

Article

Adaptive Network-Based Fuzzy Inference System–Proportional–Integral–Derivative Controller Based on FPGA and Its Application in Radiofrequency Ablation Temperature Control

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Abstract: The radiofrequency ablation temperature system is characterised by its time-varying, non-linear, and hysteretic nature. The application of PID controllers to the control of radiofrequency ablation temperature systems has a number of challenges, including overshoot, dependence on high-precision mathematical models, and difficulty in parameter tuning. Therefore, in order to improve the effectiveness of radiofrequency ablation temperature control, an adaptive network-based fuzzy inference system combined with an incremental PID controller was used to optimise the shortcomings of the PID controller in radiofrequency ablation temperature control. At the same time, the learning rate at the time of updating the consequence parameters was set by segmentation to solve the problem of poor control accuracy when the ANFIS-PID controller is implemented based on FPGA fixed-point decimals. Based on FPGA-in-the-loop simulation experiments and ex vivo experiments, the effectiveness of the ANFIS-PID controller in the temperature control of radiofrequency ablation was verified and compared with the PID controller under the same conditions. The experimental results show that the ANFIS-PID controller has a superior performance in terms of tracking capability and stability compared with the PID controller.



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Keywords: adaptive network-based fuzzy inference system; FPGA; proportional–integral–derivative; radiofrequency ablation

1. Introduction

Radiofrequency ablation (RFA) is a minimally invasive method of treating tumours by heating tumour tissue to 50–100 °C using radiofrequency signals, and is widely used in clinical practice [1–3]. Temperature control during ablation has a significant impact on the effectiveness of the treatment [4–6]. When the temperature between the radiofrequency electrode and the tumour tissue exceeds 100 °C, the tumour tissue will carbonise, resulting in a sharp increase in the impedance of the tumour tissue, which reduces the radiofrequency current density and limits the final ablation effect [7,8]. In addition, different temperatures can affect the ablation volume, and inappropriate temperatures can cause thermal damage to the normal tissue surrounding the tumour, which can lead to a range of complications [9–14]. Therefore, stable and accurate temperature control needs to be achieved to improve the therapeutic effect of RFA.

Proportional–integral–derivative (PID) controllers have a wide range of applications in the field of RFA temperature control due to their simple structure and easy implementation [15–18]. However, the temperature system for RFA has characteristics such as non-linearity and hysteresis, whereas PID controllers are designed based on linear systems. Therefore, when dealing with non-linear RFA temperature systems, PID controllers may not be able to achieve the desired control effect [19]. In addition, PID controllers have

shortcomings such as reliance on high-precision mathematical models and time-consuming parameter adjustment [20,21].

The adaptive network-based fuzzy inference system (ANFIS) controller implements the neural networking of the fuzzy inference process by integrating the learning ability of artificial neural networks and the decision-making mechanism of fuzzy logic [22]. The controller uses fuzzy inference parameters to represent the weights of the neural network, updates the parameters through a learning algorithm, and exhibits Takagi–Sugeno (T–S)-type fuzzy inference behaviour, which gives the controller the ability to approximate non-linear functions [23,24]. The ANFIS-PID controller, which is formed by combining the ANFIS controller with a PID controller, has advantages over the PID controller alone in terms of stability and tracking capability. In [25], an ANFIS-PID controller was constructed using three separate ANFIS to update each of the three parameters of the PID controller, which was applied to the temperature control system of a 3D printer, and simulated and compared with the PID controller. The results show that the ANFIS-PID controller outperforms the PID controller in terms of overshoot and steady-state error with better stability. In [26], the PID controller was combined with ANFIS in the form of selection and switching to form the ANFIS-PID controller, which was applied to the temperature control of a polyethylene reactor, and the performance of the three controllers, ANFIS, PID and ANFIS-PID, was comparatively analysed in terms of tracking and disturbance suppression. The results show that the ANFIS-PID controller performs better in terms of stability compared to the PID and ANFIS controllers.

Based on the above analysis, in this paper, the incremental PID is used to construct the ANFIS-PID controller instead of the rule output of ANFIS. At the same time, the hardware language Verilog is used to implement it in FPGA, and the calculation method of the input value error and the learning rate are set in segments according to the test, in order to improve the control accuracy of FPGA in the implementation of ANFIS-PID.

2. ANFIS-PID

2.1. Theory

The standard ANFIS controller has a five-layer structure, including a fuzzification layer, rule layer, normalisation layer, defuzzification layer, and summation layer [27]. In the defuzzification layer, the output of each rule is usually defuzzified using T–S-type fuzzy inference (see Equation (1)). In order to solve the problem that the change in the target temperature during the RFA process may lead to the decrease in the control effectiveness of the fixed-parameter PID controller, an improved scheme is proposed in this paper. Part of Equation (1) is replaced by an incremental PID controller to construct a new ANFIS-PID controller, as shown in Figure 1, Equation (2).

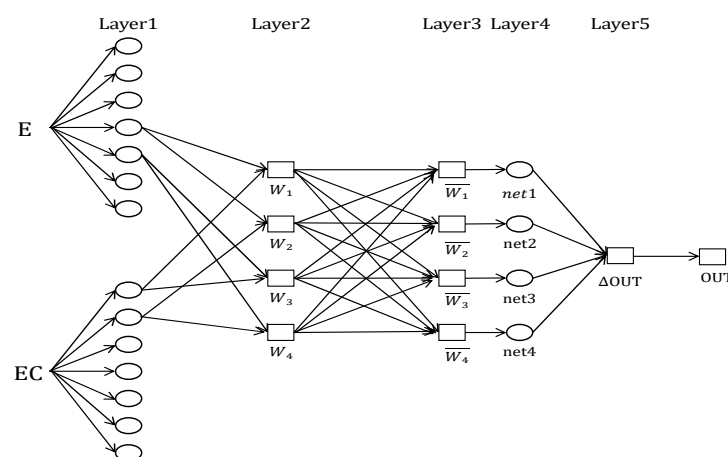


Figure 1. Structure of the ANFIS-PID.

$$net_i = \overline{W}_i * (p_i * E + q_i * EC + r_i) \quad (1)$$

where $\overline{W}_i$ is the output of layer3, p_i , q_i , and r_i are the consequence parameters, $i = 1, 2, 3$, and 4, and E and EC are the inputs.

$$net_i = \overline{W}_i * (K_p * EC + K_i * E + K_d * (E(k) - 2 * E(k-1) + E(k-2))) \quad (2)$$

Among them, $E(k)$, $E(k-1)$, and $E(k-2)$ represent the temperature error at time k , $k-1$, and $k-2$, respectively, while K_p , K_i , and K_d are the consequence parameters.

2.2. Implementation

Currently, standard ANFIS controllers are implemented in two main architectures, parallel and serial, where parallel computation is fast but consumes a lot of resources, while serial requires a lot of execution time [28]. In this paper, the ANFIS-PID controller is implemented using a combination of parallel and serial approaches. Based on the sampling frequency of the temperature acquisition chip, a timeline for a single output of the controller is created, and according to the time forward, the layers are executed serially in sequence with each other, while the contents of the same layer are executed in parallel. At the same time, an FPGA with high-speed parallel computing capability is used as the carrier for the ANFIS-PID controller implementation.

2.2.1. Input Layer

In this paper, the inputs to the ANFIS-PID controller are the error (E) between the target temperature and the actual temperature, and the amount of change between two adjacent errors (EC). In order to optimise the problem of reduced control accuracy due to the inability to perform decimal operations when using FPGAs, the input values E and EC are expanded by a factor of 10 for the overall calculation and restored at the final result.

2.2.2. Fuzzification Layer (Layer1), Rule Layer (Layer2), and Normalization Layer (Layer3)

In order to obtain richer information and achieve better control performance, the triangular membership function is used to calculate the membership of each input value mapped to seven fuzzy linguistic values (NB, NM, NS, ZO, PS, PM, PB), as shown in Figure 2 and Equation (3), where μ_l and μ_r represent the membership of the input values corresponding to the left and right fuzzy linguistic values, respectively.

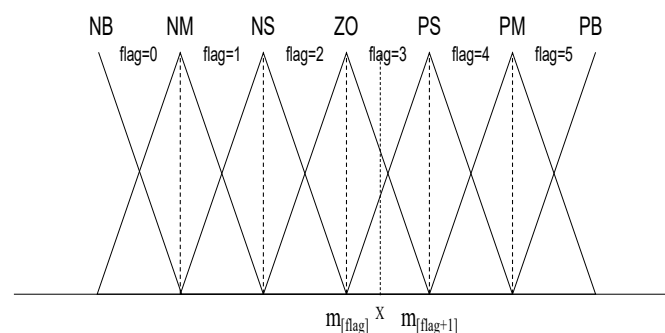


Figure 2. The triangle membership degree function.

In the fuzzy rule generation phase, each input value is mapped to seven fuzzy linguistic values using membership functions, and two input values can generate 49 ($7 \times 7 = 49$) rules in a single forward propagation. However, the midpoint of the membership function used in this paper always coincides with the boundaries of the adjacent membership functions, so each input value has only two valid memberships, the rest being zero. Therefore, during controller implementation, only the activation strengths of four ($2 \times 2 = 4$) valid rules are calculated to improve computational efficiency.

$$\mu = \begin{cases} 0 & x < m_{[flag]}, \\ \mu_l = \frac{x - m_{[flag]}}{m_{[flag+1]} - m_{[flag]}} & m_{[flag]} \leq x \leq m_{[flag+1]}, \\ \mu_r = \frac{m_{[flag+1]} - x}{m_{[flag+1]} - m_{[flag]}} & m_{[flag]} \leq x \leq m_{[flag+1]}, \\ 0 & x > m_{[flag+1]}. \end{cases} \quad (3)$$

2.2.3. Defuzzification Layer (Layer4), Summation Layer (Layer5), and Power Control

The defuzzification output of the ANFIS-PID controller is first obtained by Equation (2). Then, the sum of the four sets of defuzzification outputs (net_i) is obtained as the incremental output (ΔOUT), and, finally, the final output (OUT) of the ANFIS-PID controller is obtained by cumulative summation according to Equations (4) and (5). OUT achieves the amplitude control of the RF signal via Equation (6), where $data$ is the amplitude of the original RF signal generated by direct digital frequency synthesis technology, C is a constant selected according to the output of the ANFIS-PID controller, and RF is the amplitude of the digital RF signal.

$$\Delta OUT = \sum_{i=1}^4 net_i \quad (4)$$

$$OUT = OUT + \Delta OUT \quad (5)$$

$$RF = \frac{C - OUT}{C} * data \quad (6)$$

2.2.4. Parameter Updates

In this paper, the gradient descent method is used to update the premise parameters and consequence parameters.

1. Consequence parameters

The consequence parameters K_p , K_i , and K_d are updated by the chain rule (Equations (7) and (8)).

$$k(t) = k(t-1) - \eta * d_k \quad (0 < \eta < 1) \quad (7)$$

$$d_k = \begin{cases} \frac{\partial y}{\partial p_i} = \frac{\partial y}{\partial ture} \frac{\partial ture}{\partial out} \frac{\partial out}{\partial net_i} \frac{\partial net_i}{\partial p_i} = -E * \frac{\partial ture}{\partial out} * \bar{W}_i * EC, \\ \frac{\partial y}{\partial q_i} = \frac{\partial y}{\partial ture} \frac{\partial ture}{\partial out} \frac{\partial out}{\partial net_i} \frac{\partial net_i}{\partial q_i} = -E * \frac{\partial ture}{\partial out} * \bar{W}_i * E, \\ \frac{\partial y}{\partial r_i} = \frac{\partial y}{\partial ture} \frac{\partial ture}{\partial out} \frac{\partial out}{\partial net_i} \frac{\partial net_i}{\partial r_i} \\ = -E * \frac{\partial ture}{\partial out} * \bar{W}_i * (E(k) - 2 * E(k-1) + E(k-2)). \end{cases} \quad (8)$$

Among them, $k(t)$ and $k(t-1)$ represent the values of the consequence parameter at time t and $t-1$, respectively, d_k is the increment of the updated consequence parameter, and $\frac{\partial ture}{\partial out}$ is the intermediate value.

The update direction of the consequence parameter is significantly correlated with E . When $E = target - ture$ is fixed, the update direction of the consequence parameter may not be able to be adjusted in time to appear with overshoot or large fluctuations; therefore, the error (E) is expressed in segments (see Equation (9)).

$$E = \begin{cases} target - true \\ \left(\begin{array}{l} target > true, temperature \text{ rise} \\ and \ target < true, temperature \text{ drop} \end{array} \right) \\ true - target \\ \left(\begin{array}{l} target > true, temperature \text{ drop} \\ and \ target < true, temperature \text{ rise} \end{array} \right) \end{cases} \quad (9)$$

According to the analysis of Equations (2), (7), and (8), as the actual temperature steadily increases and approaches the target temperature, E will gradually decrease, resulting in the increment of the consequence parameter tending towards 0, so that the consequence parameter basically remains stable. As a result, the defuzzification output is gradually reduced. During the summation of the defuzzification outputs, the fixed-point

decimals must be restored, which results in the incremental output of the controller being close to 0. As a result, the final output of the ANFIS-PID controller remains constant, which can lead to large fluctuations in the controlled temperature around the target temperature.

To solve this problem, set the condition that the error between the target temperature and the actual temperature is within $\pm 3^\circ\text{C}$. A large learning rate is used when the condition is met, and a small learning rate is used when the condition is not met. Therefore, in the FPGA-in-the-loop (FIL) simulation, the learning rates η_1 and η_2 of K_p and K_d were set to 0.33 and 0.67, respectively, and the learning rates η_1 and η_2 of K_i were set to 0.005 and 0.01; in the ex vivo experiment, the learning rates η_1 and η_2 of K_p and K_d were set to 0.15 and 0.29, respectively, and the learning rates of η_1 and η_2 of K_i were set to 0.005 and 0.009, respectively.

2. Premise parameters

According to the above mapping relationship between input values and fuzzy linguistic values, two input values correspond to a total of four premise parameters. If these four premise parameters are updated separately by the objective function, a large number of multiplication and division operations will be involved, occupying a large amount of FPGA resources. For this purpose, a variable is introduced for each of the two input values to calculate the premise parameters, as shown in Equations (10) and (11), where $g_{[flag0]}$, $g_{[flag0+1]}$, $n_{[flag1]}$, and $n_{[flag1+1]}$ ($flag0 = 0, 1, 2, 3, 4, 5$, $flag1 = 0, 1, 2, 3, 4, 5$) are the premise parameters to be updated for E and EC , respectively, corresponding to $m_{[flag]}$ and $m_{[flag+1]}$ in Figure 2. $flag0$ and $flag1$ are used to locate the positions of the input values E and EC , corresponding to $flag$ in Figure 2. $S0$ and $S1$ are the variables used to calculate the premise parameters. $S0$ and $S1$ are updated by Equations (12) and (13), and θ is the learning rate.

$$\begin{cases} g_{[flag0]} = S0 * (40 * flag0 - 90), \\ g_{[flag0+1]} = S0 * (40 * flag0 - 50). \end{cases} \quad (10)$$

$$\begin{cases} n_{[flag1]} = S1 * 5 * (flag1 - 3), \\ n_{[flag1+1]} = S1 * 5 * (flag1 - 2). \end{cases} \quad (11)$$

$$S(t) = S(t - 1) - \theta * d_S \quad (12)$$

$$d_S = \begin{cases} d_S0 = \frac{\partial y}{\partial S0} \\ d_S1 = \frac{\partial y}{\partial S1} \end{cases} \quad (13)$$

3. Experiments and Discussions

The performance of the implemented ANFIS-PID controller is evaluated through experimental tests. First, FPGA-in-the-loop (FIL) simulation experiments are used to pre-validate the effectiveness of the algorithm. Then, based on the FIL simulation, the actual effect is tested using ex vivo experiments and compared with the PID controller in both simulation and ex vivo experiments. However, due to the differences between the model of the RFA temperature system in the simulation of this paper, as well as the power amplification module of the RF signals in the ex vivo experiments and the existing literature, it is not possible to directly use the parameters of the PID controllers of the existing literature to compare with the effect of the ANFIS-PID controller.

Due to the low power of the self-designed power amplifier module, the target temperature was set to 40°C and the temperature enabled by the temperature control algorithm was 30°C for the ex vivo experimental test.

3.1. FIL Simulation Experiments

FIL is a hardware-in-the-loop simulation technique. In this paper, an ANFIS-PID controller implemented on an FPGA development board is used to control the RFA temperature system model in Simulink to evaluate the performance of the FPGA-implemented ANFIS-PID controller.

In the FIL simulation, the model used is shown in Equation (15), where the range of parameter a is from 78.9 to 79. The model consists of two main parts [29]: $G_1(S)$ is the gain of the self-designed power amplification of the RF signal and $G_2(S)$ is modelled based on the temperature and applied voltage in the ablation region (Equation (14)) during the RF heating studied in [30], with minor adjustments. In order to make the system time-varying and, at the same time, not to spend too much time adjusting the parameters, the first-order coefficients in the denominator are replaced by the varying parameter a and the values of a are set based on the original coefficients.

$$G(S) = \frac{-1.24}{s^3 + 12.75 * s^2 + 78.96 * s + 248.05} \quad (14)$$

$$G(S) = G_1(S) * G_2(S) = 45.6 * \frac{-1.24}{s^3 + 12.75 * s^2 + a * s + 248.05} = \frac{-56.54}{s^3 + 12.75 * s^2 + a * s + 248.05} \quad (15)$$

Figure 3 illustrates the modelling of the ANFIS-PID controller with the PID controller. To simulate the temperature hysteresis of the RFA, a delay module was added to the model (as shown in the red block diagram in Figure 3); but, due to the complexity of the actual RFA, the exact hysteresis time could not be obtained. To ensure that the model was closer to the actual scenario, a dead-zone module with non-linearity was added to make the controlled system exhibit non-linear characteristics.

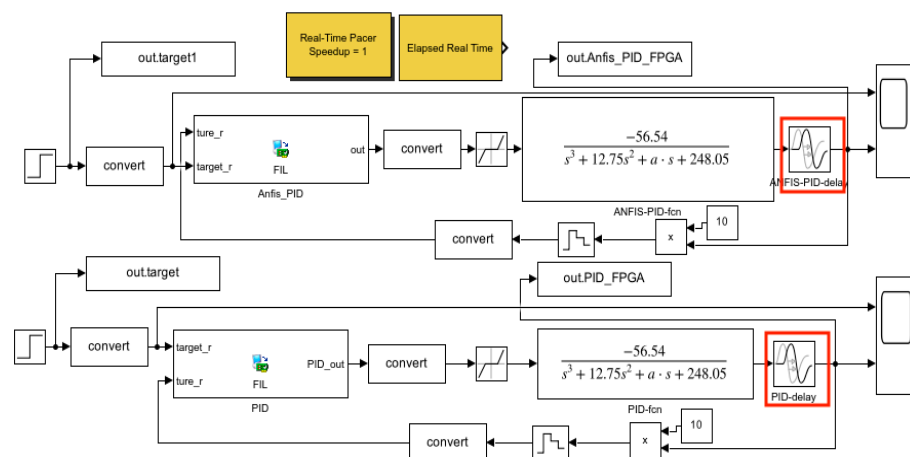


Figure 3. FIL simulation model.

A comparison of important parameters between the ANFIS-PID controller and the PID controller was carried out under three different conditions, such as simulating normal use, varying the target temperature, and external disturbance. And the artificially set parameters of both controllers were kept constant under these three conditions.

3.1.1. Simulate Normal Use

The target temperature was set to 10 °C and the simulation time was 80 s to simulate a single RFA process to evaluate the performance difference between the ANFIS-PID controller and the PID controller for RFA temperature control. The experimental results are shown in Figure 4 and Table 1. In the figure, *step* is the target temperature, *ANFIS-PID* is the temperature controlled by the ANFIS-PID controller, and *PID* is the temperature controlled by the PID controller (the above three items have the same meaning in the following figure).

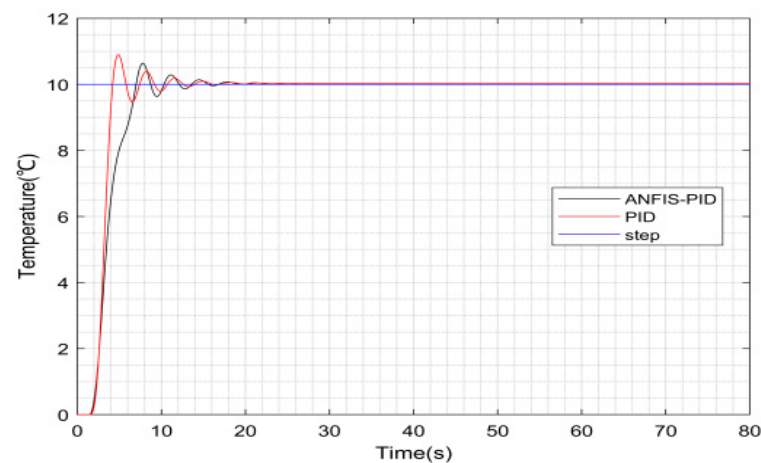


Figure 4. The temperature rise curves of the two controllers in normal use.

Table 1. The simulation results of the two controllers.

	Overshoot (%)	Undershoot (%)	Rise Time (s) (0–0.95)	Settling Time (s) (0.97–1.03)
PID	8.99	5.31	4.18	5.89
ANFIS-PID	6.43	3.69	6.84	7.03

When simulating a single RFA process, the PID controller showed a faster response with a rise time and settling time of 4.18 s and 5.89 s, respectively, which were reduced compared to the ANFIS-PID controller. However, in terms of stability, the ANFIS-PID controller performed better, with an overshoot and undershoot of 6.43% and 3.69%, respectively, which were lower than the PID controller.

3.1.2. Target Temperature Change

In practice, the target temperature will vary depending on the location and size of the tumour. To evaluate the tracking performance of the ANFIS-PID controller and the PID controller, the initial target temperature was adjusted from 10 °C to 15 °C at the 30th s of the simulation to simulate the target temperature change and compare the important parameters of the two controllers. The results are shown in Figure 5 and Table 2.

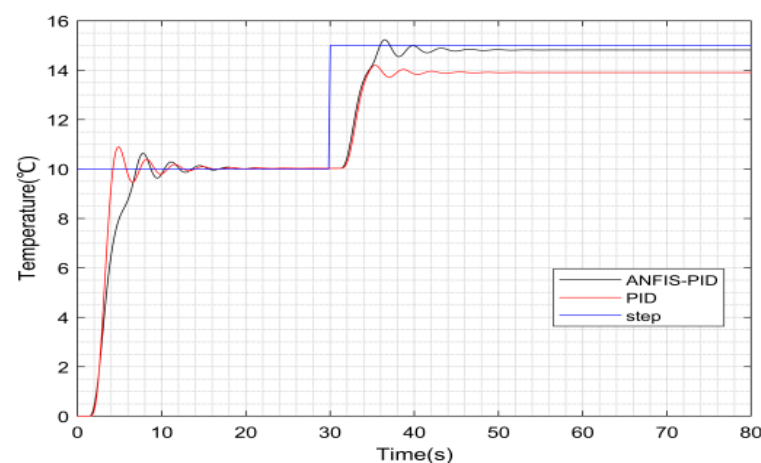


Figure 5. The temperature rise curve of the two controllers when the target temperature changes.

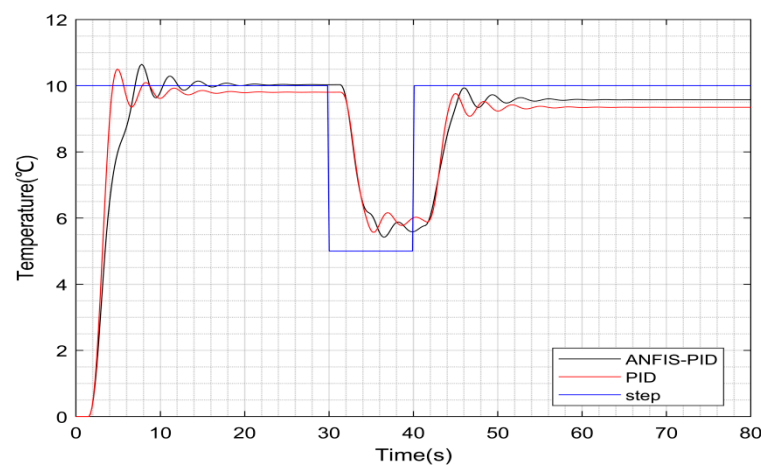
Table 2. The simulation results when the target temperature changes.

Target (°C)	15				
	Overshoot (%)	Undershoot (%)	Rise Time (s) (0–0.95)	Settling Time (s) (0.97–1.03)	Steady-State Error (°C)
PID	0	8.58	50	4.39	1.09
ANFIS-PID	1.56	3.03	5.15	5.53	0.18

Both the ANFIS-PID controller and the PID controller responded to the change in target temperature when the target temperature was changed from 10 °C to 15 °C. However, the ANFIS-PID controller showed a better performance than the PID controller. After the target temperature change, the PID controller had an undershoot of 8.58% with a large steady-state error (1.09 °C), whereas the ANFIS-PID controller could still reach close to the target temperature after the target temperature change and there was a small steady-state error (0.18 °C) with the target temperature, providing a better control effect in RFA applications where the target temperature changes.

3.1.3. External Disturbance

In normal use, the jittering of the electrode needle can cause fluctuations in the temperature data, thus affecting the temperature control effect. To evaluate the stability performance of the two controllers, a -5 °C fluctuation was added to simulate the jittering phenomenon of the electrode needle in a time range of 30–40 s. The results are shown in Figure 6 and Table 3.

**Figure 6.** The temperature rise curves of the two controllers with added disturbance.**Table 3.** The simulation results when adding noise.

	Error (°C) (Target–True)		Time (s) (When Disturbed)		
	Disturbance (max)	Restore (Steady-State)	Fall	Duration	Rise
PID	4.43	0.65	2.66	1.33	8.36
ANFIS-PID	4.58	0.42	3.8	1.52	7.79

The error and recovery time analyses presented in Figure 6 and Table 3 show that the ANFIS-PID controller has a larger disturbance error (4.58 °C) compared to the PID controller when subjected to an external disturbance. However, after the disturbance disappears, the ANFIS-PID controller shows superior a control performance to the PID

controller, with the ANFIS-PID having a smaller steady-state error (0.42 °C) and a shorter recovery time (7.79 s) from the disturbance state to a steady state.

3.2. Ex Vivo Experiments

Considering the complexity of the actual RFA environment, pork loin was selected as the experimental object in this study to verify the control effect of the ANFIS-PID controller. A self-designed device was used in the radiofrequency heating system, the target temperature was set at 40 °C, and the heating time was set at 420 s. The parameters of the PID controller were adjusted so that the control effect was similar to that of [31] (an overshoot of 3 °C).

RFA experiments were performed on pork loin using ANFIS-PID and PID controllers, respectively, and the results are shown in Figure 7 and Table 4

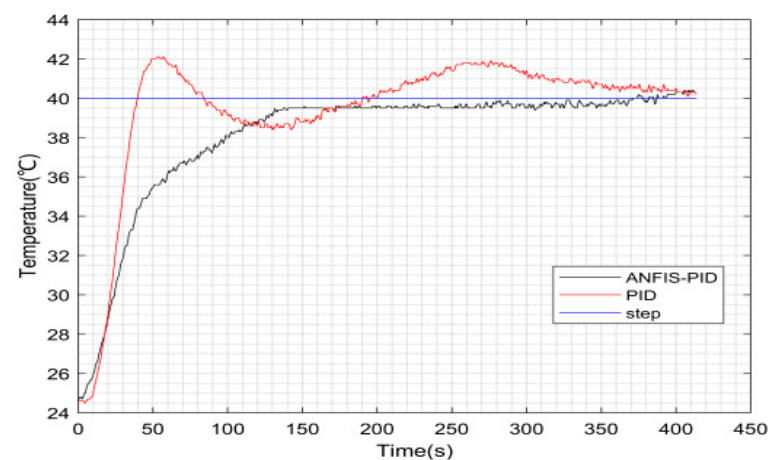


Figure 7. The temperature rise curves of the two controllers in ex vivo experiments.

Table 4. Results of ex vivo experiments with two controller parameters.

	Overshoot (%)	Undershoot (%)	Rise Time(s) (0–0.95)	Steady-State Error (°C)
PID	5.25	4	13.12	+1.9, −1.6
ANFIS-PID	0	1.25	74.08	+0.4, −0.5

The results of the ex vivo experiments show that the PID controller has a significant advantage in response speed compared to the ANFIS-PID controller. The rise time of the PID controller is 60.96 s shorter than the ANFIS-PID controller in the target temperature range of 0–0.95 times. However, the ANFIS-PID shows better stability. During the test time of 420 s, the ANFIS-PID can better maintain the temperature stabilisation around the target temperature of 40 °C with an error range of approximately ± 0.5 °C. In comparison, the PID controller showed large temperature fluctuations during this phase, with a maximum fluctuation of up to 1.9 °C. Considering the safety requirement during RFA, the ANFIS-PID controller is a suitable choice due to its better stability.

3.3. Discussions

The ANFIS-PID controller mainly optimises the problems of overshoot and difficult parameter adjustment of PID controllers in RFA temperature control. From the FIL simulation and ex vivo experimental results, it can be concluded that the ANFIS-PID controller has an advantage over the PID controller in terms of stability performance and tracking ability in the case of normal use, target temperature variation, and imposed disturbances. However, the ANFIS-PID controller and the PID controller may have some steady-state errors in the final state during the test, which may be partly due to the fact that both controllers are

implemented using fixed-point decimals based on FPGAs, resulting in a loss of accuracy in the intermediate process calculations.

In the simulation, the constitutive principle of the transfer function used is the same as that of Cheng et al. [29], which consists of two parts: 1. the relationship between the voltage of the RFA device acting on the tissue and the temperature of the tissue and 2. the relationship between the initial low-amplitude RF signal from the RFA device and the time of the RF signal applied to the tissue. However, due to the different RFA devices used, the transfer function of the first part of Cheng et al. [29]'s approach consists of two parts, while that of the present paper consists of one part, and thus there is a difference between the overall transfer functions of the two. Therefore, the parameters of the PID control algorithm of Cheng et al. [29] cannot be directly adopted, and its parameters may not work as well as they should in real ablations where there is a delay. In addition, due to the complexity of the tissues that RFA works on, there is a hysteresis between the voltage of the applied RF signal and the tissue temperature, which cannot be accurately obtained. At the same time, during the temperature rise in the actual ablation, changes in the tissue parameters cause a change in the output power of the ablation device, resulting in a slower temperature rise time, while the simulation is in the ideal state where the tissue parameters are unchanged. As a result, there is some error between the simulation results and the experimental results. Nevertheless, the trends are similar: the PID controller has a faster response and the ANFIS-PID has better stability.

In the ex vivo experimental tests, the PID controller has larger fluctuations compared to the ANFIS-PID controller, which may be partly due to the fact that the FPGA cannot directly perform decimal arithmetic when implementing the two controllers, which will cause some errors when using fixed-point decimal arithmetic; this is especially more obvious when the error between the actual temperature and the target temperature is small. Therefore, when implementing ANFIS-PID, the learning rate of the consequence parameter is set in segments, with the condition that the actual temperature differs from the target temperature by 3 °C. A larger learning rate is selected when the input error is small, and, conversely, a smaller learning rate is used to improve control accuracy. The difference in rise time between ANFIS-PID and PID controllers may be due to the fact that the learning rate of ANFIS-PID may not be set appropriately when the error between the actual temperature and the set temperature is greater than 3 °C. Therefore, the process of selecting the learning rate is complex. In future work, the implementation of the ANFIS-PID controller and the selection of the learning rate will be improved to increase the control accuracy of the controller.

4. Conclusions

This paper presented an optimised ANFIS-PID controller for RFA temperature control. The PID controller was optimised by combining the ANFIS controller with an incremental PID controller, while the learning rate of the consequence parameters was set by segmentation to improve the problem of the reduced control accuracy of FPGA-implemented controllers with small input value. Through FIL simulation experiments in the simulation of normal use, target temperature change, and the addition of −5 °C disturbance, the ANFIS-PID controller was compared with the PID controller; the simulation results showed that the ANFIS-PID controller has a better stability performance and tracking performance. Finally, the ANFIS-PID controller and the PID controller were tested in the ex vivo experiments under the same conditions, and the ANFIS-PID controller showed a more stable control performance, which is more suitable for the RFA temperature control system with safety requirements.

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