations. Reactor power fluctuations can cause changes in behavior. At the same time, the transfer of heat from the fuel to the coolant and reactivity changes resulting from differences in fuel and coolant temperatures can also make the system unpredictable. The primary goal of a power controller used in a nuclear reactor is to sustain the specified power level, which guarantees the security of the power plant. To address these challenges, this paper presents a dynamic model of a PWR and applies several control techniques to the system for power level control. Specifically, a traditional PID controller, a neural network controller, a fuzzy self-tuned PID controller, and a neuro-fuzzy self-tuned PID controller were individually designed and evaluated to enhance the performance of the reactor power control system under constant and variable reference power. In addition, the robustness of each controller was assessed against time delays and external disturbances. The system was tested with various initial power values to evaluate its performance under different conditions. The results demonstrate that the neuro-fuzzy self-tuned PID controller has the best performance, as well as the fastest response time compared to the other controllers.

Furthermore, the intelligent controllers were found to exhibit good robustness against time delays and external disturbances. The system's stability was not significantly affected by changes in the initial power value, although it had a minor effect on the transient response. Overall, the findings of this study can inform the design and optimization of control systems for PWRs, with the ultimate goal of improving their safety, reliability, and performance.

Keywords: *fuzzy self-tuned, pressurized water reactor, neural network, neuro-fuzzy self-tuned*

1. Introduction

Nuclear energy, despite not being a renewable energy source, is recyclable and is the second-largest source of low-carbon energy in the world [1]. It plays a crucial role in meeting the demand for electricity and addressing climate change by reliably supplying power around the clock. In fact, up to 95% of spent nuclear fuel can be recycled [2]. There has been an increasing interest in the use of nuclear energy to produce electricity, with current nuclear power reactors contributing to about 10.3% of the world's electricity generation [3].

Nuclear energy is produced through nuclear fission, where the atom's nucleus is divided into two or more smaller nuclei, releasing energy in the process. For example, the nucleus of an atom of uranium divides into two smaller nuclei when it is struck by a neutron, releasing heat and radiation [4]. Nuclear power plants use nuclear reactors and associated equipment to control and manage chain reactions that produce heat through fission, primarily driven by uranium. The heat is used to warm up a cooling agent, usually water, which produces steam that spins turbines to generate low-carbon power [5]. Various types of reactors, including HTGR, FNR, PWR, BWR, PHWR, GCR, and LWGR, are used globally to produce electricity [6]. PWRs are the most popular type of nuclear reactor used for energy generation due to their self-regulating and self-stabilizing characteristics, which enable them to execute load-following operations. However, fast power maneuvering is a challenging task due to the inherent nonlinearity of reactors, where the behavior varies with changes in reactor power. Additionally, the system is unpredictable due to heat transfers from the fuel to the coolant and reactivity changes resulting from temperature variations in the fuel and coolant. Consequently, designing a reliable controller for power-following operation in PWRs has long been a topic of intense research interest [6, 7]. Results have shown that a fuzzy PID controller is superior to a traditional PID controller in terms of controlling and maintaining system design pressure [8, 9]. Sabri et al. [10] also applied a state space MPC for load tracking in PWRs based on a linearized system model. Lin et al. [11] developed a robust power control strategy for PWR using the H_∞ on a linearized system. Abdelfattah [12] employed an adaptive neural network algorithm to compute the recommended power correction value that minimizes the steady-state error. Mousakazemi [13] employed a genetic algorithm (GA) to tune and schedule PID controller gains for PWR power control while emphasizing the robustness of the controller. Vajpayee et al. [14], designed a fuzzy logic controller (FLC) for controlling the PWR power.

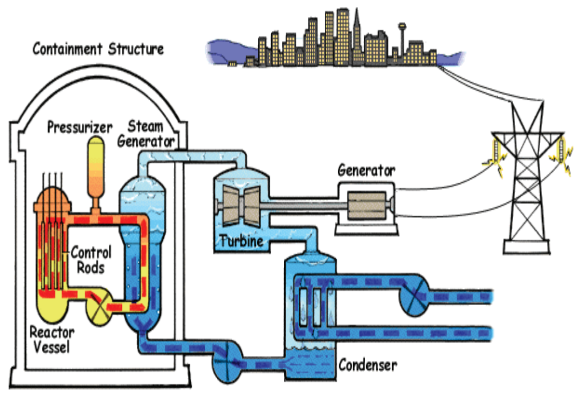

Figure 1. The basic cycle and water flow of a PWR [16]

Although many of these studies used the controllers on the linearized system, the accuracy of the linear approximation of a nonlinear system is limited to a small region around the operating point. Thus, it is crucial to design a robust controller that can be applied to the nonlinear system and ensure power level tracking at all operating points. Intelligent controllers, which do not require knowledge of the system's physics, appear to be a suitable solution for many researchers. While ANFIS self-tuned PID controllers have not been used in nuclear control systems, they have demonstrated superiority in many applications [15, 16]. This paper will design different intelligent control methods, which are neural network control, fuzzy self-tuned PID controller, and neuro-fuzzy self-tuned PID, to regulate reactor core power. The performances of these controllers will be compared with each other and with the conventional PID controller under various circumstances. This paper consists of five sections: a brief description of the PWR system accompanied by its mathematical model in Section 2, the design of the controllers in Section 3, simulation results in Section 4, and a conclusion in Section 5.

2. Pressurized Water Reactor Model

A pressurized water reactor (PWR) is a commonly used nuclear power reactor design where high-purity water is heated by fission reactions to a very high temperature, maintained under high pressure to prevent boiling, and then converted to steam in a steam generator. This steam is utilized to drive turbines, which, in turn, activate generators to produce electrical power [16]. A PWR plant consists of two main systems, namely, the primary system and the secondary system, each serving specific functions with dedicated components as described below: The primary system, also known as the Nuclear Steam Supply System, includes a reactor core, pressurizer, and three or four loops, each equipped with a steam generator and a coolant pump. The secondary system, often referred to as "the Balance of Plant," consists of a turbine, a main condenser, feed water pumps, and feed water heaters [17]. The following steps provide a summary

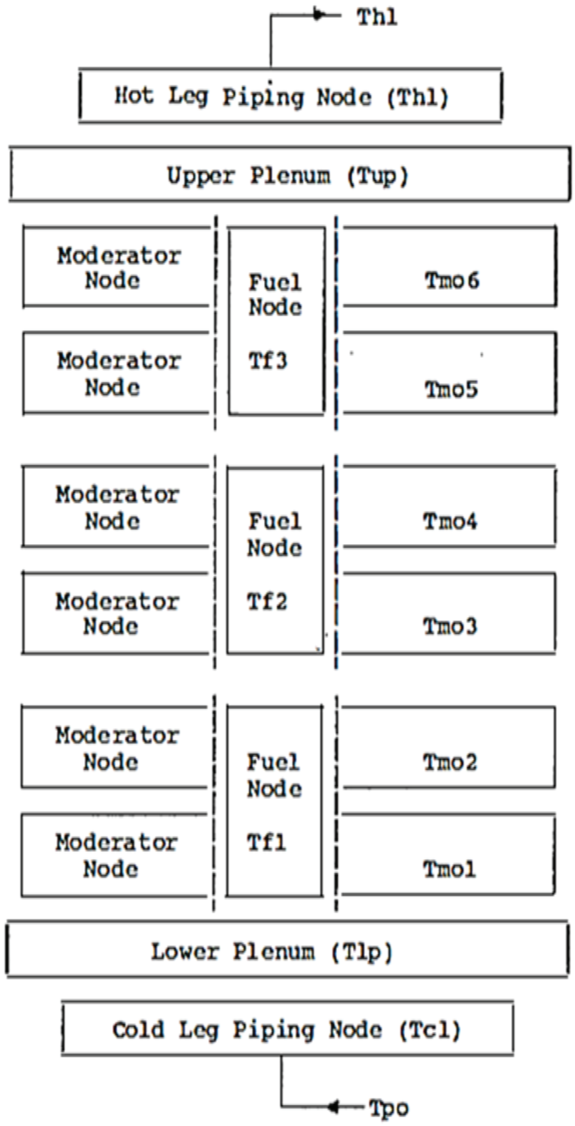

Figure 2. Reactor model diagram [17]

of the PWR's cycle and water flow, as depicted in Figure 1.

The nuclear fuel element, moderator, coolant, and control rods are all contained in a cylindrical tank that serves as the reactor vessel in the simulation. In PWR, uranium is used as a fuel element to generate heat from atom fissions and is located in the center of the vessel. Further, light water is used as a moderator as well as the reactor coolant to transfer the heat, and in order for the fission chain reaction to be more efficient, it is necessary to slow down the rapid neutrons (generated by breaking atoms). The reactor model nodalization is shown in Figure 2, including three nodes for the fuel element and six nodes for the coolant, as well as additional nodes for the upper plenum, lower plenum, hot leg, and cold leg in the reactor coolant system, according to reference [17]. Coolant enters the reactor at room temperature and flows up through the core, where its temperature increases as it passes through the fuel rods.

Then, the hotter reactor coolant reaches the upper reactor region, where it is directed out the outlet nozzle into the hot legs of the primary loop and continues to the steam generators. A large coolant pump transfers the coolant from the steam generator to the primary loop. This reactor can be controlled, improving the efficiency and security of the nuclear power system. The fission process may be controlled in real time by the control rods, which makes them essential for managing reactor power. A control rod stops more fissions from occurring by absorbing neutrons [18]. The reactor core mathematical model, which describes both the kinetics and thermal hydraulics of the reactor core under steady state and transient conditions, is composed of 15 ordinary differential equations derived from the physical model [13]. The following shows how the reactor model equations are expressed [17], and Table 1 has a definition for each of the parameters.

- *Point reactor kinetics equations:*

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

$$\frac{dC}{dt} = \frac{\beta_t}{\Lambda}\frac{P}{P_o} - \lambda c \tag{2}$$

- *Reactor core heat transfer equations:*

First node:

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

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

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

Second node:

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

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

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

Third node:

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

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

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

- ***Cold leg temperature equation:***

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

- ***The lower plenum temperature equation:***

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

- ***The upper plenum temperature equation:***

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

- ***Hot leg temperature equation:***

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

- ***Constitutive equations [17]:***

$$\begin{aligned}\rho = \rho_{ex} &+ \frac{\alpha_f}{3} \\ &\times \left[\left(T_{f1} + \cdots + T_{f3}\right) - \left(T_{f1_o} + \cdots + T_{f3_o}\right)\right] \\ &+ \frac{\alpha_c}{6}[(T_{mo1} + \cdots + T_{mo6}) \\ &- \left(T_{mo1_0} + \cdots + T_{mo6_0}\right)]\end{aligned}$$

$$\lambda = \frac{\beta_t}{\sum_{i=1}^{6}\frac{\beta_i}{\lambda_i}}, \quad \tau_C = \frac{M_C}{2\dot{M}}, \quad \tau_{cl} = \frac{M_{cl}}{\dot{M}}$$

$$\tau_{lp} = \frac{M_{lp}}{\dot{M}}, \quad \tau_{up} = \frac{M_{up}}{\dot{M}}, \quad \tau_{hl} = \frac{M_{hl}}{\dot{M}} \tag{16}$$

External reactivity is the reactivity due to control rods [4]:

$$\frac{d\rho_{rod}}{dt} = G_r Z_r \tag{17}$$

In this study, the external reactivity and outlet temperature are considered forcing functions on the isolated model of the steam generator. The reactor power system has two outputs, namely, the hot leg temperature and the reactor power, both of which can be maintained by controlling either of them [11]. For the purposes of this paper, these outputs are assumed to be constant, while the variable that will be controlled using the control rods is the reactor power. The design parameters utilized in this study are obtained from various sources, including references [18, 19].

Table 1. Parameters of a reactor model [17]

P	Power distribution across nodes in the reactor core	ρ	Total reactivity
P_o	Reactor nominal output power	ρ_{ex}	External reactivity
C	Precursor concentration	α_f	Reactivity coefficient of the fuel
β_t	Total delayed neutron group fraction	α_c	Reactivity coefficient of the coolant
λ	Average of six group decay constants	$\dot{M}$	Mass flow of the coolant
Λ	Time of neutron generation	M_C	Coolant mass in two fluid nodes
F_r	Proportion of power generated in the fuel	M_{cl}	Cold leg water mass
M_F	Fuel mass in each node	M_{lp}	Lower plenum water mass
C_{p_F}	Heat capacity of the fuel	M_{up}	Upper plenum water mass
h	Average overall heat transfer coefficient	M_{hl}	Hot leg water mass
A	Effective heat transfer surface area between fuel and coolant	G_r	Control rod reactivity
$T_{f1\to3}$	Fuel temperatures in nodes (1–3)	Z_r	Control rod speed
$T_{mo1\to6}$	Moderator temperatures in nodes (1-6)	T_{po}	Outlet temperature of the primary water leaving steam generator U-tubes
T_{lp}, T_{up}	Fluid temperature in lower and upper plenums, respectively	T_{cl}, T_{hl}	Cold and hot leg temperatures
C_{p_c}	Heat capacity of the coolant	τ_C , $\tau_{cl}, \tau_{up}, \tau_{lp}, \tau_{hl}$	Time constants of moderator nodes, cold leg, upper plenum, lower plenum, and hot leg, respectively

3. Control System Algorithms

Control system algorithms for pressurized water reactors (PWRs) are crucial for maintaining safety, efficiency, and stability in nuclear power generation.

3.1. PID Controller

Due to their ability to deliver adequate performance with a straightforward algorithm for various processes, PID controllers are extensively employed in the process industries [20, 21]. It is popularly known as a "three-term" controller, the proportional (K_p), integral (K_i), and derivative (K_d), since it controls a process through these three parameters. These parameters can be tuned to adjust their impact on the process. The formula of the control signal $u(t)$ for the PID controller is described as [22, 23]:

$$u\,(t) = K_p e(t) + K_i \int_0^t e(\tau) d\tau + K_d \frac{d}{dt} e(t) \quad (18)$$

There are many methods and approaches for tuning a PID controller, which can provide improved performance and reduce the error signal $e(t)$ [24, 25]. The parameters of the PID controller were tuned using the Ziegler-Nicholas tuning method to obtain the initial/estimated set of working PID parameters for the system [26, 27].

In the context of a PWR model, the PID controller is employed to control important variables like the coolant flow rate, reactor power, and reactor coolant temperature. The actual application of PID control to a PWR model will be determined by factors such as the characteristics of the system, control goals, and safety considerations [28].

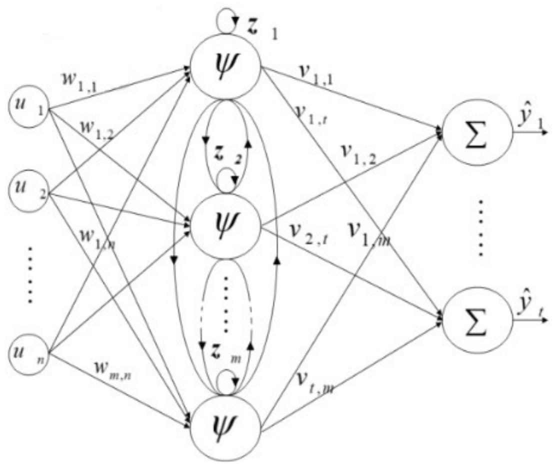

Figure 3. Neural network structure [32]

3.2. Neural Network Controller

A neural network controller (NNC) was used to implement the controller directly. The NNC must be trained first according to some criteria, using either numerical I/O data or a mathematical model [29]. Through neural network training and learning, the weights are adjusted to reduce errors. The procedure continues until the result is satisfactory or the designated amount of learning time has been completed. The parameters (weight and bias) of a neural network system may be determined using a variety of techniques [30, 31]. The system identification method utilizes observed input–output data to approximate the original controller. Prior to designing the neuro controller, system identification is a crucial aspect to consider. The proposed approach utilizes a backpropagation neural network to predict the system's output for new inputs based on past inputs and outputs [32].

The advantages of neural networks, such as adaptive learning, self-organization, and fault tolerance, make them suitable for system identification applications. Figure 3 illustrates a recurrent neural network with n inputs, t outputs, and m hidden layer nodes. The network's input, internal state, and output vectors are represented by u, z, and y, respectively [33, 34].

$$\begin{cases} u(k) = [u_1(k) \;\dots\; u_n(k)]^T \\ z(k) = [z_1(k) \;\dots\; z_m(k)]^T \\ \hat{y}(k) = [\hat{y}_1(k) \;\dots\; \hat{y}_t(k)]^T \end{cases} \tag{19}$$

The equations of the network are

$$\{z(k) = \psi(Wu(k) + Sz(k-1)) \;\; \hat{y}(k) = Vz(k)\} \tag{20}$$

ψ is the tangent hyperbolic function and is the activation function of the interior layer neurons.

$$\psi(x) = tanhtanh\ (x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{21}$$

where $W\ m\times n$, $S\ m\times m$, and $V\ t\times m$ are weight matrices. The weight matrices of the network are determined through training. The mean square error (MSE) is utilized as the cost function, which is calculated for each training sample. Here, N represents the number of training samples, y denotes the actual output, and $\hat{y}$ represents the predicted output of the neural network.

$$MSE = \frac{1}{N}\sum_{k=1}^{N} e(k)^T . e(k)$$

$$= \frac{1}{N}\sum_{k=1}^{N} (\hat{y}(k) - y(k))^T . (\hat{y}(k) - y(k)) \tag{22}$$

An NNC designed for a PWR is a controller that utilizes artificial neural networks to regulate the operation of the PWR system.

This controller harnesses the capabilities of neural networks to model the intricate relationships and dynamics of the reactor and make control decisions based on input data.

The typical components of an NNC are as follows [35]:

- Neural Network Model: The neural network model is specifically designed to capture the behavior and characteristics of the PWR system. It takes various input variables, such as coolant flow rate, reactor power, temperature, and pressure, and employs hidden layers and activation functions to process this information and generate an output control signal.
- Training Data: To train the NNC, a dataset is necessary. This dataset contains historical data or simulated outputs of the PWR system, along with the corresponding desired control actions. By learning from these data, the neural network adjusts its internal parameters and enhances its predictive capabilities.
- Control Action Generation: Once the neural network model is trained, it can generate control actions based on the current state and input data of the PWR system. The neural network processes the input variables using its trained network architecture and produces an output control signal. This control signal is then applied to the reactor control system to regulate the behavior of the system.

The NNC holds advantages in dealing with the complex and nonlinear dynamics of the PWR system. By leveraging neural networks, it can make precise control decisions and adapt to changing conditions in real-time.

In summary, an NNC for a PWR system utilizes artificial neural networks to model and regulate the behavior of the reactor. By learning from training data, it improves its control performance, making it a valuable tool for managing the operation of a PWR.

3.3. Adaptive Fuzzy Self-Tuned PID Controller

Fuzzy logic control has been effectively utilized in numerous control issues in recent years because it does not require precise mathematical models of the uncertain nonlinear systems being controlled. A language control approach was developed by humans and transformed into an automated control method via FLC [36]. In the self-tuning fuzzy PID controller, the PID controller parameters (K_p, K_i, and K_d) are adjusted using fuzzy logic rules, which, in turn, makes the control system capable to modify its own operation for changing process conditions to achieve the best possible mode of operation and excellent performance. An adaptive fuzzy self-tuned PID controller is designed specifically for regulating the operations of PWRs. It combines principles from fuzzy logic, adaptive control, and PID control to optimize control performance in real time.

This controller comprises three primary components:

PID Controller: The PID controller is a well-known control algorithm that employs proportional, integral, and derivative terms to calculate control actions. It ensures stability, accuracy in steady state, and responsiveness within the control loop.

FLC: The FLC utilizes linguistic rules and membership functions to handle complex and nonlinear behaviors observed in the PWR system. By employing fuzzy inference rules, it determines the appropriate control actions based on the system's current state and error signals.

Adaptive Mechanism: The adaptive mechanism continuously monitors the system's response and adjusts the parameters of both the PID and FLCs to optimize control performance. It dynamically tunes the gains of the PID controller or modifies the fuzzy logic rules and membership functions based on real-time system behavior.

The integration of these three components allows the controller to adapt to changes in reactor conditions, disturbances, and other factors as they occur. Through its adaptive fuzzy self-tuning approach, the controller ensures control performance and stability within the PWR system.

In summary, the adaptive fuzzy self-tuned PID controller for PWR aims to deliver robust and efficient control by leveraging the advantages of PID control, fuzzy logic, and adaptive mechanisms.

A two-input–three-output FLC is shown in Figure 4. The inputs are $e(t)$ (error between the reference input and the controlled variable) and $\Delta e(t)$ (change of error with respect to time). The gains K_{P1}, K_{I1}, and K_{D1} are the FLC outputs [37].

These gains are used to adjust the parameters of the PID controller online. The PID controller control signal can be expressed as:

$$u(t) = K_{P1}e(t) + K_{I1}\int_0^t e(\tau)d\tau + K_{D1}\frac{d}{dt}e(t) \quad (23)$$

where K_{P1}, K_{I1}, and K_{D1} are the FLC outputs that are used to tune the PID controller online. The description of each input comprises a range of expressions such as NB (representing negative big), NS (negative small), Z (zero), PS (positive small), and PB (positive big). Additionally, each output is denoted by a range of expressions: Z (zero), MS (medium small), S (small), M (medium), B (big), MB (medium big), and VB (very big). A set of 25 rules for the fuzzy rule base can be derived from Table 2 [38].

3.4. Adaptive Neuro-Fuzzy Self-Tuned PID Controller

The PID controller now has the capacity to modify its settings online thanks to a combination of the benefits of the FLC and PID controller. Choosing the parameters of the fuzzy system, such as input and output membership functions, is a difficult task and one of the drawbacks of designing a fuzzy controller that relies on expert knowledge. To overcome this challenge, some researchers have proposed a neural fuzzy self-tuned PID controller, which allows for the modification of membership function parameters using fuzzy logic [38]. The self-tuning neuro-fuzzy PID controller combines a fuzzy logic method with a five-layer ANN structure. The first layer in this five-layer structure is for inputs, the second layer is for fuzzification, the third and fourth layers are for evaluating fuzzy rules, and the fifth layer is for defuzzification [39]. An adaptive neuro-fuzzy self-tuned PID controller designed for a PWR is a controller that utilizes adaptive control, fuzzy logic, neural networks, and PID control principles to regulate the operation of a PWR system. This controller continuously adjusts its parameters in response to real-time information and system feedback, aiming to optimize control performance [40, 41].

The controller comprises four key components:

- PID Controller: The PID controller is a well-established control algorithm that calculates control actions using proportional, integral, and derivative terms. It ensures stability, steady-state accuracy, and responsiveness within the control loop.

- FLC: The FLC employs linguistic rules and membership functions to handle complex and nonlinear system behavior. By utilizing fuzzy inference rules, it determines the appropriate control action based on the system's current state and error signals.

- Neural Network: The neural network component employs artificial neural networks to model and capture the intricate relationships and nonlinear dynamics of the PWR system. By learning from historical data or simulation outputs, the neural network enhances its predictive capability and improves control performance [42].

- Adaptive Mechanism: The adaptive mechanism continually monitors the system's response and adjusts the parameters of the PID controller, FLC, and neural network component to optimize control performance. It can adaptively tune the gains of the PID controller, modify the fuzzy logic rules and membership functions, and update the internal parameters of the neural network based on real-time system behavior [43–45].

The combination of these four components empowers the controller to adapt to changes in reactor conditions, disturbances, and other factors in real time. The adaptive neuro-fuzzy self-tuning approach enables the controller to maintain control performance and stability in the PWR system.

In summary, the adaptive neuro-fuzzy self-tuned PID controller for a PWR system aims to deliver robust and efficient control by integrating the advantages of PID control, fuzzy logic, neural networks, and adaptive mechanisms. The block diagram of the proposed neuro-fuzzy controller has two inputs and three outputs, as presented in Figure 5. The two inputs for the system are $e(t)$, which is the difference between the reference input and the controlled variable, and $\Delta e(t)$, which is the change in error over time, and the outputs are K_{P1}, K_{I1}, and K_{D1}, which are used to adapt the parameters of the PID controller.

The neuro-fuzzy controller has been created to produce an appropriate control signal to modify the PID controller's settings. It was trained with input and output data obtained after the study of system response in the nominal case, dividing it into regions, and testing the system response at several proposed values for each region. The structure of the neuro-fuzzy model for each output is described in Figure 6. The algorithm used for training is the hybrid learning algorithm (HLA) with seven and six triangular membership functions for error and change of error inputs, respectively, and the fuzzy rule base contains 42 rules.

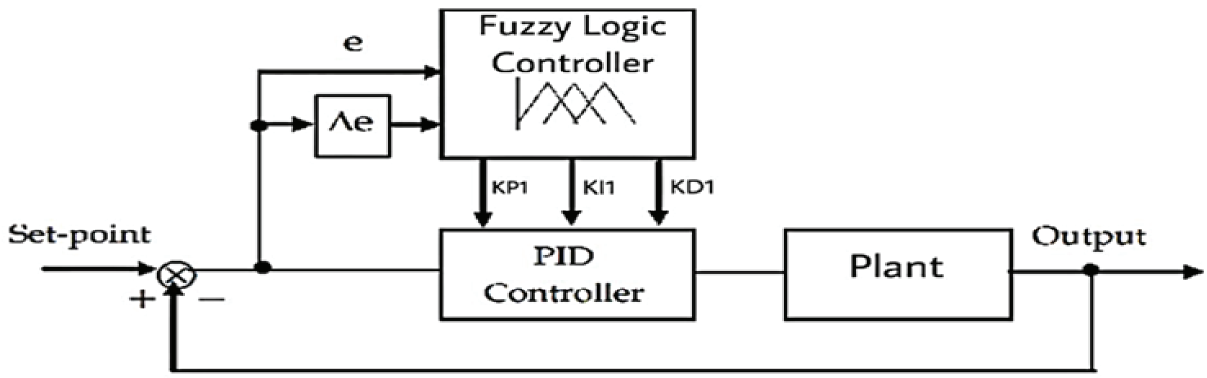

Figure 4. Fuzzy self-tuning PID controller structure

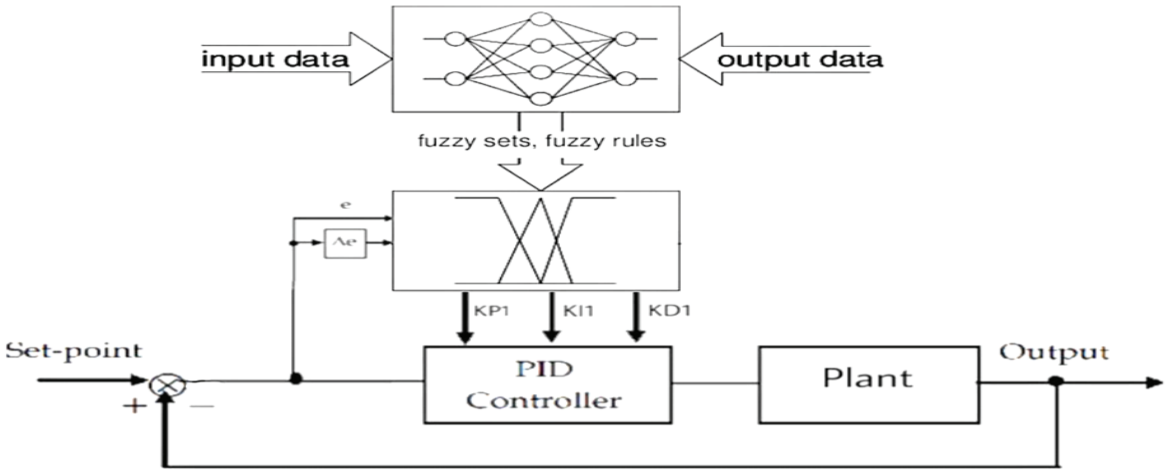

Figure 5. Block diagram of an adaptive neuro fuzzy self-tuned PID controller with the system

Table 2. Rule base of the fuzzy self-tuned PID controller

$K_{P1}/K_{I1}/K_{D1}$			$\triangle\mathbf{e(t)}$		
e(t)	NB	NS	Z	PS	PB
NB	VB/M/Z	VB/M/S	VB/M/M	VB/M/MB	VB/M/VB
NS	B/S/S	B/S/B	B/S/MB	MB/S/VB	VB/S/VB
Z	Z/MS/M	Z/MS/MB	MS/MS/MB	S/MS/VB	S/MS/VB
PS	B/S/B	B/S/VB	B/S/VB	MB/S/VB	VB/S/VB
PB	VB/M/VB	VB/M/VB	VB/M/VB	VB/M/VB	VB/M/VB

4. Results and Discussion

This section presents the simulink model of PWR with different controllers as shown in Figure 7 and simulation results of the PWR power control system using MATLAB Simulink. The section is divided into five parts. Firstly, the simulation results under constant and variable reference power are presented in Section 4.1.

The output of the fuzzy controller can be represented as follows:

Rule i: If (e is inputmf x) and (ce is inputmf y), then $K_n = p_i(e) + q_i(ce) + r_i$

r_i, p_i, and q_i are the design parameters determined during the period of training phase.

$(1 \leq i \leq 42), (1 \leq x \leq 7)$, and $(1 \leq y \leq 6)$.

K_n represents K_{P1}, K_{I1}, or K_{D1}.

Secondly, the response of the controllers against time delay is discussed in Section 4.2 Sections 4.3 and 4.4 assess how resilient the controllers are to external disturbances introduced at both the input and output respectively for the reactor system. Lastly, the effect of the change in the initial value of the relative output power is analyzed in Section 4.5.

4.1. Hard Alteration of Reference Power

The simulations are carried out with an initial relative power of zero. The first set of simulations is conducted with a constant reference relative power (P/P_o) of 1. The response of the reactor with the neuro-fuzzy self-tuned PID controller is compared to the responses of the PID, neural network, and fuzzy self-tuned PID controllers, as shown in Figure 8.

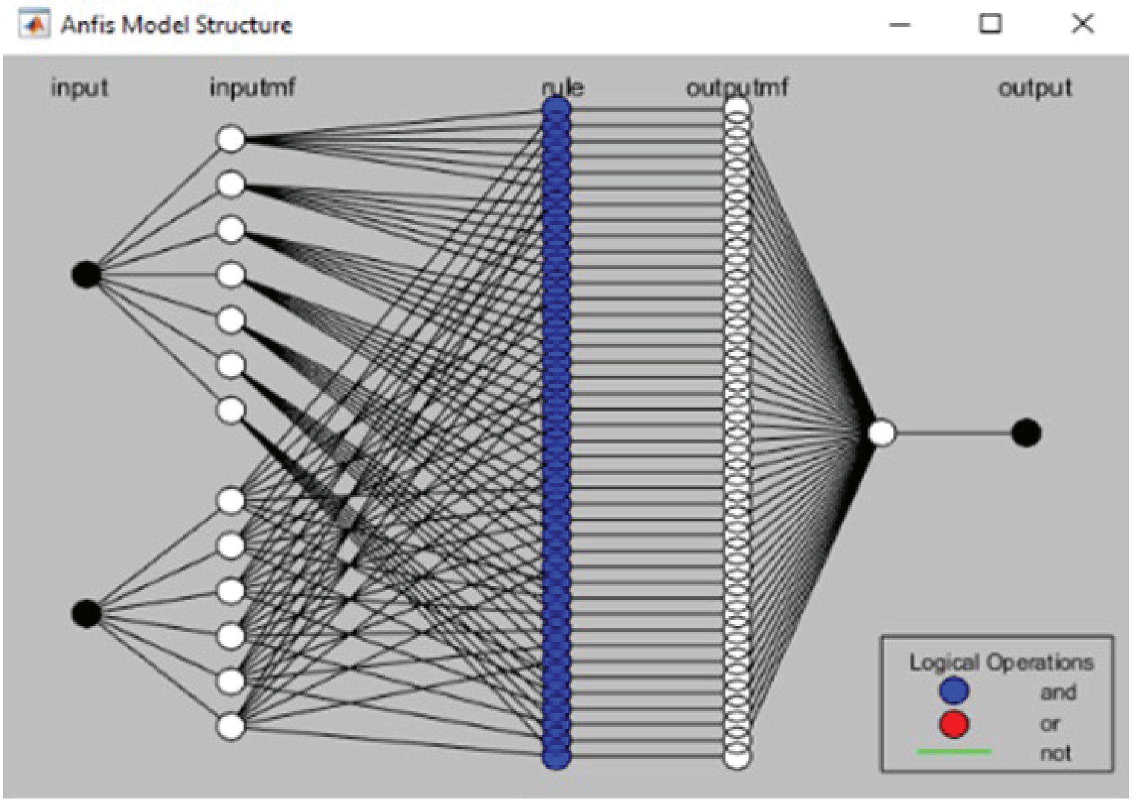

Figure 6. Structure of an adaptive neuro fuzzy system

Next, a variable reference relative power (P/P_o) is applied to the system, starting at 1 and dropping to 0.3 at the 60th second. It remains at 0.3 until the 140th second when it rises to 0.9. The response of the reactor with the neuro-fuzzy self-tuned PID controller is compared to the responses of the other controllers under variable reference power in Figure 9.

The reactor output relative power is examined in three intervals (0–15 s, 60–85 s, and 140–155 s) to compare the controllers. The settling time and overshoot for the four controllers in each region are summarized in Table 3. It is evident from the previous simulation results that the three intelligent controllers, neural network, fuzzy self-tuned PID, and neuro-fuzzy self-tuned PID, are capable of ensuring good reference tracking performances in terms of minimal overshoots and settling time. The results demonstrate that the neuro-fuzzy self-tuned PID controller has the smallest error-integral performance indexes ISE and IAE, as compared to the other controllers as presented in Figure 10.

4.2. System with Time Delay

To evaluate the system's robustness against time delay, a 10-ms delay was introduced and the response of each controller was analyzed under variable reference relative power. As depicted in Figure 11, all designed controllers were able to maintain the reference, indicating their robustness against time delay. Despite a slight overshoot in the response of the fuzzy self-tuned PID and neuro-fuzzy self-tuned PID controllers, the moderator's temperature remained within the permissible range [46].

4.3. External Input Disturbance

To observe the response of the designed controllers to external disturbances, the input temperature from the steam generator system, represented by T_{P_o}, was considered as an external disturbance to the reactor core system. The input temperature was increased by 6°F at the 35th second of the simulation, with a total simulation time of 200 s, and as the input temperature T_{po} increased, the reactor's power decreased rapidly due to the negative temperature feedback relationship. However, the controllers were able to regulate the reactor's power and maintain the reference power by increasing the control action. As shown in Figure 12, all the controllers exhibited good disturbance rejection capabilities [47].

4.4. External Output Disturbance

The controllers' robustness is evaluated by introducing an external disturbance in the output of the reactor system, as shown in Figure 13. The disturbance signal, with a relative power amplitude of 0.01 (approximately 11,453 kW), was injected every 20 s with a pulse width of 25% of its period. As demonstrated from the result, when the relative output power increased due to the disturbance signal, the control rods were inserted into the reactor core to reduce the relative power. The intelligent controllers demonstrate their robustness as they were able to return to tracking the reference after approximately 1 s [48].

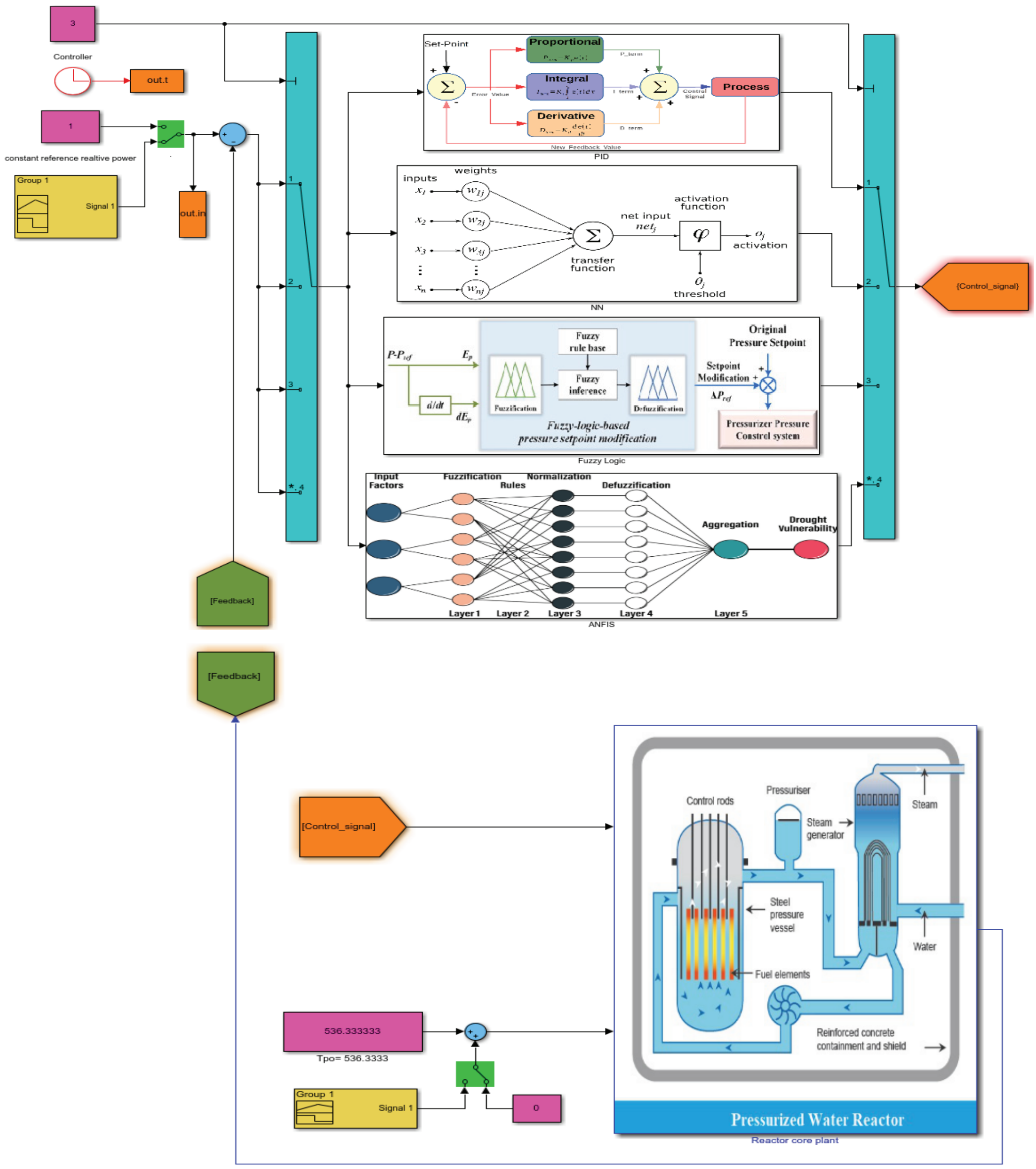

Figure 7. Simulink model of PWR with diffrent controllers

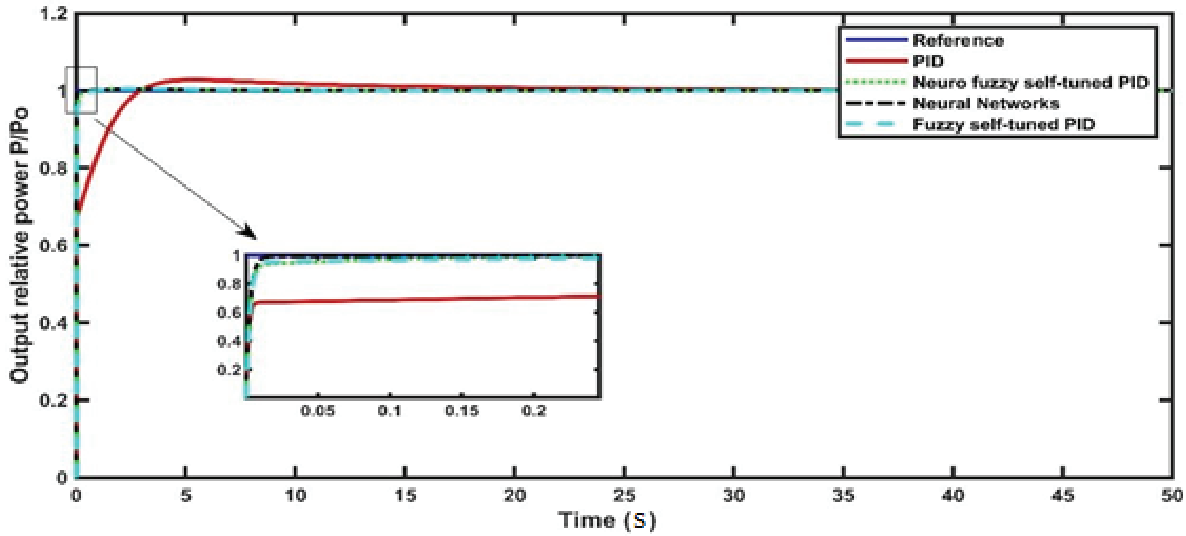

Figure 8. System response under constant reference power

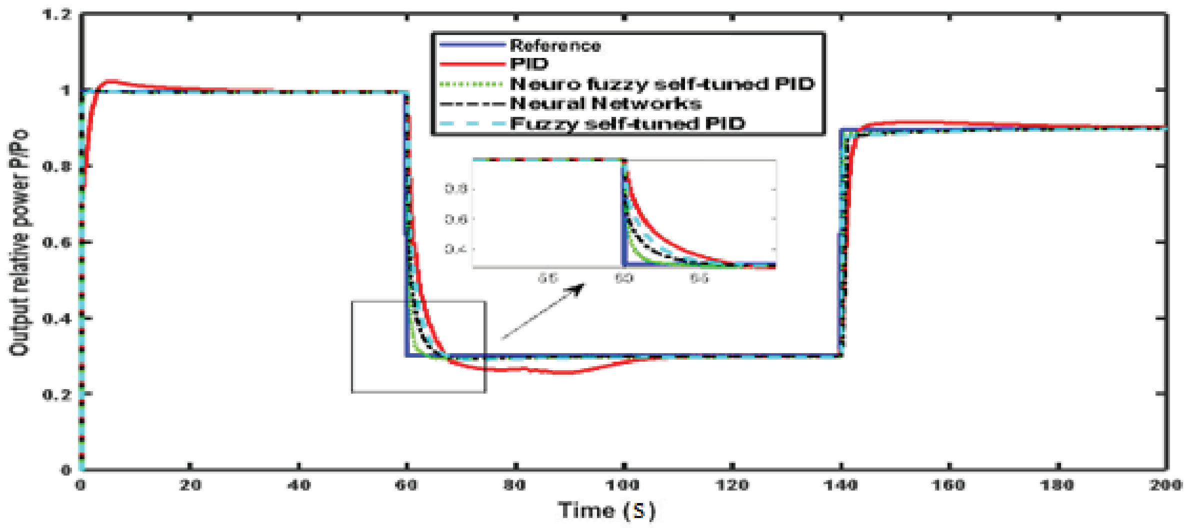

Figure 9. System response under variable reference power

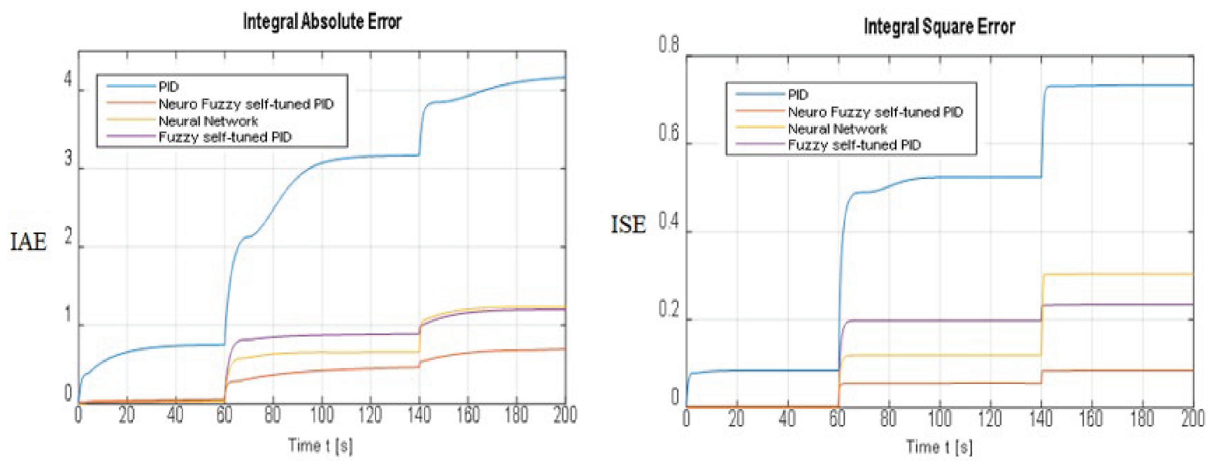

Figure 10. IAE and ISE versus time

Table 3. Settling time and overshoot for the four controllers in each region

	Ts (s)				OS %			
Time interval	**PID**	**NNC**	**Fuzzy self-tuned PID**	**Neuro-fuzzy self-tuned PID**	**PID**	**NNC**	**Fuzzy self-tuned PID**	**Neuro-fuzzy self-tuned PID**
(0–15) s	2.079	0.079	0.395	0.09	0.7692	0	0	0
(60–85) s	70.4	67.53	68	62.4	20	2.167	1.83	1.67
(140–155) s	145	141.2	142	140.1	1	0	0	0

4.5. Different Initial Conditions

To evaluate the stability of the nonlinear system, the reactor core-controlled system was tested with multiple initial relative power values. As the initial condition has a significant impact on system stability, the initial relative power values of 0.5 were examined. The response of the system for each controller is shown in Figure 14.

Each control method can help reduce the impact of time delay and disturbances in a PWR system. The effectiveness of each controller depends on factors such as the duration of the time delay or disturbances, the accuracy of the system model, and the optimization of control parameters. When selecting and implementing the most appropriate control strategy, it is crucial to consider the unique characteristics and requirements of the PWR system. The PID controller continuously adjusts control actions by monitoring the error between the desired setpoint and the measured process variable. This minimizes the influence of uncertainty. The proportional term responds promptly to sudden changes and provides immediate corrective action. The integral term addresses steady-state errors caused by disturbances, gradually adjusting the control action to counteract their effects.

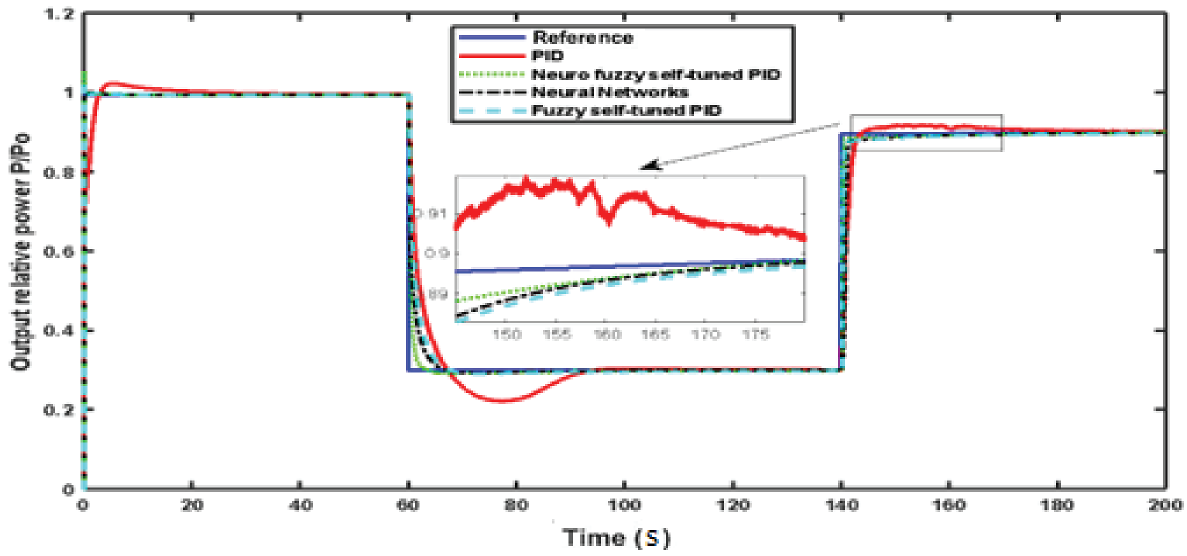

Figure 11. System response due to time delay

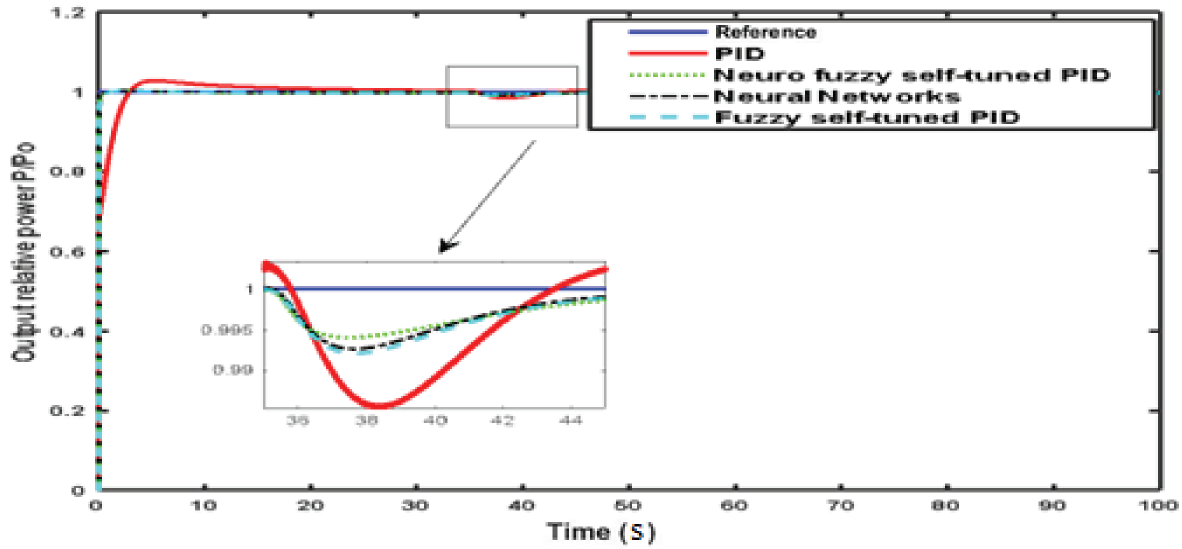

Figure 12. System response due to external input disturbance

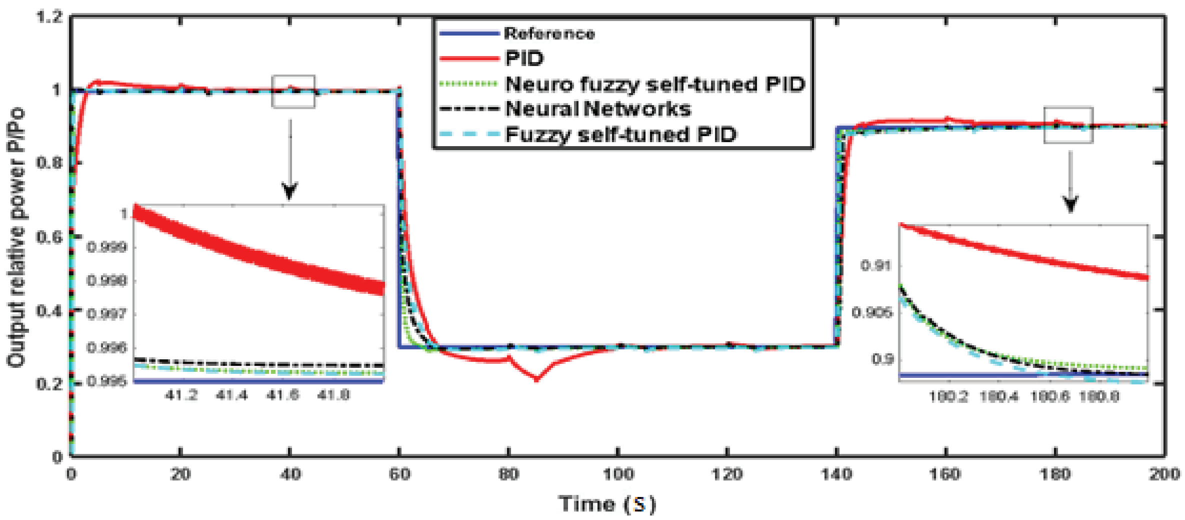

Figure 13. System response due to external output disturbance

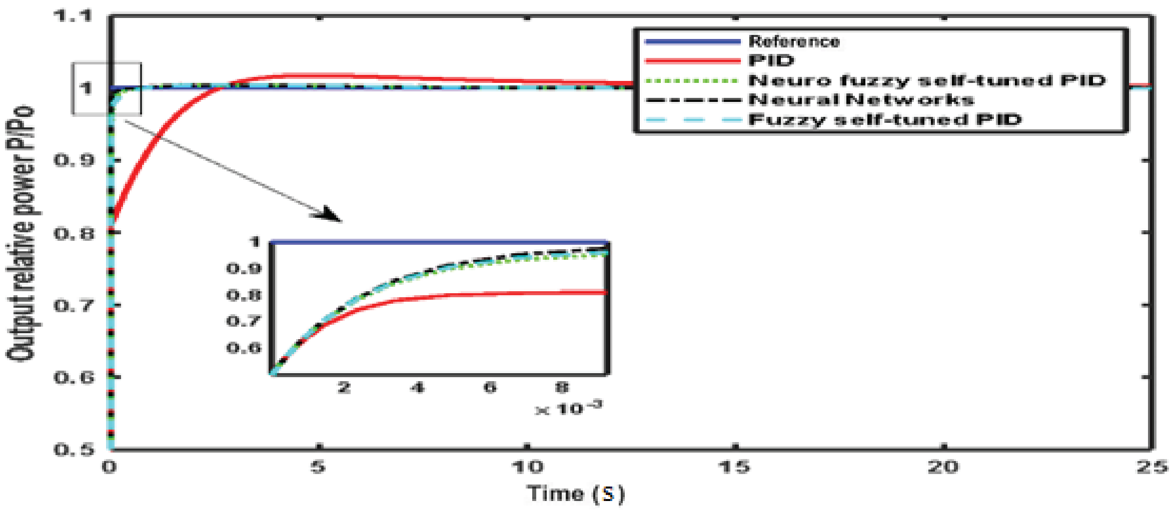

Figure 14. System response with different initial output relative power values

The derivative term enables a rapid response to the rate of change of the disturbances, assisting in stabilizing the system's behavior. The NNC effectively handles both external input and output disturbances in a PWR system. By learning the relationships between the disturbances and the reactor's behavior, the neural network can predict and model their effects. It adjusts the control actions based on this learned information to minimize the impact of the disturbances on the reactor's output. The adaptive fuzzy self-tuned PID controller combines fuzzy logic and PID control with adaptive capabilities. It continuously monitors the system's response and the effects of both external input and output disturbances, adaptively adjusting the PID control parameters. This adaptive mechanism enables the controller to respond to and mitigate the impact of disturbances on both system inputs and outputs in real time. The adaptive neuro-fuzzy self-tuned PID controller further improves control performance by integrating neural networks and fuzzy logic. The neural network component models the system and disturbances, while the fuzzy logic component handles uncertainty and linguistic rules. The controller's adaptive mechanism dynamically adjusts the PID control parameters, fuzzy logic rules, and neural network's internal parameters to optimize control performance and effectively counteract the effects of both external input and output disturbances.

5. Conclusion

Nuclear reactors are critical components of nuclear energy systems, with the control of reactor power being of paramount importance. The main objective of the power controller in nuclear reactors is to maintain the reference power level, which ensures safe and reliable operation of the power station. PWRs are the most common and widely used type of reactor, and fast power maneuvering is a challenging task due to the inherent nonlinearity of the system. Reactor power fluctuations can cause changes in behavior, while the transfer of heat from the fuel to the coolant and reactivity changes resulting from differences in fuel and coolant temperatures can also make the system unpredictable. To address these challenges, this paper presents a dynamic model of a PWR and applies several control techniques to the system for power level control. Specifically, a traditional PID controller, an NNC, a fuzzy self-tuned PID controller, and a neuro-fuzzy self-tuned PID controller were individually designed and evaluated to enhance the performance of the reactor power control system under constant and variable reference power.

In addition, the robustness of each controller was assessed against time delays and external disturbances. The system was also tested with different initial power values to ensure stability. The results demonstrate that the neuro-fuzzy self-tuned PID controller has the fastest response time compared to the other controllers. Furthermore, the intelligent controllers were found to exhibit good robustness against time delays and external disturbances. The system's stability was not significantly affected by changes in the initial power value, although it had a minor effect on the transient response. Overall, the findings of this study can inform the design and optimization of control systems for PWRs, with the ultimate goal of improving their safety, reliability, and performance. As a potential future direction, rather than training the neural network and adaptive neuro fuzzy controllers using input/output data selected after analyzing the system's response in nominal conditions and choosing suitable output signals, an alternative approach to enhancing the performance of these controllers is to train their parameters using an optimal PID controller. This optimal PID controller can be designed using an optimization algorithm, thereby offering the potential for improved controller performance.

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