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GA-BP Optimization Using Hybrid Machine Learning Algorithm for Thermopile Temperature Compensation

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ABSTRACT

Thermoelectric pile, which uses non-contact infrared temperature measurement principle, is widely used in various precision temperature measuring instruments. This paper analyzes environmental temperature's influence on thermoelectric piles' measurement accuracy and proposes a environment temperature compensation based on GA-BP (Genetic Algorithm-Back Propagation) neural network. The GA algorithm makes up for the slow iterative speed and easy to fall into local optimization of BP algorithm. The experimental simulation results show that environment temperature compensation based on GA-BP can accurately correct the measurement error caused by environmental temperature and other factors.

KEYWORDS

Environment Temperature Compensation, GA-BP Algorithm, Thermoelectric Piles

INTRODUCTION

As a non-contact infrared temperature measurement device, thermopile is widely used in various fields (Xu et al., 2022). However, the temperature measurement accuracy of thermopiles is often affected by changes in ambient temperature, which leads to inaccurate temperature measurement results. In order to solve this problem, researchers have proposed a method to optimize the design of the thermopile ambient temperature compensation algorithm using a genetic algorithm-backpropagation neural network (GA-BP) (Ding et al., 2011).

GA-BP is an optimization algorithm that combines genetic algorithm and back propagation neural networks (Mehboob et al., 2016). Genetic algorithm gradually optimizes the problem-solving

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ability by simulating the process of biological evolution, based on the gene combinations of optimal individuals in a population, using operations such as selection, crossover and mutation (Yang et al., 2014). The back propagation neural network, on the other hand, is a commonly used artificial neural network model with powerful learning and approximation capabilities (Chen & Wang, 2021).

Traditional back-propagation (BP) neural networks have some shortcomings in dealing with complex problems, such as easily falling into local optimal solutions, slow training speeds, sensitivity to initial weights and thresholds, and easily overfitting (Shi et al., 2023). To overcome these problems, we use a hybrid method that incorporates genetic algorithms and BP neural networks (the GA-BP method).

The GA-BP method effectively improves the performance and stability of traditional BP neural networks by taking advantage of the genetic algorithm's global search capability, stable parameter initialization, accelerated network convergence speed, and reduced risk of overfitting (Han et al., 2021). First, the structural parameters and initial weights and thresholds of the network are determined by a genetic algorithm to improve the generalization ability and convergence speed of the network. Then, during the training process, the weights and thresholds of the neural network are further optimized by a combination of genetic manipulation and backpropagation to obtain better performance (Moisello et al., 2022).

In the study, the GA-BP method was found to have significant applications in dealing with the modelling and solving of complex problems. It provides researchers with an effective tool and method for data mining, pattern recognition, predictive analytics, and other fields. As the GA-BP method makes full use of the respective advantages of BP neural networks and genetic algorithms, it can search for the optimal solution in the global range and improve the performance and stability of the network through the optimization operation of genetic algorithms.

In designing the ambient temperature compensation algorithm for the thermopile, the researchers first built a neural network model containing an input layer, a hidden layer, and an output layer. The input layer receives the original temperature data from the thermopile, the hidden layer processes and converts the data, and the output layer gives the corrected temperature data. Then, the weights and thresholds of the neural network are optimized by the GA-BP algorithm to minimize the influence of ambient temperature changes on the temperature measurement results (Wang & Xie, 2016).

Using GA-BP to optimize the design of the ambient temperature compensation algorithm of the thermopile has the following advantages: first, through the global search ability of the genetic algorithm, a better combination of parameters can be found, which improves the effect of the compensation algorithm. Second, the back propagation neural network can learn and fit according to the input training samples, which makes the compensation algorithm more accurate and stable. Finally, the optimization method can be adapted to the temperature measurement needs under different ambient temperature conditions, which has a certain degree of universality and flexibility (Shubha & Shastrimath, 2022).

The GA-BP optimization design of the ambient temperature compensation algorithm for thermopiles can improve the temperature measurement accuracy of thermopiles and reduce the influence of ambient temperature changes on the temperature measurement results. This will bring important application value in many fields, such as industrial production, medical diagnosis, and energy management (Han et al., 2021). Future research work can further explore the improvement of the optimization algorithm and the expansion of the application areas to meet the requirements of temperature measurement accuracy of thermopiles in different fields.

The GA-BP algorithm proposed in this paper is a hybrid method that combines the BP neural network algorithm with the GA genetic algorithm. By leveraging the strengths of the GA genetic algorithm, the limitations of the BP neural network algorithm in weight are compensated for, improving the mapping ability and generalization of the BP neural network algorithm and enhancing its convergence speed.

RELATED WORKS

Genetic algorithm and simulated annealing (SA) methods were employed to optimize the current distribution of a cooler made up of a large number of thermoelectric (TE) modules (Chen et al., 2002). Optimization results based on the design parameters of a large TE cooler showed considerable improvements in energy efficiency and refrigeration temperature when compared to the results of uniform current for the parallel-flow arrangement. Thermoelectric cooling (TEC) systems have grown significantly because of the need for a steady, low-temperature operating environment for numerous electronic devices. Cheng et al. (2005) propose a novel approach of optimizing the dimensions of thermoelectric elements via genetic algorithm (GA) to maximize the cooling capacity. Cheng et al. (year) also present a new approach that uses a genetic algorithm to optimize the arrangement of two-stage thermoelectric coolers (TECs). The optimal design of two-stage TECs can be realized using GA, and this method has considerable potential in designing a complex TEC system (Cheng et al., 2006). Thermoelectric heat pumps (TEHPs) have been applied to many electronic devices to create a steady, low-temperature operating environment. Cheng et al. (2007) use a hybrid genetic algorithm (hGA) to maximize the cooling capacity of a two-stage TEHP under the condition that the amount of material being used is limited. Leonov et al. (year) study theory and simulation of a thermally matched micromachined thermopile in a wearable energy harvester. A new theoretical concept in the thermoelectric theory is discussed, which is important for the design optimization of a thermoelectric energy harvester. It is shown that the knowledge of thermal properties of the environment, those of a heat source and a heat sink, play the key role in the optimization procedure. The performance of TEM largely depends on the temperature difference driving the heat flux and causing thermo-mechanical stress within the module (Leonov et. al., 2011). Heghmanns et al. (2015) introduce a multi-objective optimization procedure based on a genetic algorithm with which this conflict in objectives can be solved under realistic boundary conditions. For MOGA optimization of a thermoelectric generator, five decision variables as number of thermoelectric element pairs at the bottom and top stage as m and n, heat source temperature and heat sink temperature and working electric current has been considered in the current study. MATLAB environment is used to obtain the Pareto-optimal frontier between power output and thermal efficiency, and their best optimal values are selected by the Bellman-Zadeh fuzzy decision making technique (Hans et. al., 2015). An exo-reversible two-stage thermoelectric heat pump is thermodynamically optimized in consideration of finite time thermodynamics and multi-objective optimization using non-dominated sorted genetic algorithm (NSGA) approaches (Hans et al., 2015). We have considered five decision variables as working electric current (I), number of thermoelectric element pairs at the top and bottom stage as n and m, heat source temperature (Th), and heat sink temperature (Tc) for multi-objective optimization of thermoelectric heat pump. One approach is to install a thermoelectric generator system near the exhaust pipes in order for the high temperature gases to come in contact with the hot side of the thermoelectric generator module and thus increasing its temperature. The temperature of the cold side of the thermoelectric generator module is maintained at low levels through forced flow of atmospheric air. The performance of this thermoelectric generator system is studied through modelling and simulation, and various design parameters are investigated in order to increase electric power production (Charilaou et. al., 2020). Optimizing the geometry structures and operating conditions is an effective way to improve the performance of the segmented thermoelectric generator (STEG). Zhu et al. (2020) studied optimization analysis of a segmented thermoelectric generator based on genetic algorithm. A one-dimensional numerical model combined with genetic algorithm (GA) is presented for performance analysis and design optimization of the STEG (Zhu et. al., 2020).

ESTABLISHMENT OF THERMOELECTRIC PILE'S ENVIRONMENT TEMPERATURE COMPENSATION MODEL

The amount of energy emitted by objects in nature to their surrounding space is related to their temperatures, the relationship between the radiation capacity per unit area, and the temperature of the object is consistent with Stephan-Boltzmann's law.

The Stephen-Boltzmann Law of Infrared Radiation:

$$E = v\varepsilon\left(T^4 - T_0^4\right) \tag{1}$$

where E is the $radiant\ energy, W / m^3$; σ is the Stephen-Boltzmann's constant, 5.67×10^{-3} W/(m^2K^4); ε is material radiation emissivity, T is material temperature, and the unit is K; T_0 is the ambient temperature, and the unit is K.

The thermocouple is mainly composed of several miniature thermocouples in series, and its output voltage is directly proportional to the radiated power after infrared radiation, as shown below:

$$E_d = \frac{v\left(\varepsilon_0 T_0^4 - \varepsilon_d T_d^4\right)\tau A_1 A_d}{\pi f^2} \tag{2}$$

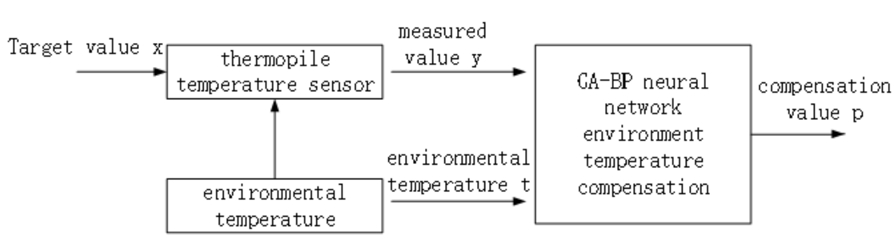
where τ is the penetration, f is the focal length, and o, d, l are the object under test, thermopile, and lens, respectively. T_0 and T_d in formula 1 and formula 2 are the same. ε is the emissivity of the object, which is a coefficient indicating the radiative capability of the object, and its range is from 0 to 1.

According to Formula 1 and 2, the ambient temperature significantly affects the thermopile output. In order to reduce the influence of the environmental temperature on the measured results and improve the accuracy of the temperature measurement accuracy, this paper adopts the GA-BP algorithm to watch environmental temperature compensation. As shown in Figure 1 below, the measured value y of the thermopile temperature sensor and the ambient temperature t are the two input values of the GA-BP neural network ambient temperature compensation model. GA-BP neural network model uses the GA algorithm to obtain weight and threshold values, and the BP algorithm to learn training samples, so that the final compensation output value p is close to the ideal target value x.

OPTIMIZATION DESIGN OF THERMOELECTRIC PILE'S ENVIRONMENTAL TEMPERATURE COMPENSATION BASED ON GA-BP

The BP neural network is a multilayer feedforward artificial neural network with backpropagation of errors. In order to obtain high-precision fitting data, the weight and threshold of the neural network

Figure 1. Ear thermometer's ambient temperature compensation model under GA-BP algorithm



are constantly modified (Shi et al., 2023). has been widely used in the field of artificial intelligence. Although there are many advantages, there are also some disadvantages:

(1) Slow convergence speed. For a simple problem, people generally have to learn hundreds or thousands of times to converge on a simple problem (Li et al., 2018).
(2) It is easy to fall into the local minimum. The BP neural network generates initial weights and thresholds randomly. According to the principle of local optimization, the neural network may not converge or fall into local extreme points (Ning et al., 2019).
(3) The optimal number of layers and neurons in the network is still being determined. In the process of BP neural network modelling, in order to reduce network errors and ensure network accuracy, it is necessary to select the appropriate number of network layers and the number of neurons to reduce network errors and ensure network accuracy. Still, there is no corresponding theoretical basis for selecting the optimal number of layers and neurons.

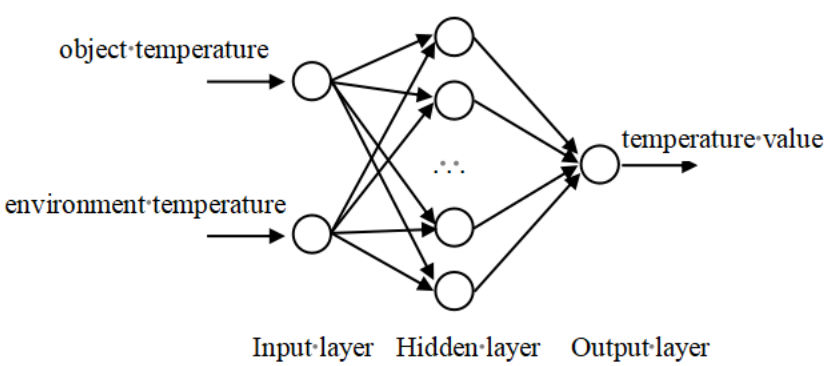
GA is an artificial intelligence algorithm based on the simulation of biological evolution and has an essential difference from the BP neural network (Mehboob et al., 2016). According to the principle of "survival of the fittest and elimination of the losers," the optimal individual is selected from the evolved population as an approximate optimal solution; that is, it has the characteristics of global optimization (Pham et al., 2021). Therefore, the combination of GA and the BP neural network can supplement the defect of the local minimum value of the BP neural network and overcome the problem of a random selection of initial weights and thresholds to improve the accuracy of the BP neural network measurement (Lu et al., 2019).

Given the drawbacks of the BP neural network, this paper uses the genetic algorithm GA to optimize the BP neural network. It uses the "trial and error method" to determine the number of hidden layer neurons. The effect of temperature compensation between the traditional BP neural network and GA-BP neural network is compared, and the sensitivity of each input variable is calculated.

The topology of the BP neural network model in this paper is shown in Figure 2. The object temperature and environment temperature values are used as input layer nodes of the BP neural network, and their corresponding temperature values are used as output layer nodes. The number of hidden layer nodes is determined by empirical formula 3 to establish a range, and then a trial-and-error approach is used. It is found that the measurement performance is optimal when the number of nodes is 11.

$$l = \sqrt{n+m} + k \tag{3}$$

Figure 2. BP neural network model



where l is the number of hidden layer nodes, n is the number of input layer nodes, m is the number of output layer nodes, and k is a constant.

The traditional BP algorithm is to build a trainable artificial neural network by continuously changing the weights and thresholds of the neural network, and the result of the output layer is as close as possible to the target value, thus achieving the purpose of prediction. The GA-BP algorithm is an optimized hybrid algorithm based on the traditional BP algorithm. The GA algorithm has a solid global search capability, fast convergence speed, and other characteristics. Combining the GA algorithm and traditional the BP neural network algorithm can prevent the problem of the BP algorithm falling into local optima convergence.

In this paper, the GA and BP algorithms are effectively and reasonably combined to obtain a group of globally optimal population positions through Lamarkian evolution, which is the weight and threshold required by our artificial neural network. Then, the BP artificial neural network with optimized L-M training function is used to accelerate the learning of the optimal global solution obtained by the GA genetic algorithm to obtain the most adaptive neural network weight and threshold for the whole sample. In this way, the GA-BP artificial neural network we established can accurately evaluate and predict different samples. Its working flow chart is shown in Figure 3 below.

The algorithm steps are as follows:

(1) Select part of samples X for testing; the rest will be the training sample for the GA-BP network algorithm. Generate the topology structure and calculation parameters R, S1, S2 for the BP neural network.
(2) Initialize the population. The genetic algorithm initializes the population randomly, and the size of the population has a significant impact on the performance of the genetic algorithm. The larger the population, the longer the optimization time. If the population size is too small, it will be more difficult to find the optimal solution. Typically, a population size between 40 and 100 is selected.

The ambient temperature T0 = {15.2, 19.8, 24.9, 35.4, 40.2} was used as a training sample for the GA-BP network algorithm; the measured data with an ambient temperature of 30.3°C was used as a test sample.

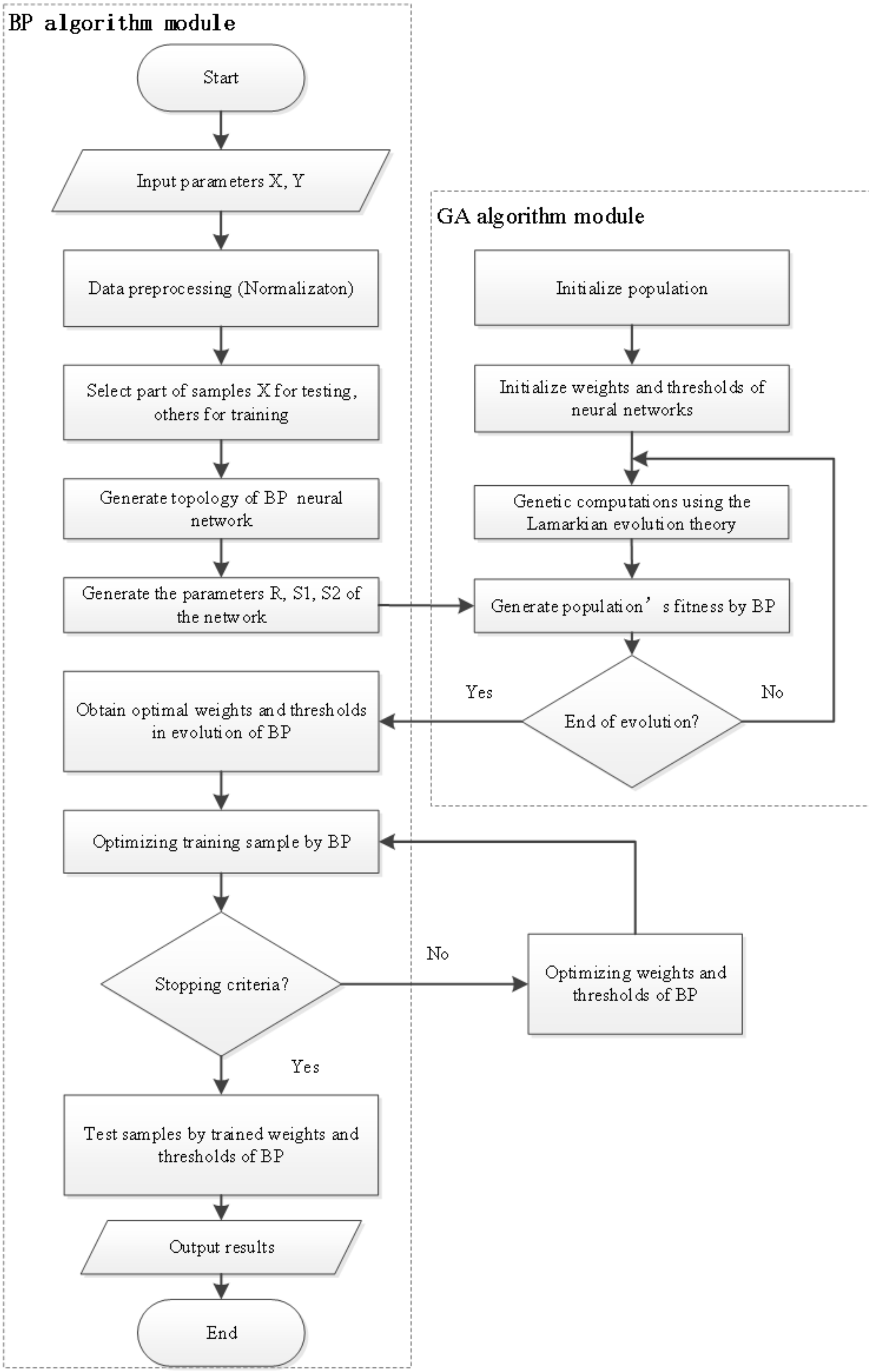
The collected data were normalized so that all data were normalized to the interval [-1, 1].

The number of hidden layer nodes was determined according to the empirical equation 3 and the number of nodes was adjusted using the trial and error method, and it was found that the measurement performance was optimal when the number of nodes was 11.

(3) Initialize the weights and thresholds of the neural network.
(4) Initialize the population and select the appropriate size of the population size.
(5) Perform genetic calculations using Lamarckian evolutionary theory and use the BP neural network to calculate population fitness and determine if the evolutionary generations of the genetic algorithm have been reached.
(6) Optimize the training samples by the BP neural network and obtain the weights and thresholds of the optimized network. The optimal weights and thresholds of the BP neural network in the evolutionary generations were obtained using a hybrid GA-BP algorithm.

Finally, the weights and thresholds of the trained BP network are used to predict the test samples and calculate the errors.

Figure 3. GA-BP neural network optimization flow chart



EXPERIMENTAL SYSTEM DESIGN AND DATA ACQUISITION

Thermal diode (Thermistor) sensing systems play an important role in precision instrumentation, and their accurate temperature measurement capabilities are critical for many applications. Precise temperature control and regulation is essential in laboratory equipment, medical devices, industrial control systems, and more. By providing highly accurate temperature measurement, thermal diode sensing systems enable these systems to take the necessary control measures in a timely manner to ensure that temperature is stabilized within the desired range. In addition, thermal diode sensing systems have potential applications in precision heating and cooling, environmental monitoring and meteorological observation, and scientific research and experimentation. Thermal diode sensing systems can provide accurate temperature feedback, realize precise temperature control, provide reliable temperature measurement data for researchers and engineers, and promote the progress of scientific research and technological development.

The same thermal diode temperature sensors were adopted to verify the effect of the GA-BP algorithm on the environment temperature compensation of the ear thermometer system. The parameters of the sensor are:

Operating temperature range: -40°C to +125°C
Resistance range: 100 Ω to 10 kΩ
Sensitivity: 5 Ω/°C
Thermal time constant: 10 ms

The temperature of 6 groups of different target objects whose temperature was calibrated was measured by thermopile temperature sensors with and without temperature compensation. The measured data are shown in Table 1.

We take the data of the environment temperature T0 = {15.2, 19.8, 24.9, 35.4, 40.2} as the training samples of the GA-BP network algorithm and the measurement data of the environment temperature as 30.3°C as the test sample. To make the data collection unified, we normalize the collected data so that all data are normalized to the interval [-1,1]:

Table 1. Original data of temperature measured by thermopile (°C)

15.2		19.8		24.9		30.3		35.4		40.2	
Standard	Measured	Standard	Measured	Standard	Measured	Standard	Measured	Standard	Measured	Standard	Measured
20.1	18.5	20.8	20.5	21.3	22.2	22	24	22.3	25.2	22.7	26.3
21.3	19.4	22	21.3	22.7	23.2	23.4	25	23.6	26.2	24	27.2
23.6	21	24	22.8	24.5	24.6	25.1	26.3	26.3	28.2	26.5	29.1
24.5	21.7	25.1	23.6	25.7	25.4	26.1	27	27.1	28.8	27.3	29.7
26.4	23.1	26.9	24.9	27.5	26.8	28.1	28.5	28.4	29.8	28.9	30.9
28.1	24.4	29.1	26.6	29.5	28.3	30.1	30.1	30.5	31.4	31	32.6
30.1	26	31.3	28.3	33	31.1	33.4	32.7	33.9	34.1	34.1	35
32.4	27.8	33	29.7	33.7	31.7	34.3	33.4	35	35	35.5	36.2
34.1	29.1	35.2	31.5	35.9	33.5	36.3	35.1	36.7	36.4	37	37.4
36	30.7	36.7	32.7	37.3	34.6	37.4	36	38.1	37.6	38.3	38.5
37.5	31.9	38	33.8	38.3	35.5	38.9	37.3	39.1	38.4	40	40

$$X^{*} = 2(X_{\text{current}} - X_{\min}) / \left(X_{\max} - X_{\min}\right) - 1 \quad (4)$$

When X is the environment temperature, X_{max} and X_{min} are the maximum and minimum values of the environment temperature respectively, and X* is the normalized data of the environment temperature. Therefore, the standardized temperature value and the normalized value of the measurement value can be obtained.

ANALYSIS OF EXPERIMENTAL RESULTS

When the population size of the GA algorithm is selected as 100, the genetic algebra is 1000 generations, and Lamarckian evolution is adopted (Wang, 2021). The BP neural network adopts a three-layer topology structure: the input layer, hidden layer, and output layer. The neurons in each layer were 2, 11, and 1, respectively. The hidden layer transfer function adopts the S-type tangent function tansig, the output layer transfer function adopts the linear transfer function purelin, and the L-M optimization algorithm is used as the training function. The learning rate of the BP training network is set as 0.05, the maximum number of training is 8000, and the expected error is 1E-8.

As shown in Figure 4, the established GA-BP neural artificial network uses GA population as the weights and thresholds of BP neural network to train the training samples and takes the fitness of the training samples as the fitness of the current GA population. From the figure, we find that with the increase of the iteration times of GA, the system's overall square error tends to be 0, and the population fitness gradually increases.

As shown in Figure 5, when the GA iteration number approaches 100 generations, the system has converged and tends to be the optimal solution, and the error and population fitness change slowly. This result is due to the excellent convergence and global search capability carried by the GA algorithm itself, which significantly improves the defects of the classic BP algorithm that it easily falls

Figure 4. Square error changes with the number of iterations

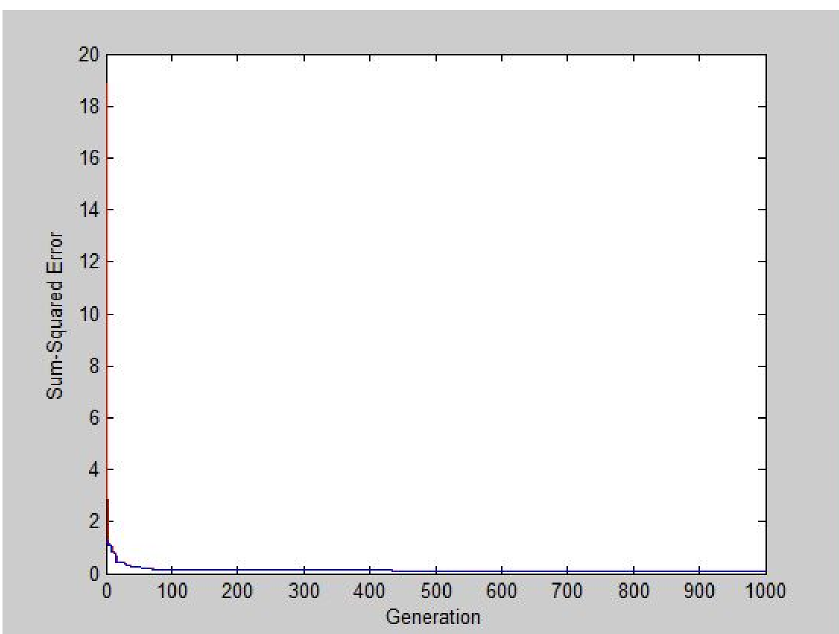
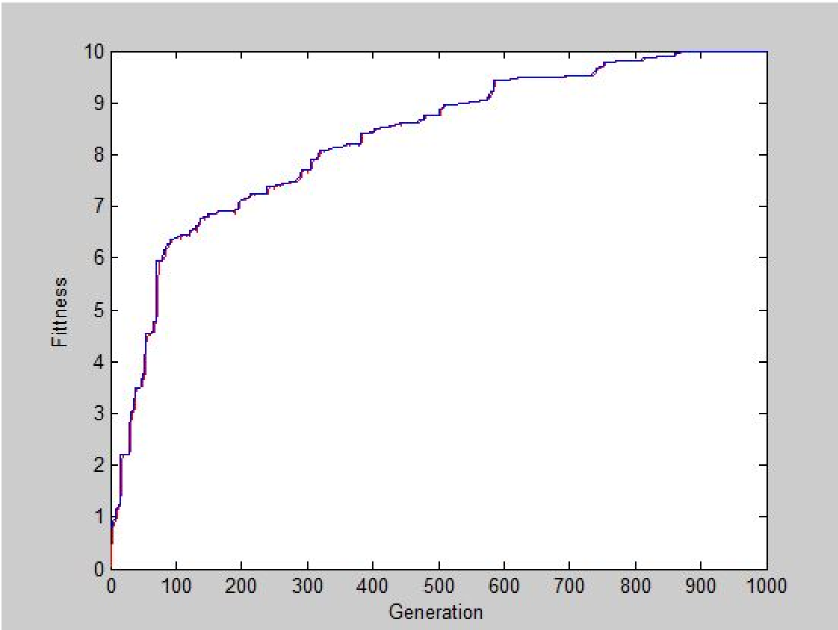


Figure 5. Fitness changes of GA population with the number of iterations



into optimal local solution and exhibits slow convergence. The whole GA-BP network can achieve the local optima convergence quickly.

The artificial neural network trained by the GA-BP algorithm is used to predict the data of the ambient temperature T0={30.3} group, and the results are shown in Table 2 and Figure 6. The results of the experiment error analysis are shown in Table 3. The results indicate that the artificial neuron network trained by the GA-BP algorithm can effectively reduce the measurement error and carry out temperature compensation. The data analysis shows that the absolute minimum error after GA-BP

Table 2. Temperature compensation result (°C)

30.3		
Standard	**Measured**	**GA-BP**
22	24	22.00955658
23.4	25	23.37523482
25.1	26.3	25.12928255
26.1	27	26.06305919
28.1	28.5	28.03782482
30.1	30.1	30.10479187
33.4	32.7	33.37986403
34.3	33.4	34.24472505
36.3	35.1	36.31672353
37.4	36	37.39784056
38.9	37.3	38.94064302

Figure 6. Temperature compensation results

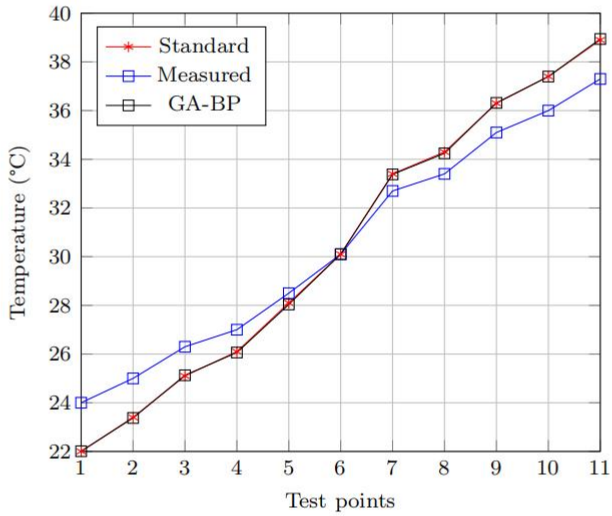


Table 3. Error analysis of experiments

30.3 °C				
Standard (°C)	**Error (°C)**	**Accuracy (%)**	**GA-BP Error (°C)**	**GA-BP Accuracy (%)**
23.4	1.6	93.162393	-0.02476518	99.894166
25.1	1.2	95.219124	0.02928255	99.883336
26.1	0.9	96.551724	-0.03694081	99.858464
28.1	0.4	98.576512	-0.06217518	99.778736
30.1	0	100.000000	0.00479187	99.984080
33.4	-0.7	97.904192	-0.02013597	99.939713
34.3	-0.9	97.376093	-0.05527495	99.838849
36.3	-1.2	96.694215	0.01672353	99.953930
37.4	-1.4	96.256684	-0.00215944	99.994226
38.9	-1.6	95.886889	0.04064302	99.895519

compensation is only 0.00215944, and the corresponding accuracy is 99.994226%. The maximum absolute error is 0.06217518, and the corresponding accuracy is 99.778736%. Therefore, GA-BP neural network can effectively reduce the influence of ambient temperature on measurement results.

CONCLUSION

This paper integrates the advantages of the GA genetic algorithm and the BP artificial neural network algorithm to establish a trainable GA-BP artificial neural network. By taking full advantage of the feature of global optimization of the GA genetic algorithm, the weight and threshold of the neural network are matched and optimized first to avoid the defect of the BP neural network, which is easily falling into the local optima. A hardware test platform was established for multiple groups of different calibrated temperature training and testing. Experiments proved that the improved GA-BP artificial neural network algorithm can effectively compensate for the impact of ambient temperature on the thermopile accuracy, reduce the measurement error, and improve the temperature measurement accuracy, which has high application value in practical applications.

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