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Development of an Adaptive Fuzzy-Neural Controller for Temperature Control in a Brick Tunnel Kiln

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Abstract: This research focuses on developing an adaptive fuzzy-neural control system to manage and maintain temperature in brick tunnel kilns. The problem is how to optimize performance and energy consumption in the brick production process. A control algorithm using a combination of a fuzzy logic system and neural network is proposed to automatically adjust temperature parameters, optimize production efficiency, and reduce energy consumption. Simulation and experimental results demonstrate the outstanding performance of the presented system, with significant improvements in energy efficiency and product quality compared to traditional control methods. Moreover, the obtained results exhibit the potential for wide application of the adaptive neuro-fuzzy control method in academic study or industrial production processes.

Keywords: fuzzy-neural network; fuzzy logic system; PID; brick tunnel kiln; temperature control

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1. Introduction

Traditional control systems for brick tunnel kilns (BTK) often struggle to adapt the dynamic and nonlinear nature of the firing process. Many external factors such as weather conditions, variations in raw materials, and the demand for various models in the production process can reduce the efficiency and quality of brick products [1,2]. To address these challenges and improve brick production efficiency, brick factories have transitioned from manual to automatic production. The automatic system can precisely adjust the kiln's heat according to the specific requirements at each stage of brick production. The quality of bricks produced by this automatic system is significantly better than that by manual control, and damage to bricks during firing is avoided because the temperature is automatically adjusted [3–5]. This research focuses on developing an adaptive control system approach, specifically an adaptive fuzzy-neural control that conforms to the specific requirements, such as temperature control accuracy, energy savings, and environmental protection, of brick tunnel kilns.

In the BTK system, the identification aspect is a crucial part of the control design procedure. Due to the nonlinear characteristics of the BTK system, designing the controller using conventional approaches is ineffective. In [6], the BTK system model was developed in two types, differing in the treatment of unsteady conditions with recorded kiln temperature data. While this model allowed for testing of physical principles, it has a drawback in designing the control system for the BTK. In [7], Mancunhan et al. introduced a model of drying bricks in the preheating zone of the BTK system. However, the presented model was developed through a simulation study and lacks experimental work. The authors in [8–10] provided a numerical simulation to evaluate the BTK thermal performance with several control methods. Nevertheless, the knowledge of the dynamic model of the BTK system is negligible. Therefore, formulating an accurate BTK system model is crucial to developing the control design system and enhancing brick production efficiency.

To prevent brick fires in automatic systems, researchers have devised various methods, including traditional proportional-integral-derivative (PID), robust control, adaptive control, intelligent control, and so on [11]. The authors in [11–14] proposed a PID controller to adjust the thermal therm of the brick tunnel kilns. However, the tracking performance was poor with the low accuracy of temperature control due to the fixed control parameters. Refs. [15,16] presented a fuzzy logic controller (FLC) for a brick automatic temperature control system. Nevertheless, the design of the FLC is simplistic, featuring only one input and one output, which cannot guarantee good tracking performance. In pursuit of enhanced product quality and system reliability, scholars in [17–19] proposed an adaptive fuzzy-PID controller to improve the tracking qualification. In addition, the authors in [20–22] presented intelligent control for the BTK system. Each controller has distinct advantages but is still suboptimal in the temperature control process. Furthermore, there is a scarcity of experimental studies; most previous works focus on simulation studies for temperature control. Hence, the development of an advanced control algorithm capable of mitigating negative factors, along with providing experimental studies for brick tunnel kilns, is imperative.

Based on the above literature review, the FLS is frequently chosen as an effective tool for system regulation addressed to various negative factors; for instance, an unmodeled dynamics system. Nevertheless, the FLS is designed depending on the experience of the engineer, which is not capable of self-learning proficiency [23–26]. In recent decades, neural networks (NN) have been extensively researched in control algorithms, possessing energetic self-learning capabilities. It is noteworthy that both FLS and NN have their own merits and demerits in terms of control algorithms. To leverage the advantages of fuzzy logic techniques and neural networks [27,28], a new approach—fuzzy neural networks—has been investigated, possessing a structure well-suited for fuzzy reasoning and self-learning abilities. However, there are limited studies utilizing the fuzzy neural network algorithm for temperature control in the BTK system.

Motivated by the aforementioned analysis, this article aims to present the design, implementation, and evaluation of an adaptive fuzzy-neural controller to regulate the temperature in a tunnel brick kiln with high efficiency. The main contributions of this paper are summarized as follows:

(1) As far as the authors are aware, this is the first instance of a fuzzy neural network controller proposed for the BTK system, combining the capabilities of fuzzy logic and neural networks. The advanced control system aims to offer a robust and adaptable solution to optimize temperature levels while minimizing energy consumption for the BTK system.
(2) The controller leverages sensor data, historical information, and real-time adjustments to optimize temperature control, taking into account variables such as fuel type, external environmental conditions, and furnace load.
(3) Outstanding performance of the suggested methodology is exhibited via simulation and experimental results as compared with two controllers, i.e., PID and fuzzy controllers.

The structure of the article includes the following: Section 2 includes system modeling and problem statements. Section 3 includes control system design. Section 4 includes implementation and evaluation results through simulation and experiment. Ultimately, the conclusion is summarized in Section 5.

2. Modelling of the Brick Tunnel Kilns

The brick tunnel kilns (BTK) are nonlinear plants and very complex. In the BTK operation, the air and bricks go in opposite directions, as depicted in Figure 1. Commonly, the BTK system includes three zones: preheating, firing, and cooling. Firstly, the bricks are dried to obtain a 12% moisture and then moved to the preheating zone. Herein, bricks are heated with the temperature about 700 °C. Next, the bricks enter the firing zone, and the temperature rises slowly to about 1000 °C. Finally, the bricks are cooled in the cooling zone with the desired temperature of approximate 30−50 °C.

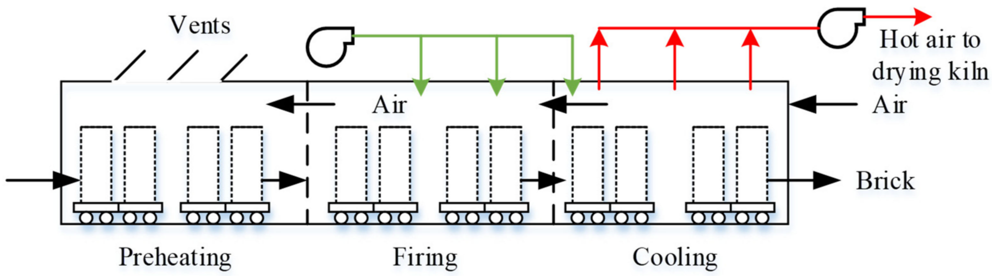

Figure 1. Schematic of a typical brick tunnel kiln.

In this paper, the simplified BTK system focuses on the temperature control of the firing zone, which is a significant stage during the brick production process. The model of the firing zone can be found in the previous work [29,30]. In detail, the testbench of the firing zone for the BTK system contains a solid-state relay, an arduino board, light bulbs, laptop-integrated Matlab/Simulink software 2020a, and the temperature sensor, as illustrated in Figure 2. To facilitate the control design, the linearization step is applied to be able to find the simple brick tunnel kiln (BTK) model in particular. Herein, the System Identification tool in Matlab is utilized to formulate the transfer function of the presented system while using frequency-domain experimental data.

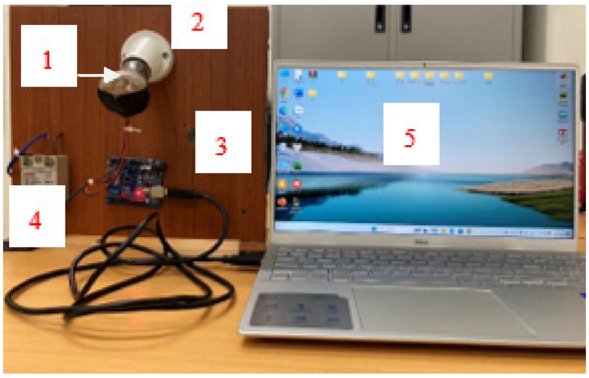

Figure 2. Simplified experiment of the firing zone for the BTK. 1: temperature sensor; 2: heater; 3: microcontroller board; 4: relay, 5: computer-integrated MATLAB/SIMULINK.

Firstly, the input and output data of the BTK system are recorded in the real system. Herein, the applied voltage input is a sinusoidal wave formed through Matlab to provide the BTK system and then get the returned data as output temperature, as depicted in Figure 3. The input and output data are collected by two 'To workspace' blocks, namely, out.controlsignal and out.temperature, respectively. The data is written in the MATLAB base workspace.

After obtaining the input and output data of the system, we can find the transfer function of the system in the System Identification tool. This process includes four stages: Import data, Working data, Estimate (Transfer function model), and Import model.

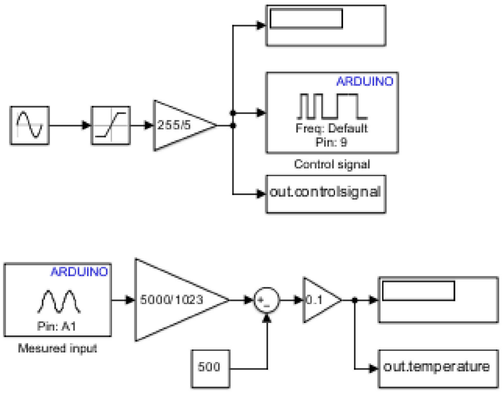

Figure 3. Diagram of data collection function.

Finally, the brick tunnel kilns can be described in the form of the transfer function with an accuracy of 88.52% via the presented tool.

$$G(s) = \frac{T(s)}{U(s)} = \frac{3.839}{s + 0.08521} \tag{1}$$

Remark 1. *The ideal of the control goal is to ensure an excellent temperature tracking performance, and enhance energy saving and environmental protection under external disturbance. Inspired by the merits of the fuzzy-neural network, the adaptive intelligent controller is constructed to obtain the control goal for the brick tunnel kiln.*

3. Controller Design

This section provides the fuzzy-neural controller and two other controllers (PID and fuzzy controller) with the compared proposal. All controllers are presented as follows.

3.1. PID Controller

The Proportional-Integral-Derivative (PID) controller is a widely used feedback control system that operates based on three main components as shown in the below equation. These three components work together to maintain and adjust the system's output in response to changing conditions.

$$u(t) = k_p e(t) + k_i \int e(t)dt + k_d \frac{de(t)}{dt} \tag{2}$$

where k_p, k_i, and k_d represent the P-gain, I-gain, and D-gain, respectively.

3.2. Fuzzy Logic Controller

The fuzzy controller is a control system based on the principles of Fuzzy Logic. Fuzzy Logic allows handling uncertain information and fuzzy sets to make decisions. Here, we design a fuzzy controller to control the temperature in the brick tunnel kilns. The fuzzy logic controller includes four stages: fuzzification, rule definition, fuzzy inference system, and defuzzification. For the BTK system, the error of the output temperature and its desired signal (e) is taken as two inputs of the FLC to conduct one control signal (u). Five triangle membership functions (MFs) are utilized to describe the input variable e, such as VL (very low), L (Low), AV (Average), H (High), and VH (Very high) within the range of (0,20). And five gauss MFs are utilized to describe the input variable de, such as NB (negative big), NS (negative small), ZE (zero), PS (positive small), and PB (positive big) within the range of (-1, 1). The output u is characterized by five triangle MFs: VL (very low), L (Low), AV (Average), H (High), and VH (Very high) within the range of (0,5). The input of the fuzzy controller is the error between the set value and the output temperature of the BTK system, as depicted in Figure 4. Meanwhile, the inhomogeneous MFs of the output are shown in Figure 5. The rule base of temperature FLC for the BTK system is displayed in Table 1.

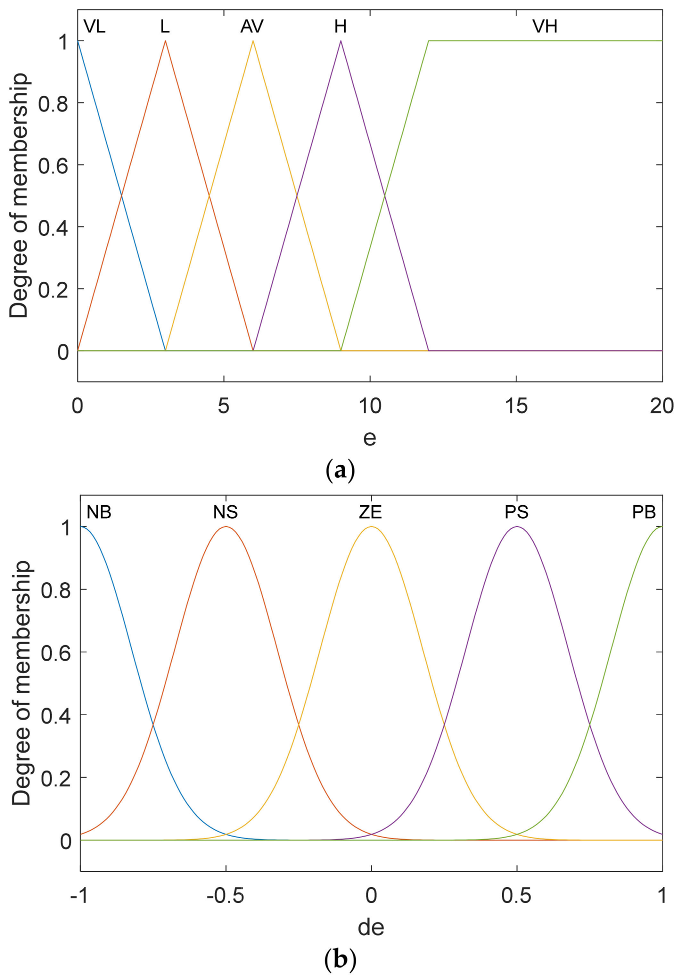

Figure 4. Input membership functions of the FLCs: (**a**) error; (**b**) derivative of error.

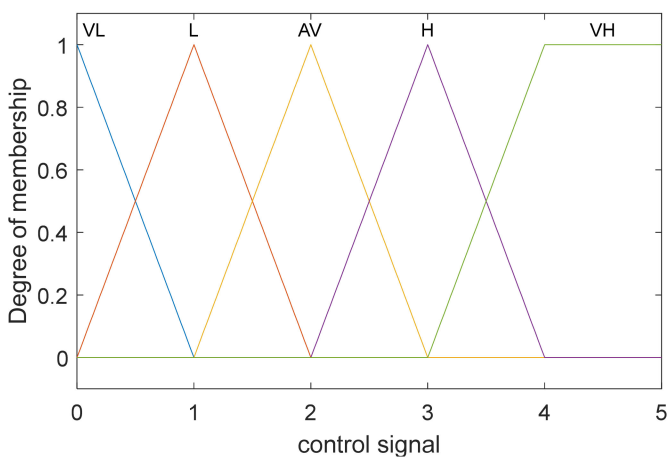

Figure 5. Output membership functions of the FLCs.

Table 1. Fuzzy rule for temperature control.

u		*e*				
		VL	**L**	**AV**	**H**	**VH**
de	NB	L	L	AV	H	VH
	NS	VL	L	AV	H	VH
	ZE	VL	VL	L	AV	H
	PS	VL	VL	L	H	H
	PB	L	L	AV	H	VH

The system output is the control signal of the BTK system after defuzzification with any input. Herein, the defuzzification of the FLC is designed to follow the centroid method as follows:

$$u(t) = \frac{\int_{\mathrm{S}} \mathrm{y}_i \mu(\mathrm{y}_i)\mathrm{dy}}{\int_{\mathrm{S}} \mu(\mathrm{y}_i)\mathrm{dy}} \tag{3}$$

where S is the determined set and $\mu(y_i)$ is the membership value for point y_i in the universe of discourse.

3.3. Fuzzy-Neural Controller

For fuzzy logic, the engineer can easily develop a desired system using only If-Then rules, which are close to human processing. With the majority of applications, this allows for a simpler solution within a shorter time. However, along with the advantages of fuzzy control systems, there are still some experience requirements of designing and optimizing fuzzy logic systems in object control.

As for neural networks, they have some advantages such as parallel processing and fast processing speed. Furthermore, neural networks have the ability to learn and train the network to approximate any nonlinear function, especially when a set of in/out data is known. Nevertheless, the main drawback of neural networks is the difficulty to explain clearly how neural networks work. So, the regulation of neural networks is very difficult.

From Table 2, it can be observed that if fuzzy logic and neural networks are combined, there will be a hybrid system with the advantages of both: fuzzy logic allows easy system design easily and explicitly, while neural networks allow learning what we require about the controller. It modifies the shape, position, and coherence dependency functions and automatically fits them completely. The structure of a three- layer fuzzy neural network with inputs $X(t) = [x_1(t), x_2(t), x_3(t)]^T$ and one output u is depicted in Figure 6. The ReLU is defined as follows: $f(y) = \max(0,y)$. The input data source $X(t)$ can be achieved from a sample dataset in array format.

Table 2. Fuzzy and Neural Review.

Criteria	Neural Network	Fuzzy Logic
Demonstrate knowledge	Not clear, difficult to explain, and difficult regulation	Clear and easy to check its works and fix change.
Learning ability	Able to learn through data sets.	Inability to learn, need for experience requirements of designer

The three-layered fuzzy neural network is formulated with M fuzzy If-Then rules as follows:

Rule Rl: If $x_1(t)$ is A_1^i, $x_2(t)$ is A_2^i, and $x_\mathrm{n}(t)$ is A_n^i, then the output u (control signal) is B_i,
where $A_1^i,\ A_1^i,\ A_1^i$, and Bi denote the fuzzy sets.

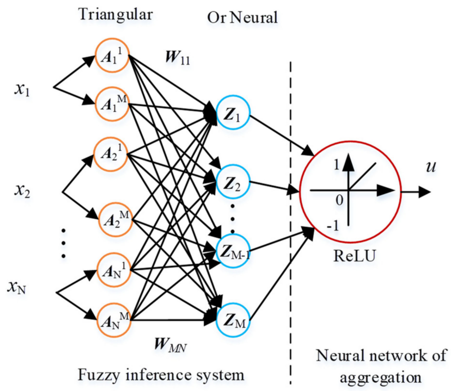

Figure 6. The structure of fuzzy-neural network.

The output of fuzzy neural can be obtained by

$$u(t) = \frac{\sum_{i=1}^{M} w_i(t)\left(\Pi_{k=1}^{n}\mu_{A_k^i}(Z_k)\right)}{\sum_{i=1}^{M}\left(\Pi_{k=1}^{n}\mu_{A_k^i}(Z_k)\right)} \tag{4}$$

where M defines the number of If-then rules, $w_i(t)$ is the adjustable weight, and $\mu_{A_k^i}(Z_k)$ represents the MFs value of the fuzzy variable Z_k.

In this paper, for the sake of the fuzzy controller design, the Anfis tool is built in Matlab so we can train the fuzzy-neural network. In the command prompt, type "anfisedit" to enter the Anfis tool. Herein, the collected data is used to train the fuzzy-neural network. In addition, we can set up the network configuration as required.

The block diagram for the learning process of an adaptive fuzzy neural network is summarized in Figure 7. Because of the supevisor learning approach, the training document is recorded that comprises three inputs and one output. Three inputs include tracking error, the integral of the error, and the derivative of the error, while the control effort is one output. The data is recorded to the simout workspace block in Matlab/SIMULINK under the temperature control of the FLC or PID controller. Since the collection of the sample data is finished, the general fuzzy inference system (FIS) is created. Herein, the number and the kind of membership function are selected. Then, the configuration for FIS is established, such as error tolerance, training method, and the number of epochs. The accepted output of the fuzzy-neural controller can be achieved since the training error is low or at the end of epochs.

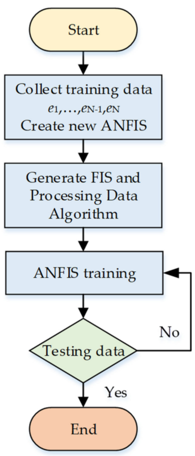

Figure 7. The principle of ANFIS for small PEMFC system.

4. Simulation and Experimental Validation

4.1. Simulation Results

To evaluate the tracking performance of the presented controller, simulation firstly is conducted in Malab/SIMULINK software as shown in Figure 8. The desired input is a sinusoidal signal that is described as follows:

$$x_{1d} = 70 + 10 \sin (2\pi t) \ [^{\circ}\mathrm{C}] \tag{5}$$

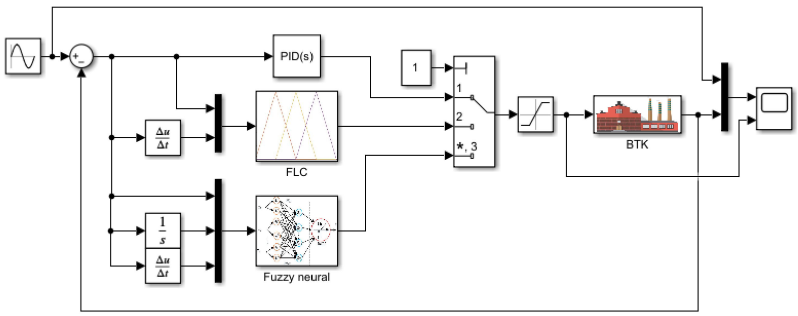

Figure 8. System simulation diagram.

The simulation results are exhibited in Figure 9. The temperature tracking performance and tracking error are shown in the first and second subgraph. It is observed that the proposed controller achieved the best tracking performance as compared to the PID and fuzzy controller. The control input signal of all controllers is displayed in the third subgraph of Figure 9a. The proposed fuzzy-neural controller obtains the output temperature stably at around 5 s with non-overshoot and less fluctuation than the PID and fuzzy controller. Meanwhile, the fluctuation of temperature under the PID has peak values within °C by 42% overshoot. Moreover, compared to the fuzzy controller, the proposed method exhibits better performance, as shown in Figure 9b.

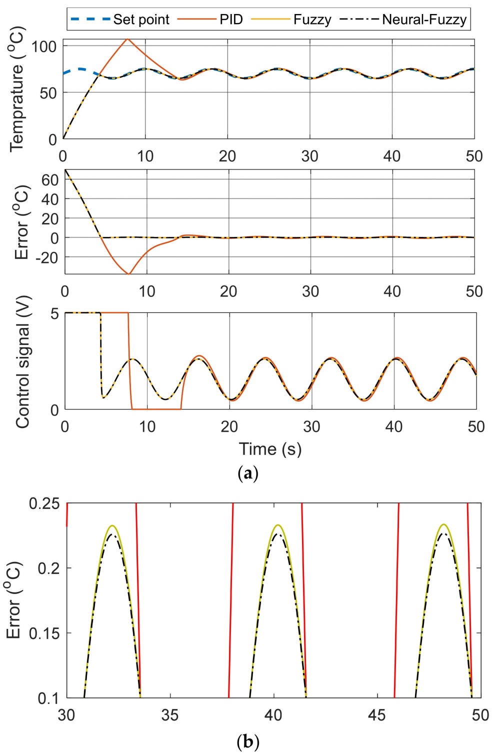

Figure 9. Simulation result: (**a**) tracking performance; (**b**) zoom-in of error from 30 to 35 s.

4.2. Experimental Verification

4.2.1. Experimental Setup

The experimental platform is established in Malab/SIMULINK software, as depicted in Figure 10. The output temperature of the BTK is measured through the analog A_1 pin of the microprocessor. Meanwhile, the control signal input is provided via the arduino Pulse Width Modulation (PWM) pin. Similar to the simulation study, three controllers (i.e., PID, fuzzy controller, and proposed fuzzy-neural controller) are given to evaluate the control performance. The components of the BTK experiment are simplified and listed in Figures 11 and 12, which include the following:

- Laptop: used to design and control the system.
- Arduino: receive program from Matlab; control the system.
- Temperature sensor TMP36: used to read the returned temperature and feed back to the main controller.
- SSR relay: used to control temperature bulbs.
- Incandescent light bulbs: act as a source of heat.

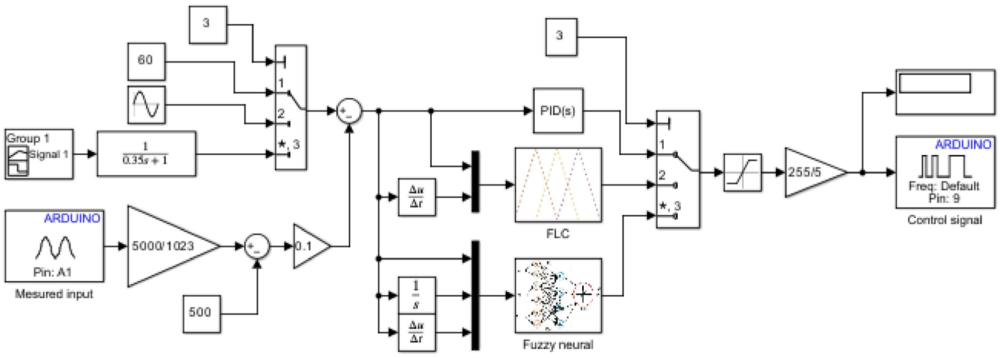

Figure 10. System experimental diagram.

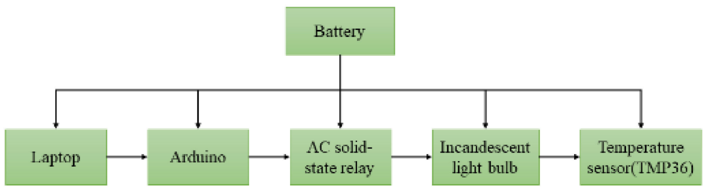

Figure 11. System block diagram.

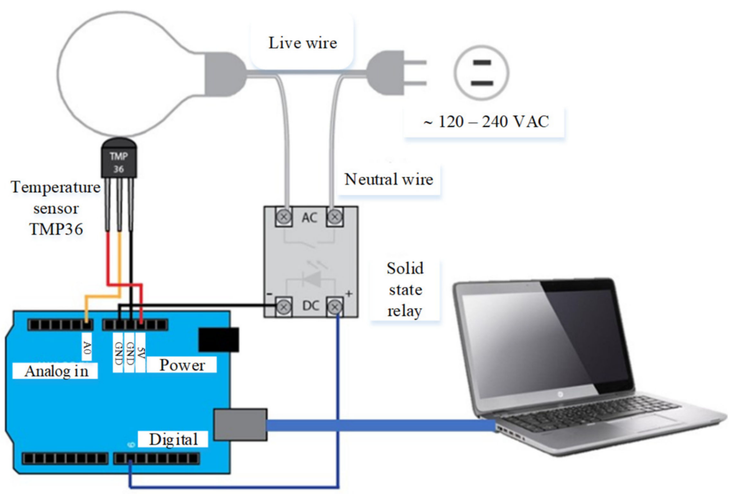

Figure 12. System connection diagram.

4.2.2. Experimental Results

To further evaluate the tracking performance of the presented controller, experimental verification is carried out with the combination of hardware and Malab/SIMULINK software, as shown in Figure 10. The desired inputs in the experiment are constant, sinusoidal, and multistep signal.

The experimental results are depicted in Figures 13–15. The temperature tracking performance and tracking error are shown in the first and second subgraph of Figures 13–15. It is noted that the proposed controller obtained the outstanding tracking performance as compared to the PID and fuzzy controller. The control input signal of all controllers is displayed in the third subgraph of Figures 13–15.

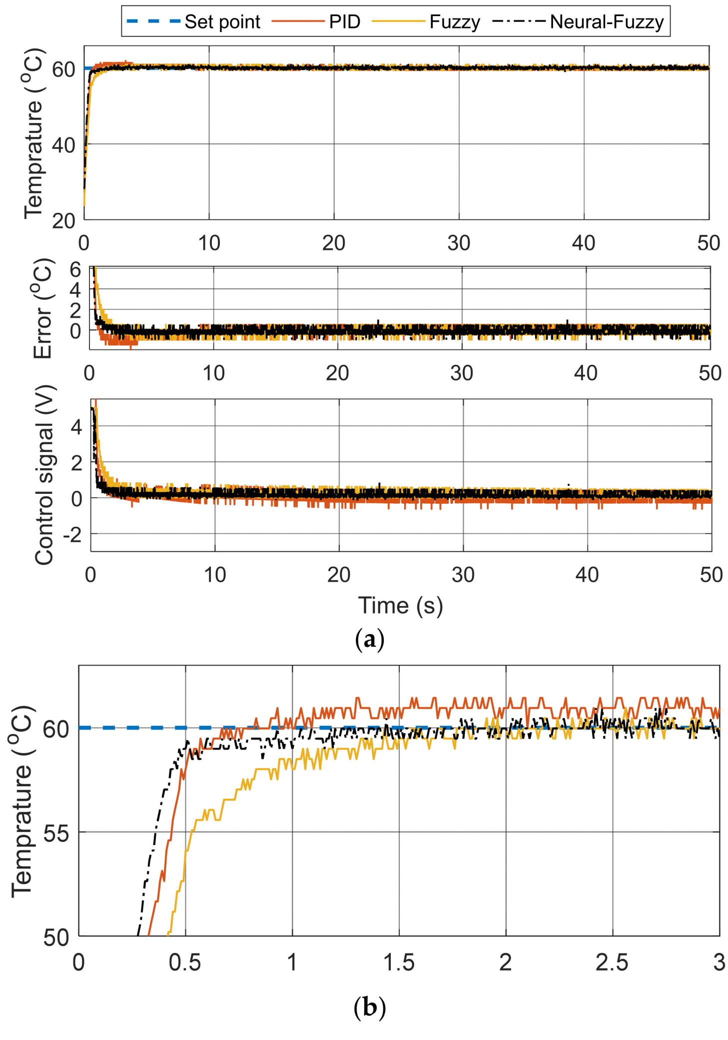

Figure 13. (**a**) Tracking performance with constant input; (**b**) Zoom-in temperature from 0 to 3 s.

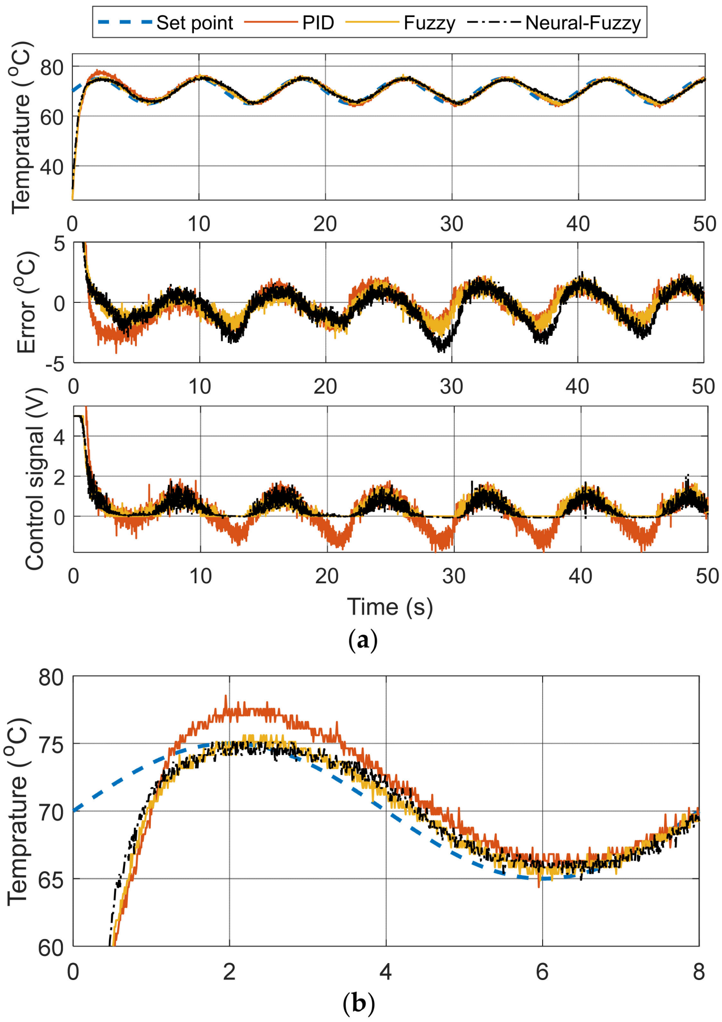

Figure 14. (**a**) Tracking performance with sinusoidal wave input; (**b**) Zoom-in temperature from 0 to 8 s.

Case study 1: desired constant input (x_{1d} = 60 °C)

The desired and response signals at the temperature relative to the desired constant signal corresponding to each controller are described in Figure 13. The dashed blue line is the reference signal, and the red line is the response signal of the output temperature when utilizing the PID control. Otherwise, the orange line is for the fuzzy controller, and the dashed black line is for the proposed control method. The enhancement of the output temperature tracking performance is illustrated in Figure 13b with zoom-in from 0 to 3 s. As observed in the figure, the response of the temperature in all three controllers to the desired signal is at an acceptable level. However, it is noteworthy that the proposed controller demonstrates a smooth and rapid response in the BTK system, without any peak overshoot, as compared to the other two controllers. Hence, to see more fairly the effectiveness of the proposed method or the difference between the response signal and the desired signal, the sinusoidal signal is carried out to compare the three controllers. The experimental results of this desired signal are shown in the following case study.

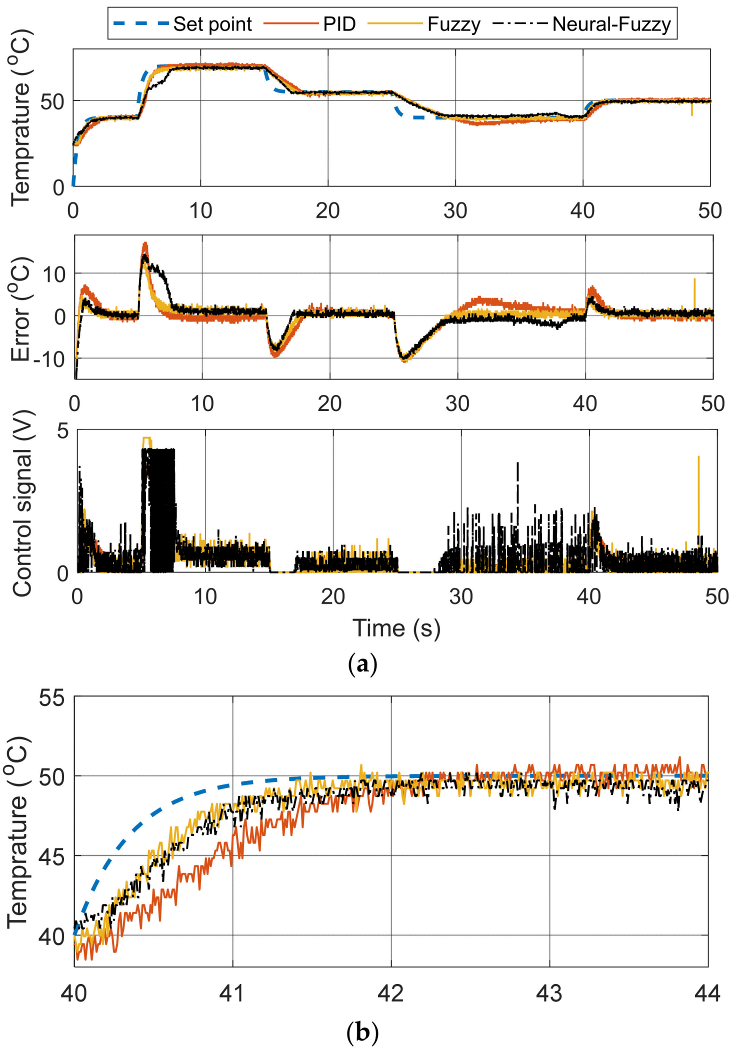

Figure 15. (**a**) Tracking performance with signal builder waveform input; (**b**) Zoom-in temperature from 40 to 44 s.

Case study 2: desired sinusoidal input (similar to simulation study)

Figure 14 displays the temperature tracking performance, tracking error, and signal control input of three controllers with sinusoidal wave input. Similar to the above figure, the dashed blue line, the red line, the orange line, and the dashed black line are the setpoint signal, PID, fuzzy, and proposed controller, respectively. The zoom-in of the output temperature from 0 to 8 s is illustrated in Figure 14b. Based on the data in Figure 14, it can be observed that the temperature error of the PID controller is bigger than that of the two controllers (i.e., fuzzy and suggested controller). With the combination of the merit of fuzzy and neural networks, the proposed controller brings the best qualification with smallest error as compared to the remaining controllers. Thereby, the robustness of the suggested methodology in this paper is confirmed.

Case study 3: desired signal Builder waveform input

The experimental results of case study 3 are depicted in Figure 15. As seen in this figure, the control tracking qualification of the PID and fuzzy controller became much poorer in the multistep condition. The signal control input and the tracking error significantly increase since there is a significant changing of the desired signal at t = 6 s, 16 s, and 25 s. The zoom-in of the output temperature from 40 to 44 s is illustrated in Figure 15b. These results can be explained by the insufficient adaptation of two controllers to the disturbance environments. Otherwise, due to the robustness of the fuzzy controller and the learning ability of the neural network scheme, a big enhancement was obtained by taking the merits of the intelligent control approach.

4.3. Performance Index Evaluation

To evaluate and compare the quality of controllers, we evaluate based on indicators such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) that are formulated as follows [31,32]:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{7}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|^2} \tag{8}$$

where n is the number of data points, y_i is the actual value, and $\hat{y}_i$ is the predicted value.

4.3.1. Evaluation of the Simulation Result

The simulation performance indexes are listed in Table 3. It can be seen that all performance indexes of the suggested controller is smallest as compared to other controllers. It confirms again the effectiveness of the proposed control method. The RMSE tracking errors of PID, fuzzy, and proposed controllers are achieved as 6.9222, 3.3363 and 3.1362 °C, respectively. Moreover, MSEs are, in turn, calculated as 3.3202, 2.6211, and 2.6006 °C. It can be concluded that the outstanding effectiveness of the suggested methodology once again is verified.

Table 3. Simulation performance indexes.

Controller	RMSE [°C]	MAE [°C]	MSE [°C]
PID	6.9222	15.2748	3.3202
Fuzzy	3.3363	12.3540	2.6211
Fuzzy neural	3.1362	12.1143	2.6006

4.3.2. Evaluation of the Experimental Results

The experimental performance indexes are listed in Tables 4–6. It is obvious that the suggested controller provided the best tracking performance where RMSE, MSE, and MAE is lowest as compared to two controllers. It reconfirms again that the efficiency of the suggested strategy.

Table 4. Experimental performance indexes with constant desired.

Controller	RMSE [°C]	MAE [°C]	MSE [°C]
PID	1.8288	3.3444	0.4639
Fuzzy	2.1753	4.7320	0.5135
Fuzzy neural	1.7001	2.8903	0.3877

Table 5. Experimental performance indexes with sinusoidal desired.

Controller	RMSE [°C]	MAE [°C]	MSE [°C]
PID	3.2364	10.4746	1.4054
Fuzzy	3.0923	9.5621	1.2288
Fuzzy neural	2.9407	8.6478	1. 3148

Table 6. Experimental performance indexes with multistep desired.

Controller	RMSE [°C]	MAE [°C]	MSE [°C]
PID	3.6306	13.1812	2.1694
Fuzzy	3.5385	12.5208	2.0202
Fuzzy neural	3.0097	9.0585	1.6396

From Table 4, it can be observed that the temperature tracking performance of the suggested control approach has been enhanced by 27% and 7.2% over the fuzzy and PID controllers, respectively. The result of performance index data analysis with constant desired validates the predominant properties of the suggested methodology compared to the relevant controllers.

Through the simulation and experimental system evaluation tables (Tables 3–6), it is seen that the MSE, MAE, and RMSE indexes of the proposed fuzzy-neural controller are all the lowest. Hence, it is concluded that the fuzzy-neural controller is the best controller with the highest performance and smallest deviation, and that it can respond to rapid changes in the system's operation, thereby improving brick performance in the production process of brick tunnel kilns.

5. Conclusions

In this study, an adaptive fuzzy-neural controller has been proposed and developed successfully for controlling temperature of the firing zone of brick tunnel kilns. The simulation and experimental results show that control laws are not only highly stable but also can be developed and implemented. However, the accuracy of the fuzzy-neural controller depends on input data, so to get the best fuzzy-neural controller we have to collect different data sets for training.

In the future work, we will research on how to combine fuzzy-neural networks with deep learning to take advantage of the benefits of both methods and developing a fuzzy-neural model capable of handling real-time fuzzy data.

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