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Electronic Device Control Method Based on Improved Neural Network Algorithm

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Abstract
Smart home appliances are one of the development directions of home appliances. Using artificial neural network or fuzzy artificial neural network to realize intelligent control of electrical appliances has the characteristics of powerful functions and strong adaptability. The control of household appliances is relatively simple, but the artificial neural networks currently used in industry are implemented using large-scale field programmable gate arrays (FPGAs), which is not cost-effective for general electrical applications. The purpose of this research is to study the artificial neural network control of electrical equipment based on simple analog circuits. Has the following characteristics: to meet the basic requirements of automatic control of electrical equipment; simple structure, low cost, strong economic and practical; simple learning and training, easy to operate, suitable for large-scale production; with general characteristics, that is, different learning and training can Different application needs. This article uses PSpice circuit simulation software to model, simulate and optimize the circuit. In this paper, PSpice simulation software is used to model, simulate and optimize the nonlinear function generator circuit, adder circuit and analog multiplier circuit, and finally obtain the expected results. PSpice circuit simulation software is convenient and fast. Using simulation results to guide the experiment, you can achieve twice the result with half the effort. This article designs a load cell that can convert different weights into electrical signals, then normalize them, and then amplify the signals as the input to the ANN. Using the error analysis of the ANN overall circuit, the calculated maximum error is only 1.17%. In the end, this article draws the results of a simple artificial neural network circuit design scheme that is simple in structure, low in cost, and common for learning and training programs, which is convenient for manufacturers to mass produce.

Keywords: *Artificial Neural Network, PSpice Software, Operational Amplifier, Adder, Multiplier;*

1. Introduction

Since the 1980s, the theoretical research results of neural networks have achieved fruitful application results in many engineering fields, such as automotive engineering, military engineering, chemical engineering, and hydraulic engineering. This article uses analog circuits to implement a simple artificial neural network (ANN). Intelligence is a major trend in the development of household appliances in the future. This article uses analog circuits to implement a simple artificial neural network (ANN). By training the artificial neural network by self-programming and normalizing the variables, it realizes that the objective function can

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be expanded into a polynomial with finite terms under the premise of certain accuracy, so as to realize the specified artificial neural network model function. The self-programming training theory in this paper has universality, that is, given any curve, specific coefficients can be trained on the premise of satisfying the required accuracy through the program given in this paper. The hardware circuit using analog circuits to achieve specific functions is not complicated in structure, and the price of the integrated block is low, the performance is reliable, and it is convenient for mass production. For the future, it is of great significance to study analog circuits to realize the artificial neural network control of electrical equipment.

The research on hardware implementation of artificial neural network started in the late 1950s. At that time, scholars proposed various neural network models and their training methods. In order to apply advanced neural networks to actual production, some scientific research institutions have begun to try to implement neural networks in hardware [1]. Alan Saied proposed a perceptron model that can solve simple linear classification problems. At the same time, Amirmahyar Khorasani proposed an adaptive linear unit model that can continuously obtain values. Both types of models can automatically update input connection weights by learning. Value (synaptic strength), where the sensor changes the size of its synaptic strength through the rotation of the motor, but it has the disadvantages of large volume and low cost [3]. Song Mingli Song proposed and implemented a neural network model with a feedback channel through an operational amplifier. This model can solve nonlinear optimization problems in some complex network systems, such as the traveling salesman problem. Entering the climax once [4]. Chirag Deb et al. A method for implementing each unit circuit of a radial basis function neural network is proposed, and an RBF neural network circuit with six hidden layer neurons is realized through a CMOS analog circuit, which can be used to solve the nonlinear function approximation problem [5]. Dergachev V A implemented an RBF neural network circuit with dynamic weight adjustment based on the error back-propagation algorithm, and verified it by solving the XOR problem and data classification problem [6]. Johan Strandgren has published an article that has played an important role in the revival of neural network research. He summarized and borrowed the results and experience of previous research on neural networks, summarized the various structures and algorithms of the network, and shaped a new and powerful network model [7]. Sabato Marco Siniscalchi has conducted in-depth research on multilayer feedforward neural networks whose excitation function is a non-linear function. The network is very flexible and plays a very important role in many applications [8]. Adriano Lino and other companies have launched their own digital or analog neural network chip products. These chips have reached the practical level in terms of network scale and operating speed, which greatly promoted the development of artificial neural network applications [9]. However, the complete hardware implementation of artificial neural networks also has many disadvantages. Due to the lack of flexibility and programmability of the connection methods between processing units implemented in hardware, the lack of versatility makes it difficult to meet the needs of different users. Therefore, in some existing artificial neural network systems implemented in hardware, a compromise method is usually adopted-the basic neuron or neural network module device is implemented by hardware.

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Programmable control to process, which improves the flexibility and programmability of the neural network and meets the needs of different users [10]. Comprehensive frontier. The application of neural networks has penetrated into various fields of pattern recognition, image processing, nonlinear optimization, speech processing, natural language understanding, automatic target recognition, robotics and expert systems, and has achieved significant results [11-12]. At the same time, the United States, Japan and other countries have also made some substantial achievements in hardware neural network computers.

This article uses a self-programming method to train the hardware circuits of an artificial neural network. The training of artificial neural network is one of the key tasks in this paper. Artificial neural network training can be divided into hardware and software hybrid methods and pure software training methods. Pure software training methods can be divided into circuit simulation software optimization methods and self-programming training methods. The training procedure in this article is universal, which is convenient for related personnel to set different parameters according to different application requirements to obtain the required training effect. This is the main function of this article. In this paper, the adder circuit and the multiplier circuit are used to form a complete artificial neural network circuit that meets the requirements. The result of this paper is to provide a simple artificial neural network circuit design scheme with simple structure, low cost, and universal learning and training process, which is convenient for manufacturers to mass produce. Using the error analysis of the ANN overall circuit, the maximum calculation error is reduced to only 1.17%.

2. Proposed Method

2.1 Overview of Artificial Neural Networks

(1) So far, each generation of computers is based on the working principle of von Neumann: its information is stored and processed decentralized, that is, the memory and processor are independent of each other. The processed information must be formal information, that is, text defined by binary encoding, tags, numbers, instructions, and various standardized data formats, command formats, and so on. [13]; and the information processing method must be serial, that is, the CPU repeatedly addresses the four steps of decoding, execution, and storage [14]. The structure of a computer and its serial working mode determine that it is only longer than digital and logical operations. People have combined the microscopic level obtained through molecular and cell level technology with the system level obtained through behavioral research, thus forming a basic understanding of the human brain neural network [15]. Based on this basic understanding, artificial neural networks (ANN) were imagined from mathematical and physical methods and information processing, and simplified models were created. Artificial neural network is far from the true description of human biological neural network, but its simplification, abstraction and simulation [16]. Happily, this simplified model can reflect many basic characteristics of the human brain, such as adaptability, self-organization, and strong learning capabilities [17].

(2) Basic characteristics and functions of artificial neural networks

The basic characteristics of artificial neural networks mainly include: structural characteristics; information processing characteristics; intelligent characteristics.

1) Structural characteristics: It consists of a

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large number of simple functional neurons, which are connected by synapses. This connection can be achieved through the organic transfer of weighted information [18]. The so-called organic transmission refers to excitation and strong or weak transmission that can achieve connection (unhindered connection) or prohibit (block connection). The structure is plastic.

2) Characteristics of information processing: Information processing is parallel, with high nonlinearity and fault tolerance. It can handle inaccurate, incomplete and obscure information [19]. The information store is distributed and associated.

3) Intelligent feature: it has adaptive features, that is, the ability to learn and construct itself. This is an important feature of artificial neural networks [20]. The learning device of artificial neural network, its training and recognition for a period of time, when the external environment changes, the artificial neural network can adjust the structural parameters of the internal network to generate the required specific inputs and outputs. Artificial neural network, including basic functions: associative memory; classification and recognition; optimization calculation functions; nonlinear mapping functions.

(3) Artificial neural network model

Artificial neural network is a data processing model inspired by biological neural network. The human brain contains 100 billion neurons, and its computing power is several times that of today's most advanced computers. ANN is a network that mimics the structure of the human brain. There are a large number of artificial neurons in the network. They are interconnected and calculated. They modify their parameters based on external information. They mainly adjust the connection weight of each neuron through network training. Model the input data of the input layer, store the learned knowledge in the adjusted connection weights, and finally make the network capable of solving practical problems [21-22]. In artificial neural networks, neurons are often referred to as "processing units," and sometimes from a network perspective, sometimes called "nodes." Artificial neurons are the formal description of biological neurons. Its abstract biological neurons process information and describe it using mathematical language. It mimics the structure and function of biological neurons, as shown in Figure 1.

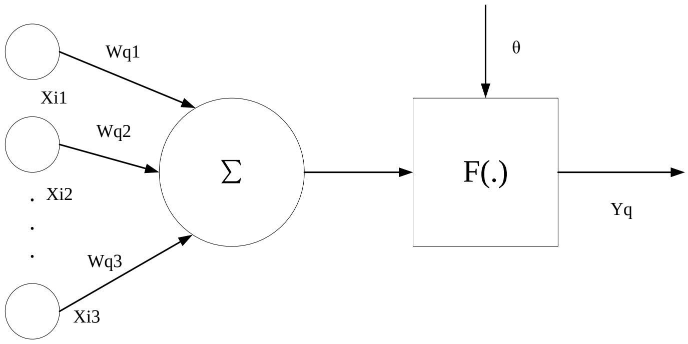

Figure 1. Block diagram of a neuron

The figure above shows the structure of artificial neurons. In the figure, $x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}$ is the multi-dimensional input of the neuron; $w_{q1}, w_{q2}, w_{q3} \ldots, w_{qn}$ is the weight of the connection between the input sample and the neuron. In a suppressed state; Σ indicates a sum connector, and its role is to inner product and sum the input samples and corresponding connection weights; θ indicates the threshold or deviation of the neuron; $f(\ )$ indicates the input-output relationship function of the neuron, called the activation function or output function, its role is to transform the input sample data through some activation functions, so that the output sample value is within the specified specific range; y_q is the output value of the neuron, and its expression such as (1) shown.

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$$y_q(t) = f\left(\sum_{i=1}^{n} Wqi X_i - \theta\right) \quad (1)$$

Where X represents the input of the entire sample and can be expressed as:

$$X_i = [x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}] \quad (2)$$

The weight vector can be expressed as:

$$W_q = [w_{q1}, w_{q2}, w_{q3}, \ldots, w_{qn}]^T \quad (3)$$

In ANN, the structure of the network can affect the ability and efficiency of the network to solve practical problems, and the activation function in the hidden layer of the network will also affect it. The activation function is an important part between the hidden layer neurons and the output layer. Different types of activation functions will have a huge impact on the convergence speed of the network. For specific practical problems, the choice of activation function should be different. Here are some common activation functions:

1) Threshold function

$$f(x) = \begin{cases} 1, x \geq n \\ 0, x < n \end{cases} \quad (4)$$

This function is similar to a step function. When the activation function uses this function, the artificial neuron model is the MP (McCulloch-Pitts) model. This function has a simple structure and is easy to understand. Its main function is to randomly input samples through function expression. The data is converted to a value of 1 or 0, which reflects the excitation or inhibition of the neuron.

2) Sigmoid function

$$f(x) = \frac{1}{1+\exp(-ax)}, 0 < f(x) < 1 \quad (5)$$

Sigmoid function, which is a logarithmic shape function, whose output is in the range of (0, 1), suitable for the output range of 0-1Between signals is the most widely used activation function in ANN.

3) Hyperbolic tangent shape function

$$f(x) = \frac{1-\exp(-2a)}{1+\exp(-2a)} \quad (6)$$

The hyperbolic tangent function is similar to a smooth step function. The shape is the same as the Sigmoid function. It is symmetrical at the origin and its output value is between -1 and 1. The range of the output of the Sigmoid function is improved in the range (0,1) and the output values are all defects with positive values, which is suitable for outputting signals in the range (-1, 1) [23].

(4) Feedforward network

Feedforward networks are also called multi-layer or layered networks. In addition to the input and output layers, there is a hidden layer. Name different types of feedforward neural networks based on the number of hidden layers. If there is only one hidden layer, it is called a single hidden layer feedforward neural network (SLFN). If there are multiple hidden layers, it is called a multilayer hidden feedforward neural network. Compared with the above feedback network, neurons in the same layer of the feedforward network are not connected to each other, and there is only horizontal connection between neurons from one layer to another. The structure of the feedforward neural network is shown in Figure 2.

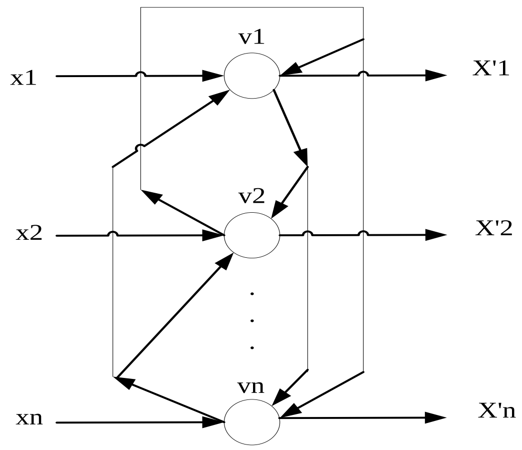

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Figure 2. Basic block diagram of feedback neural network

The solid line in the figure represents the actual flow of the input signal, and the dashed line represents the back-propagation of the output signal. From a system perspective, feedforward neural networks can obtain complex non-linear processing capabilities by performing simple non-linear processing on synthetic maps. BP neural network, LVQ network, CMAC network and MPL network are typical examples of feedforward networks [24]. According to the learning method of the model, the basic structure of artificial neural networks is mainly divided into the following two types: feedback networks and feedforward networks.

1) Feedback network

Feedback networks are also called recursive networks. A neural network is formed by the interconnection of multiple neurons. The network output of some neurons can be fed to neurons in the same layer or in the previous layer, that is, the input signal can flow from the forward neuron, and the reverse neuron can also flow from the reverse neuron to the reverse Neurons. Forward neurons have at least one feedback loop. $x_{i1}, x_{i2}, x_{i3}, \ldots, x_{in}$ is the input signal, x_i is the current state of the i-th node, $x'_{i1}, x'_{i2}, x'_{i3}, \ldots, x'_{in}$ is the output value after convergence, and $v_1, v_2, v_3, \ldots, v_n$ is the number of hidden layer neurons. Hopfield network, Jordan network, ELman network, etc. are typical representative models of recursive networks.

2) Feedforward network

Feedforward is named because the direction of network information processing is from the input layer to the hidden layer to the output layer, which is carried out layer by layer. From the perspective of information processing capabilities, nodes in the network can be divided into two types: one is the input node, which is only responsible for introducing information from the outside to the first hidden layer; the other is the input node. The other is processing nodes, including each hidden layer node and output layer node.

2.2 Simulation of Nonlinear Function Generator with PSpice

(1) Theoretical analysis of nonlinear function generator

In the field of science and technology, analog circuits called nonlinear function generators are often required. Its voltage transmission characteristic $v_0 = f(v_s)$ is consistent with some non-linear functions. There are three types of typical non-linear function generators: finite amplitude, extended, and inverse. In order to simulate the non-linear function, piecewise linearization is usually used, that is, the polyline is similar to the non-linear voltage transmission characteristic curve of the function being simulated [25].

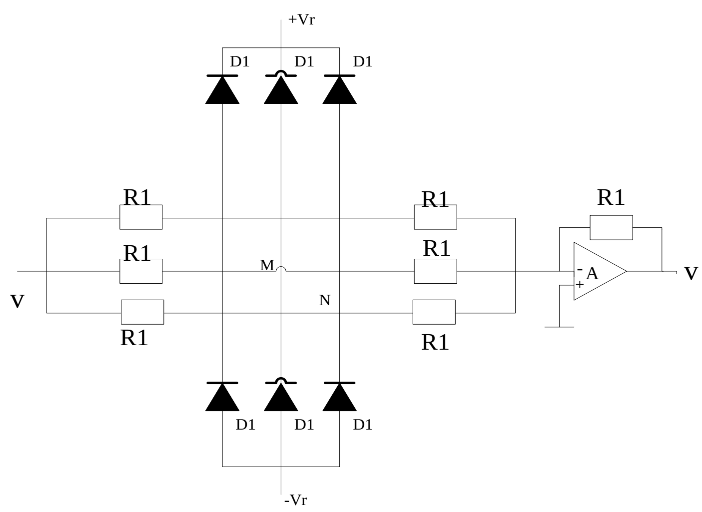

Figure 3. Limiting type function generator (a) circuit

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When $|v_s|$ is small, $D_1 \sim D_6$ is cut off due to reverse bias. At this time, the $r_1 = (R_1 + R_2)//(R_3 + R_4)//(R_5 + R_6)$ resistance is the smallest, and the slope of the AA' section of the characteristic curve is:

$$S_0 = \frac{dv_0}{dv_s} = -\frac{R_f}{r_1} = -\frac{R_f}{(R_1 + R_2)//(R_3 + R_4)//(R_5 + R_5)} \quad (7)$$

Let D be the ideal diode, then when v_s increases to

$$V_{s1} = \frac{R_1 + R_2}{R_2} V_R \quad (8)$$

When D_2 is turned on and the potential at point M is clamped to $+V_R$, the slope of the characteristic curve of BC segment is:

$$S_2 = \frac{dv_0}{dv_s} = -\frac{R_f}{R_5 + R_6} \quad (9)$$

When v_s increases to

$$V_{s3} = \frac{R_5 + R_6}{R_6} V_R \quad (10)$$

When D_3 is turned on, the current of R_2, R_4, R_6 no longer changes, which is equivalent to r_1 equal to ∞ , so the CD segment

The slope of the characteristic curve is:

$$S_3 = \frac{dv_0}{dv_s} = 0 \quad (11)$$

Similarly, the characteristic curve at $v_s < 0$ can be obtained. OA'B'C'D.

(2) Theoretical analysis of the adder circuit

Circuits that implement the sum of multiple input signals with their different ratios are collectively referred to as adding circuits. All input signals are applied to the same input terminals of the integrated operational amplifier and addition operations can be performed. Figure 4 shows a schematic diagram of the inverting summing circuit. Multiple input signals of the inverting summing circuit all act on the inverting input of the integrated operational amplifier.

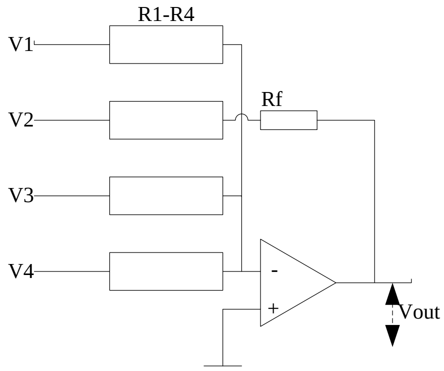

Figure 4. Inverting summing circuit

Set up the circuit schematic model of the adder in PSpice, set the value of each component, select the DC voltage scan, the voltage scan range is -20V ~ + 40V, and the scan interval is 0.01. With the input voltage as the abscissa and the output voltage as the ordinate, a coordinate system is established, and the corresponding parameter values and formulas of each element can be seen that the simulation curve is consistent with the theoretical calculation, and the simulation results are satisfactory.

(3) Theoretical analysis of analog multiplier circuit

The logarithmic-logarithmic analog multiplier circuit technology is mainly based on the following two principles: One is the basic nature of logarithmic operations, that is, the logarithm of two numbers and the logarithm of the product of these

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two numbers, which can be expressed as

$$\ln X + \ln Y = \ln(XY) \quad (12)$$

The second is the basic characteristics of the transistor, that is, the forward voltage drop of the transistor PN junction and the current have a logarithmic relationship, which is expressed by the formula:

$$V_{be} = (KT/q)\ln(I_c/I_s) \quad (13)$$

Where V_{be} is the voltage drop of the transmitting junction, I_c is the collector current, I_s is the reverse saturation leakage current, KT / q is a coefficient, and some are written as V_T, which is actually a voltage coefficient related to temperature. By combining the above transistor characteristics with an operational amplifier, a logarithmic and antilogarithmic amplifier can be obtained. The output of the two logarithmic amplifiers can be summed (adder), and then the antilogarithmic amplification can be performed to achieve the multiplication of the analog signal.

The key to realizing four-quadrant operation is to solve the problem that the logarithmic amplifier and antilogarithmic amplifier in the circuit can only input positive (or negative) voltage signals due to the unidirectional conductivity of the transistor. We can imitate the method of amplifying the AC signal (positive and negative signal) after the triode is added with a forward bias voltage, and the logarithmic amplifier and the antilogarithmic amplifier can be forward biased to make the logarithmic transistor when a negative signal is input. It is still conducting positively, so that logarithmic and antilogarithmic operations can be completed regardless of the input of positive or negative signals.

3. Experiments

3.1 Experimental Environment

This article uses analog circuits to implement a simple artificial neural network (ANN). By training the artificial neural network by self-programming and normalizing the variables, it is realized that the more the terms of the polynomial expansion are, the more complicated the circuit is, and the higher the cost is, under the premise of certain accuracy. Therefore, within the range allowed by the error, try to reduce the number of polynomial expansion terms as much as possible. In this paper, four-term polynomial expansion is selected. Twenty-seven resistors and five potentiometers are used in the ANN overall circuit. After testing, the error of the resistor is about 2% -3%, so the error of the resistor itself cannot be ignored, and it is one of the main sources of error. Properly increase the cost and use high-precision resistors can effectively reduce errors. The potentiometer WS5 can be used for error correction of the entire ANN circuit. The objective function is expanded into a polynomial with finite terms, so as to achieve the specified artificial neural network model function. The ANN integrated circuit in this article is the most critical part of the overall system of household appliances, and is necessary to achieve intelligent control of household appliances. For the entire system of household appliances, there are many aspects to achieve intelligent control. For example, the weight of a heated object needs to be converted into an electrical signal by a sensor. If the strength of the electrical signal is too weak or does not meet the requirements, an operational amplifier can be used make level adjustments.

3.2 Experimental Steps

(1) The experiment first is to design a load cell that can convert different weights into electrical

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signals, then normalize them, and then amplify the signals as the input of the ANN. Then the self-programming is used to train the ANN. Based on the hardware training of the artificial neural network of the power series, the initialized (that is, any set of resistance values to be determined) ANN corresponding to the normalized sample group composed of samples. The mathematical model of the circuit, let its output, the number of finite orthogonal basis functions, and then learn from the ANN circuit sample training, simplified to a mathematical optimization problem, take one of the minimum or least square method.

(2) Then, the exponential function is trained and simulated. Taking the $y = e^x$ function as an example, first write a program in Fortran to generate the required data, then use the origin drawing software to draw the curve, and then use MatLab programming to obtain the final result. Among the array data, the curve drawn by Origin is used to achieve the least square fitting in MatLab. The usual approach is to use the polyfit function for polynomial fitting. Run the above program, train the polynomial coefficients, compare the polynomial fitted curve with the target curve in the same coordinate system, and use the polynomial fitted curve to match the target curve to obtain the error analysis.

4. Discussion

4.1 Implementation of Adder Circuit

Take three voltage inputs in the experiment, fix the value of two input voltages and change the value of the other input voltage. The experimental circuit is shown in Figure 5-6. The fixed two input voltage values are 0.5V and 1.5V, and they are sampled ten times. The data are shown in Table 1:

Table 1. Data table of adder circuit implementation

Serial number	V1(v)	Vout(v)
1	0.02	-2.05
2	0.04	-2.07
3	0.08	-2.11
4	0.16	-2.19
5	0.21	-2.25
6	0.29	-2.31
7	0.35	-2.38
8	0.41	-2.44
9	0.49	-2.52
10	0.57	-2.61

Draw a curve based on the above data, and compare the experimental curve with the theoretical curve in the same coordinate system, as shown in Figure 5.

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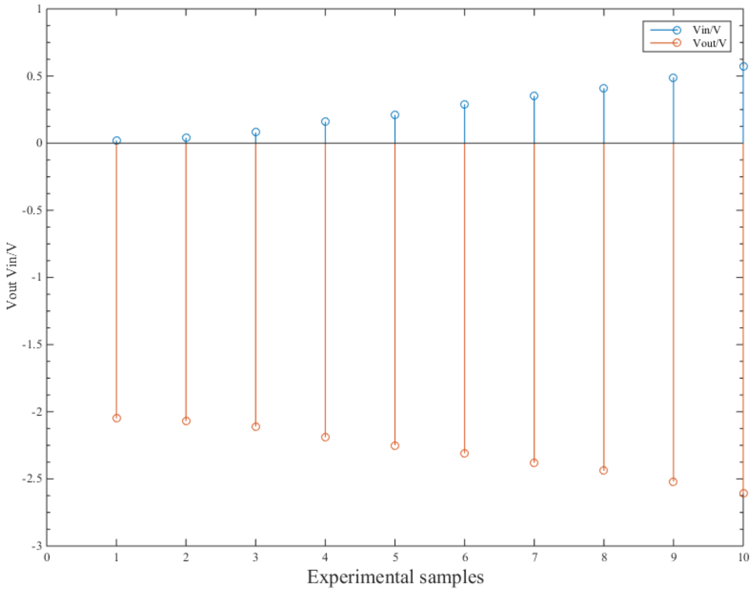

Figure 5. The comparison between the experimental curve and the theoretical curve of adder

As can be seen from Figure 5, the voltage scan range is -20V ~ + 40V, and the scan interval is 0.01. The input voltage is then used as the abscissa, and then the output voltage is used as the ordinate to create a coordinate system. In order to achieve the sum of multiple input signals according to different proportions, the parameter values and formulas corresponding to each element are collectively referred to as an adding circuit. Multiple input signals of the inverting summing circuit all act on the inverting input of the integrated operational amplifier. And all input signals are applied to the same input of the integrated operational amplifier, which is used to implement the addition operation. We can see that the experimental curve and the theoretical curve are basically the same, and the calculated maximum error is 1.94%.

4.2. Implementation of the Multiplier Circuit

Take three voltage inputs in the experiment, fix the value of two input voltages, and change the value of the other input voltage. The experimental circuit is shown in Figure 6. The two fixed input voltage values are 0.5V and 1.5V, and the samples are taken ten times. The experimental data are shown in Table 2:

Table 2. Data realized by multiplier circuit

Serial number	Vx1(v)	V0t(v)
1	0.4	0.13
2	0.5	0.22
3	0.7	0.48
4	0.9	0.80
5	1.5	2.25
6	1.8	3.28

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7	2.0	4.05
8	2.4	5.9
9	2.7	7.37
10	3.0	9.21

Map based on the measured data, and compare the experimentally measured curve with the theoretically calculated curve in the same coordinate system, as shown in Figure 6.

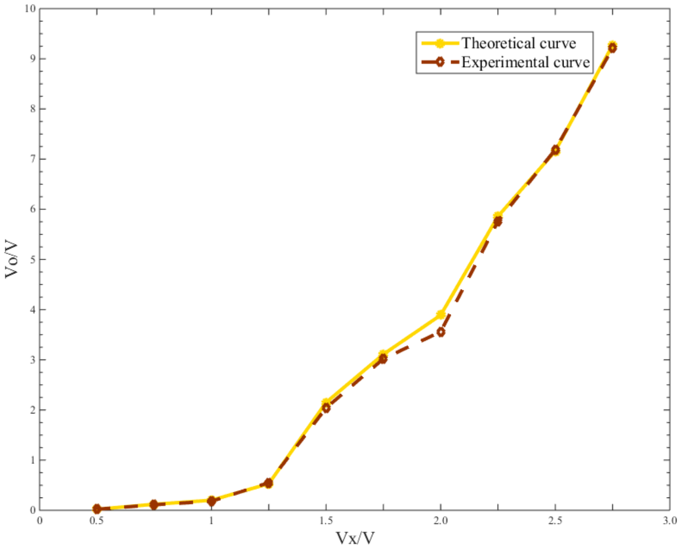

Figure 6. The comparison of experimental curve and theoretical curve of multiplier

As shown in Figure 6, during the calculation of the error, we found that the smaller the value of the input voltage, the larger the error. Schematic diagram of a four-quadrant analog multiplier circuit. The key to realizing the quadrant operation is to solve the problem that the logarithmic amplifier and antilogarithmic amplifier in the circuit can only input positive (or negative) voltage signals due to the unidirectional conductivity of the transistor. We can imitate the method of amplifying the AC signal (positive and negative signal) after the triode is added with a forward bias voltage, and the logarithmic amplifier and the antilogarithmic amplifier can be forward biased to make the logarithmic transistor when a negative signal is input. It is still forward, and is used to calculate. Among the above ten measured data, the first group has the largest error, and the calculated maximum error is 25%.

4.3 Training and Simulation of the Curve Obtained from the Boiling Water Experiment

Induction cooker heating cold water experiment: ambient temperature: 22.7 degrees Celsius, initial temperature of water: 15.5 degrees Celsius, temperature when water boils: 97.4 degrees Celsius. Use electronic weighing to take samples ten times. The experimental data are shown in Table 3:

Number Paramete	1	2	3	4	5	6	7	8	9	10

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r										
M/g	600	750	1054	1359	1787	1951	2415	2846	3304	3614
T/s	114	139	186	2251	308	341	426	485	571	634

Normalize the above experimental data. The quality is divided by 5000 and the time is divided by 600. The processed data is as follows: m1 = 0.12, t1 = 0.19167 m2 = 0.151, t2 = 0.23333, m3 = 0.203, t3 = 0.30833 m4 = 0.274, t4 = 0.41167, m5 = 0.341, t5 = 0.51167 m6 = 0.395, t6 = 0.57833, m7 = 0.494, t7 = 0.70333 m8 = 0.569, t8 = 0.82333, m9 = 0.668, t9 = 0.95667 m10 = 0.735, t10 = 1.05333 Draw the experiment with Origin, as shown in Figure 7.

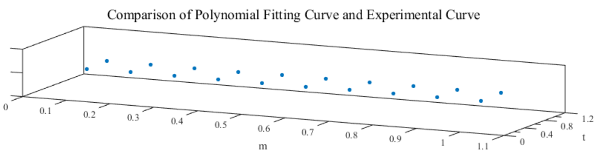

Figure 7. Comparison of Polynomial Fitting Curve and Experimental Curve

It can be seen from the figure that when the polynomial is used to fit the above curve and run the above program, the training polynomial coefficients obtained are: a (0) = 0.4661, a (1) =-0.6100, a (2) = 1.6282, a (3) = 0.0019. In the same coordinate system, the curve fitted by the polynomial is compared with the curve obtained by the experiment. The curve fitted by the polynomial is basically consistent with the curve obtained by the experiment. The maximum error calculated is 1.45%.

4.5 ANN Overall Circuit Implementation

Combined with the schematic of the ANN overall circuit, the Xo term is generated by the potentiometer WS3, the X1m term is generated by the operational amplifier connected to the resistors R18 and R19, the X2m ^ 2 term is generated by the multiplier U3, and the X3m ^ 3 term is generated by the multiplier U4, and then added the inverter and inverter obtain the output T (m). Then use Protel software to draw a PCB diagram, adjust potentiometer WS3 so that its output is 0.4661V, and adjust WS1 so that its output is 0.92V. Because the two inputs of the multiplier that produces the cubic term are m and 22x m, adjust WS2 to output 12V, and adjust WS4 to output 1.4KΩ. This can make the coefficient before the cubic to be 0.0019. The experimentally measured data are shown in Table 4:

Table 4. Implementation data of ANN overall circuit

Serial number	Vx1(v)	V0t(v)
1	0.4	0.13
2	0.5	0.22
3	0.7	0.48
4	0.9	0.80
5	1.5	2.25
6	1.8	3.28
7	2.0	4.05
8	2.4	5.9
9	2.7	7.37
10	3.0	9.21

The theoretical calculation formula is:

$$f(m) = 0.4661 - 0.61m + 1.6282m^2 + 0.0019m^3 \quad (14)$$

Draw a curve from the above ten sets of data, and compare it with the theoretically calculated curve in the same coordinate system, as shown in

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Figure 8.

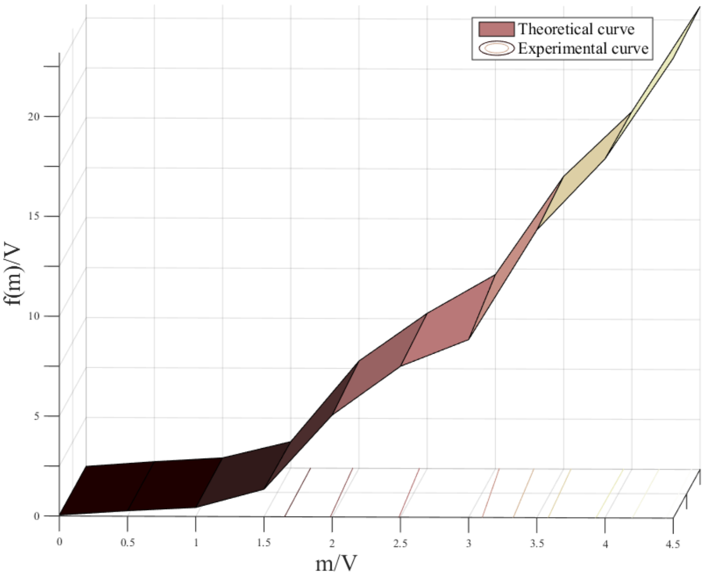

Figure 8. The comparison between the measured curve and the theoretical curve of an integrated circuit

As shown in Figure 8 above, draw a curve from the above ten sets of data, and compare it with the theoretically calculated curve in the same coordinate system.

By comparison, the maximum error between the measured curve and the theoretical curve of the ANN overall circuit is 7.78%, and the minimum error is 1.07%. In this paper, a polynomial fitting method is used to approximate the target curve, so the number of polynomial expansion terms has become one of the main sources of error. In addition, the inherent error of the resistor used in the assembly of the entire ANN circuit is also a factor of the error. After testing, the error of the resistor is about 2% -3%. After calculation, the cost is appropriately increased, and the use of high-precision resistors can effectively reduce the error.

4.4ANN Error Analysis of the Overall Circuit

In this paper, a polynomial fitting method is used to approximate the target curve, so the number of polynomial expansion terms has become one of the main sources of error. In addition, the self-resistance of the resistor used in the assembly of the entire ANN circuit is also one of the main sources of error.

Let the polynomial be:

$$f(m) = x_0 + x_1 m + x_2 m^2 + x_3 m^3 + x_4 m^4 + \ldots\ldots \quad (15)$$

If the polynomial is expanded into four terms, the polynomial coefficients obtained through self-programming training are:

$x_o = 0.4661, x_1 = 0.6100, x_2 = 1.6282, x_3 = 0.0019$

The calculated maximum error is 1.45%;

If the polynomial is expanded into five terms, the polynomial coefficients obtained through self-programming training are:

$x_o = 0.2492, x_1 = 0.8910, x_2 = 0.8578, x_3 =$

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$$1.6852, \quad x_4 = 0.0023$$

The calculated maximum error is 1.43%;

If the polynomial is expanded into six terms, the polynomial coefficients obtained through self-programming training are:

$$x_o = 1\ 7.2543, \quad x_1 = 36.3903, x_2 \ = 2\ 8.1756, x_3$$

$$= 9.7559, \quad x_4 = 0.0685, x_5 \ = 0.1007$$

The calculated maximum error is 1.17%.

The more polynomial expansion terms, the more complicated the circuit and the higher the cost. Therefore, within the range allowed by the error, try to reduce the number of polynomial expansion terms as much as possible. In this paper, four-term polynomial expansion is selected.

Twenty-seven resistors and five potentiometers are used in the ANN overall circuit. After testing, the error of the resistor is about 2% -3%, so the error of the resistor itself cannot be ignored, and it is one of the main sources of error. Properly increase the cost and use high-precision resistors can effectively reduce errors. The potentiometer WS5 can be used for error correction of the entire ANN circuit.

In addition, although the integrated analog multiplier NJM4200 and quad op amp integrated block LM324 have very high accuracy, the error still exists to a greater or lesser extent, which is one of the factors affecting the overall circuit error of the ANN.

5. Conclusions

Intelligence is a major trend in the development of household appliances in the future. This article uses analog circuits to implement a simple artificial neural network (ANN). By training the artificial neural network by self-programming and normalizing the variables, it realizes that the objective function can be expanded into a polynomial with finite terms under the premise of certain accuracy, so as to realize the specified artificial neural network model function.

The self-programming training theory in this paper has universality, that is, given any curve, specific coefficients can be trained on the premise of satisfying the required accuracy through the program given in this paper. The hardware circuit using analog circuits to achieve specific functions is not complicated in structure, and the price of the integrated block is low, the performance is reliable, and it is convenient for mass production. The next work to be done is to design an ANN signal input circuit. First, we need to design a load cell that can convert different weights into electrical signals, then perform normalization processing, and then amplify the signal as ANN. For different heating modes, such as boiling water, cooking rice, etc., how to carry out unified standard sampling and learning is also a problem that needs further discussion.

This article considers that different regions have different air pressure and ambient temperature. Whether manufacturers can produce different models of products for different regions is one of the options for manufacturers. Field Programmable Gate Array (FPGA) technology provides the reliability, dedicated parallel execution, and lightning-fast fast closed-loop control performance unique to dedicated hardware circuits. But compared to the integrated blocks used in analog circuits, the FPGA chip price is many times higher. For small household appliances, the cost is high, uneconomical, and impractical.

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