

EMBEDDED PROCESSOR SYSTEM FOR FUZZY LOGIC TEMPERATURE CONTROLLER

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Abstract:

An embedded processor system for controlling the runtime of devices based on the input temperature value was build and validated using ANFIS approach. The system was constructed on an Pynq-Z2 field-programmable gate array (FPGA). The software part was coded using the C language which provides memory efficiency and high performance in exception. A set of fuzzy rules was designed and the ANFIS model was trained and validated using training and tests sets. The validation parameters of both the training and test sets showed that the model is efficient and reliable with low error rates in prediction. The prediction of the model is used to compute the duty cycle which controls the runtime of different devices. Thus, the newly designed system is robust and can be used in various applications to provide efficient and accurate control.

Key words and phrases: fuzzy control system; embedded system; temperature control; membership function; Pynq-Z2; ANFIS; FPGA; temperature sensor.

INTRODUCTION

In the world today, artificial intelligence (AI) has become an essential part in controlling and managing various technologies [1]. Fuzzy logic based systems tend to mimic human thinking by using fuzzy sets and rules instead of the exact values. Therefore; Fuzzy controllers have been utilized in various embedded systems to control devices and make decisions in manner similar to human's decision making process [2]. The Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithm combines fuzzy logic systems with neural networks to produce a more robust system for control by utilizing the learning abilities of the neural networks [3]. This paper presents a novel ANFIS model for controlling the runtime of embedded devices based on the input temperature. The ANFIS model is used in an embedded system to provide accurate control over the runtime of devices, such as cooling fans, air conditioners, and other temperature-sensitive components [4].



The designed system can be integrated with various technologies and devices. With the rapid popularization of the Internet of Things (IoT) and smart edge devices, the demand of implementing machine learning algorithms on embedded devices is an increasing, embedded systems are being more complex where a greater number of constituent components are merged into systems on-chips (SoCs) [5-7]. Systems utilizing these devices usually blend traditional boundaries between hardware and software, The embedded processor system has designed to get a pulse width modulation (PWM) that signals engage a wide range of applications in electrical drives and power electronics, for design an embedded processor system [8]. Embedded design techniques are an excellent tool to configure it on field programmable gate arrays (FPGAs) board, also program it to work in according to the target which can generate a PWM signal controller [9, 10].

Hardware Design and Implementation

The initial step in designing the system is to get the input temperature and convert it to voltage. The conversion of temperature to voltage is done by using an LM35 sensor with an Arduino, by connect the LM35 sensor to the Arduino board. The LM35 sensor has three VCC, GND, and OUT. Connect the VCC pin to the 5V pin on the Arduino board, the GND pin to the GND pin on the Arduino board, and the OUT pin to an analog input pin on the Arduino board, the voltage output from the LM35 sensor is proportional to the temperature, these have done by using the following formula to convert the voltage to temperature (Eq. 1).

$$\text{Temperature (}^{\circ}\text{C)} = \text{Voltage Output from LM35 Sensor} * 100 \quad (1)$$

The Vivado integrated development environment (IDE) software was used to construct the hardware part [11]. The hardware architecture is presented in Figure 1. The system was built using Pynq-Z2 FPGA processor with the AXI BRAM memory, AXI GPIO, AXI Timer (8), XADC Wizard. Thus, the system takes a temperature as an input and converts it to voltage, then it will use the ANFIS model to determine the duty cycle that controls the runtime of the devices. This can be utilized for various applications.

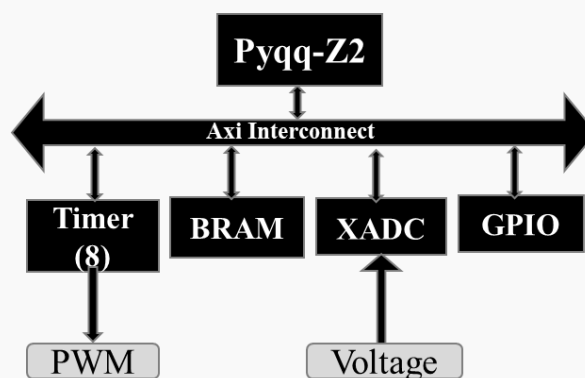
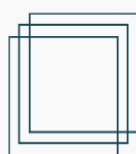


Figure 1. The hardware components of the designed system.

2.1. PWM

Pulse Width Modulation (PWM) is a technique used to generate analog output signals from digital inputs. It is commonly used in embedded systems to control motors, servos, also other devices that require precise control and can be used to create complex control systems [5]. PWM works by varying the width of a pulse over time, which is then used to control the power output of the device. The frequency of the pulse determines the resolution of the output, while the duty cycle determines the average power output, the duty cycle of the pulses is used to control the amount of power delivered to the device. The duty cycle is the ratio of the pulse width to the total period of the signal. A duty cycle of 50% means that the power is on for half of the time and off for the other half. The formula for computing the duty cycle is shown in Eq.2.

$$\text{Duty cycle (\%)} = (T_{\text{On}} / (T_{\text{On}} + T_{\text{Off}})) * 100 \quad (2)$$

Where T_{on} is the active part of the duty cycle which (High part of the wave) and T_{off} is the off part of the duty cycle (Low part of the wave). The frequency of PWM is calculated via Eq.3

$$\text{Frequency (PWM)} = 1 / (T_{\text{On}} + T_{\text{Off}}) \quad (3)$$

ANFIS

The ANFIS approach operates by utilizing artificial neural networks combined fuzzy logic systems, thus taking advantage of the two methods to provide a more robust control system [12]. The first step of any fuzzy control system is the fuzzification of the input values.

This step converts the input values from the crisp (i.e. real-world) values to a fuzzy value which is in range [0, 1]. A membership function is used for this purpose. In this study, the triangular membership function was used, which is suitable for this type of application. In the next step, the fuzzified values are used in rules evaluation which takes the form of a set of IF-THEN rules [13]. For example, IF Temperature is HIGH THEN Voltage is HIGH. Following the evaluation of the rules, the strength values from each rule are combined and defuzzified to produce a crisp (i.e. real-world) value, which is the output of the system. The central area method was used as the defuzzification method. The input value was the temperature and the output value is the Ton, which is used to calculate the duty cycle (d) to determine which timers of the system are going to be used which will ultimately control the system run.

3.1 ANFIS Layers

The architecture of the ANFIS artificial neural network is depicted in Figure 2. As can be seen, the network consists of five distinct layers. The input value is processed by the layers sequentially to produce the output value. The weights are updated after each training cycle (epoch) to adjust and learn the correct values. In the first layer, the input values are fuzzified by the triangular membership function to produce the fuzzy values. The next layer takes the output of the first layer (the fuzzified values) and calculates the firing strength of each linguistic variable (i.e. HIGH Temperature, Low Temperature, etc.). In the third layer, normalization of the weights of the pervious layer occurs. The normalization process ensures that the weights values are normalized in the range of [0, 1]. In the fourth layer, the rules evaluation takes place using the output of the previous layer and the set of IF-THEN rules previously defined. In the final layer, the output from the previous layer are summed via a summation method to produce the output value [4].

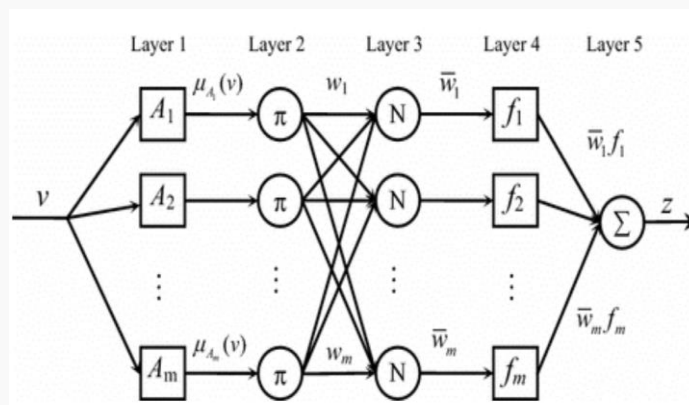
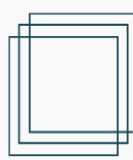


Figure 2. Depiction of the architecture of the ANFIS neural network.



3.2. Implementation and Model Training

The ANFIS network of this study was implemented using the C language, which provides better performance and memory management compared to other high level languages such as the Python language. This ensures that the system can perform efficiently with minimum requirements on embedded systems which do not have same memory or CPU of other computer systems.

The dataset was split into a training and test set. The test set was used to train the ANFIS model while the test set was used to validate the model. The training of the ANFIS model is done in cycles. In each cycle the network modifies the weight to minimize the error. This error is calculated using a cost function. In this study, a simple and efficient cost function was used which is the root mean squared error (RMSE). The optimum number of cycles was calculated based on the RMSE of the training set. In other words, the number of cycles that gave the lowest error was determined to be the optimum number of training cycles and the model corresponds to it was obtained. The obtained model was validated using the test set and validation parameters such as the mean absolute error (MAE) were computed to assess the performance of the model.

Results

4.1. ANFIS Model

The ANFIS model was trained using the previously described procedure. Determining the number of optimum training cycles was done via running the network and measuring the RMSE at each training cycle. The training cycles number corresponding to the lowest RMSE was found to be 200 training cycles. As can be seen in Figure 3. The RMSE value initially drops rapidly in the beginning, as expected. Then, the RMSE starts to stabilize and reaches the lowest value at 200 training cycles. Then the error starts increasing, which indicates overfitting of the network is starting to occur due to excessive training of the network. The model obtained at 200 training cycles was further validated.

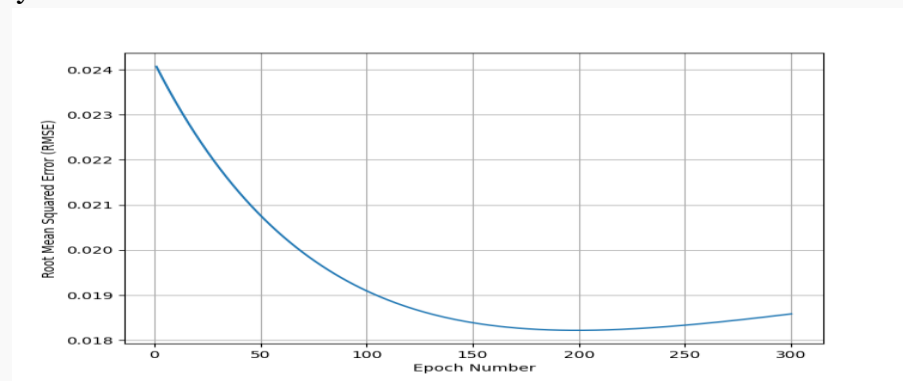
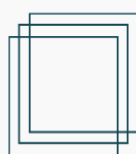


Figure 3. The plot of the number of training cycles corresponding to the RMSE.



Internal and external validation parameters were computed. The values for the training and test sets are presented in Table 1. As can be seen in the table. The coefficient of determination (R^2) had values of 0.999 and 0.999 which indicates that the model is able to correlate the input and output values. Also, the prediction error was low as demonstrated by the MAE and RMSE values. The test set had values of 0.002 and 0.013 for the MAE and RMSE, respectively, which reflects that the model is able to predict the output of entries outside the training set, which means the model is reliable.

Table 1. Validation parameters of the ANFIS model for the training and test sets.

Parameter	Value
R^2	0.999
MAE	0.002
RMSE	0.019
$R^2_{(\text{test set})}$	0.999
$MAE_{(\text{test set})}$	0.002
$RMSE_{(\text{test set})}$	0.013

The predicted and the experimental values of the training and test sets are plotted in Figure 4. Overall, the model is able to efficiently predict the output value of the system and can be used in applications.

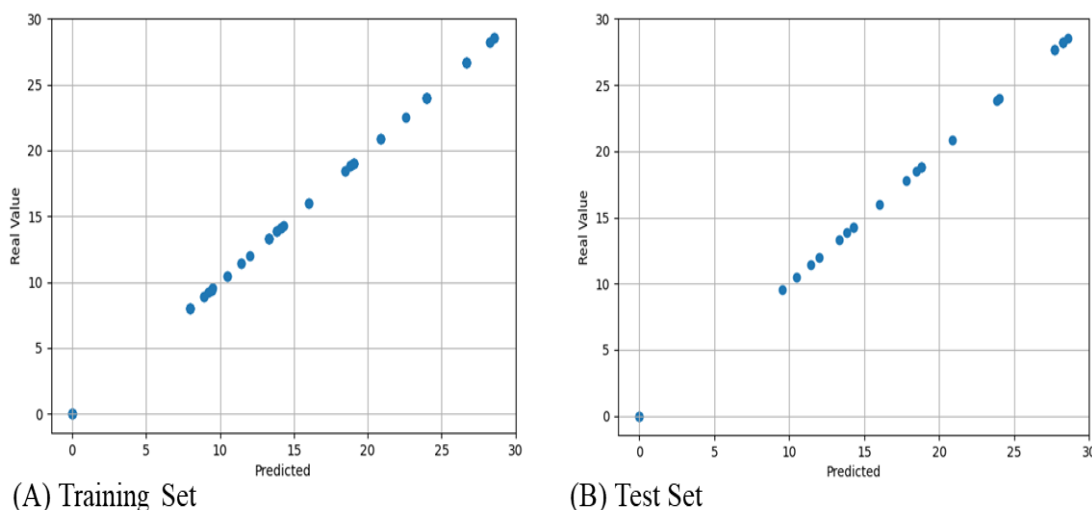


Figure 4. The plot predicted values against the experimental values for: A) the training set and B) the test set.

The system can generate PWM signals that can control the runtime of motors and various devices. An example of the generated PWM waveforms is shown in Figure 5.

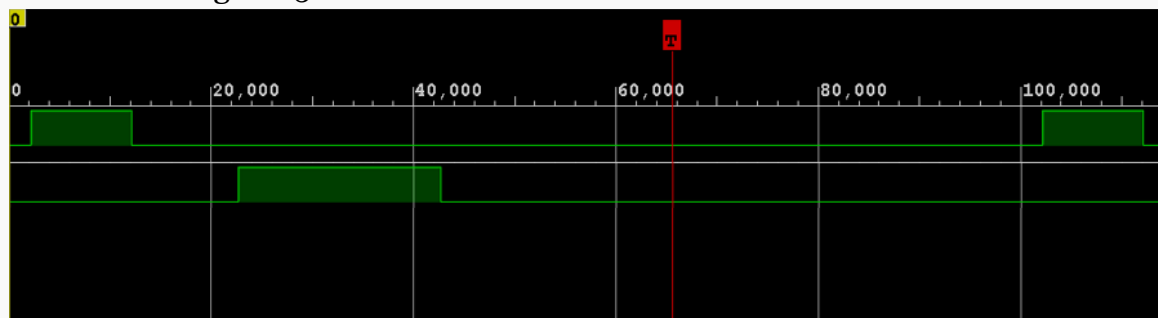


Figure 5. Example of PWM waveforms generated by the system.

Conclusion

An embedded system was designed which controls the runtime of devices from the input temperature. The output of the system is determined by using a developed ANFIS model. The model was training and validated using training and test sets. The validation parameters of the model indicated that the model is reliable and efficient, hence it can be used to predict the output from the input temperature. The output is then used to compute the duty cycle which in turn generates PWM signals to control the runtime of various components such as motors. Thus, the system can be utilized in various areas and technologies to provide efficient control and performance.

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