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Nonlinear Correction of Pressure Sensor Based on Depth Neural Network

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Abstract: With the global climate change, the high-altitude detection is more and more important in the climate prediction, and the input-output characteristic curve of the air pressure sensor is offset due to the interference of the tested object and the environment under test, and the nonlinear error is generated. Aiming at the difficulty of nonlinear correction of pressure sensor and the low accuracy of correction results, depth neural network model was established based on wavelet function, and Levenberg-Marquardt algorithm is used to update network parameters to realize the nonlinear correction of pressure sensor. The experimental results show that compared with the traditional neural network model, the improved depth neural network not only accelerates the convergence rate, but also improves the correction accuracy, meets the error requirements of upper-air detection, and has a good generalization ability, which can be extended to the nonlinear correction of similar sensors.

Keywords: Depth neural network; pressure sensor; nonlinearity correction; wavelet transform; LM algorithm

1 Introduction

The high-altitude weather detection is an important means to acquire the atmospheric change information. In the process of high altitude detection, the air pressure value is one of the important parameters, and the measurement accuracy of the air pressure sensor directly affects the final detection result. In the process of meteorological measurement, the pressure sensor will show nonlinear characteristics affected by the external environment, for many reasons: (1) The nonlinear characteristics of the sensor cannot be completely eliminated due to the limitations of its own material, design scheme, fabrication process and so on. (2) There is interference in the calibration environment of the sensor, so that the characteristic point of the sensor is drifting, and the measurement result is deviation, so that the non-linearity is caused [1].

For nonlinear correction, a large number of experiments have been carried out by relevant researchers. The authors in [2] used a nonlinear integrator for phase correction, which improved the stability of the control system. Literature [3] used a series and parallel resistance network to correct the thermistor, which greatly improved the measurement accuracy of the temperature sensor. However, the correction by hardware circuit has the disadvantages of high cost, low precision and complex integration, which is not conducive to practical production and application [4–5]. With the development of computer technology, the error compensation of sensor is carried out by software algorithm, and the realization of nonlinear correction has become the main research method. The mainsoftware compensation is look-up table method and curve fitting method. The authors in [6] corrected the operational atmosphere of GaoFen 2 image by table lookup method and reduced the error to 0.8%. Literature [7] corrected the magnetic field sensor by the least square method and achieved a higher accuracy. The table look-up method ignores the measurement error of calibration points, and the fitting method can only reflect the overall trend of the sensor. It is the approximation of several discrete measurement points to the global model of the sensor, and cannot satisfy the nonlinear fitting in complex cases.

As a new information processing method, neural network has made some achievements in the field of sensor nonlinear correction. Literature [8] used BP neural network method to calibrate the angle sensor, which effectively reduced the measurement error and improved the measurement accuracy. The authors in [9] used BP neural network to calibrate the color sensor and improve the sensor sensitivity. However, the traditional BP network has the disadvantages of slow convergence speed and poor non-linearity, and it still needs to be further optimized to suit the nonlinear correction of the air pressure sensor.

In this paper, an air pressure sensor is used as an example to carry out the data collection and calibration experiment on the air pressure sensor by means of the standard calibration equipment under the influence of the external environment such as temperature and air pressure. The depth neural network is optimized, the wavelet function is used as the activation function of the network hidden layer, and the Levenberg-Marquardt algorithm is introduced to update the parameters of each layer, and the model of the non-linear correction of the air pressure sensor is obtained. The experimental results show that the proposed method is superior to the traditional network in the aspects of model accuracy and convergence speed, and can complete the nonlinear correction of the air pressure sensor more quickly and accurately.

The structure of this paper is as follows: The first section introduces the principle of nonlinear correction of air pressure sensor and the application method of correction model. In the second section, the depth neural network model is analyzed, and the shortcomings of the network in sensor nonlinear correction and the corresponding solutions are pointed out. In the third section, according to the nonlinear correction principle of pressure sensor, the corresponding neural network model is established, and the network parameters are designed. In the fourth section, the correction experiment is carried out according to the data of air pressure sensor, and the experimental results are compared and analyzed to verify the effectiveness of the proposed method. Finally, the paper is summarized and the conclusion of nonlinear correction of pressure sensor is given.

2 Sensor Nonlinear Correction Principle

The nonlinear error of pressure sensor is composed of its physical characteristics and environmental influence [10]. The former is caused by the production material, production process and working principle of the sensor, while the latter is caused by noise such as working environment and external circuit, which makes the sensor lag and nonlinear, resulting in measurement error. The air pressure sensor system model is shown in Fig. 1.

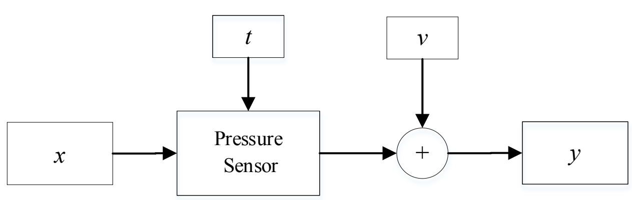

Figure 1: Nonlinear model of pressure sensor system

The model of the pressure sensor is as follows:

$$y = f(x, t) + v \#(1)$$

In the formula (1): y is the measured pressure value of the sensor output, x is the air pressure in the actual environment under measurement, t represents environmental variables, such as temperature, humidity etc. v is the interference noise of the sensor system. The function $f(x,t)$ is an unknown complex function, which is related to the characteristics of the pressure sensor and the external environmental factors. From the characteristics of the pressure sensor, for a specific environmental variable t , x and y are one-to-one correspondence, then there is a special function $X = g(y) = g\big(f(x,t)\big) = x$. That is, the search function g enables the output value of the sensor to accurately reflect the measured pressure after correction, and the correction schematic diagram is shown in Fig. 2.

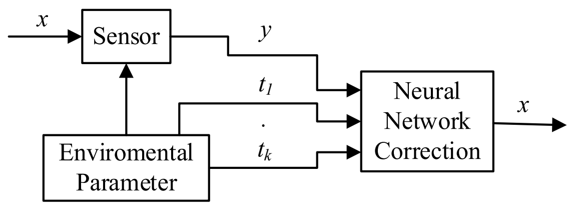

Figure 2: Correction schematic diagram

3 Depth Neural Network Model and Improved Algorithm

3.1Deep Neural Network Structure

The structure of the Deep Neural Network (DNN) model is shown in Fig. 3, which consists of an input layer, an output layer and at least one hidden layer [10]. According to the general approximate theorem, a feed forward neural network with linear output layer and at least one hidden layer can approximate any function with any precision as long as a sufficient number of neurons are given.

The training process of DNN can be divided into two stages: forward calculation of input data and back propagation of error. In the process of forward calculation, the input data from the input layer is weighted summation by the weight of the interlayer connection and the result is passed to the activation function of the hidden layer, and the nonlinear mapping of the activation function is passed to the output layer. If the expected output value cannot be obtained in the output layer, the back propagation is performed, and the error loss is minimized by modifying the connection weight between neurons.

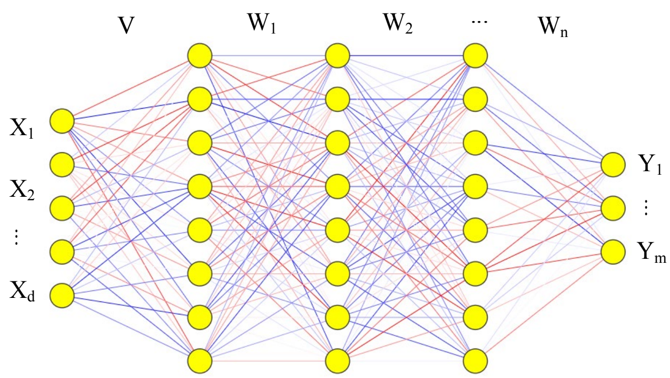

Figure 3: DNN structure

The traditional neural network uses gradient descent method to update the parameters, and the parameters of the input layer and hidden layer network are updated as follows:

$$\vartriangle V_{ih} = \alpha e_h X_i = \alpha \left(\sum_{j=1}^{l} W_{hj} g_j \right) H_h (1 - H_h) X_i \#(2)$$

$$\vartriangle \beta_h = -\alpha e_h \#(3)$$

The hidden layer and output layer network parameters are updated as follows:

$$\vartriangle W_{hj} = \alpha g_j H_h = \alpha\left(Y_j - Y_j'\right)Y_j\left(1 - Y_j'\right)H_h \#(4)$$

$$\vartriangle \beta_j = -\alpha g_j \#(5)$$

where α is the learning rate, g_j and e_h are error information, X_i is the i neuron input of the input layer, H_h is the h neuron output of the hidden layer, and Y_j' is the output of the j neuron in the output layer, and the Y_j is the corresponding real value.

3.2 Levenberg-Marquardt Algorithm

DNN has the ability to approximate arbitrary continuous function and nonlinear mapping, and can simulate nonlinear input-output relationship. However, it also has some shortcomings, such as poor modeling ability, slow learning convergence speed, easy to fall into local minima and so on. In this paper, the traditional DNN is improved by Levenberg Marquardt (LM) algorithm to improve the convergence rate of the network.

The LM algorithm is an improvement to the Gauss-Newton method. Its basic optimization idea is to use the Gauss-Newton method to generate an ideal search direction near the optimal value of the function, and to adjust the weight of the network through the adaptive algorithm, so as to overcome the shortcomings of the gradient drop method in one-way blind search and speed up the convergence speed of the network. The updated expression of the weight of each layer is as follows:

$$W_{n+1} = W_n - [J^T J^n + uI]^{-1} J_n^T E_n \#(6)$$

where I is the unit matrix, u is the proportional factor, E is the network prediction error, and J is the Jacob matrix, the matrix contains the first derivative of the prediction error to the parameters of each layer of the network, as follows:

$$J = \begin{bmatrix} \frac{\partial E_1}{\partial W_1} & \cdots & \frac{\partial E_1}{\partial W_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial E_j}{\partial W_1} & \cdots & \frac{\partial E_j}{\partial W_n} \end{bmatrix} \#(7)$$

The LM algorithm updates the weights according to the change of network error: If the prediction error of the network increases after the weight of the model is updated, u may be too small, which leads to the LM algorithm close to the Gaussian Newton method, and there is the possibility of divergence. At the same time, u is magnified to approach the gradient drop method.On the contrary, if the error is small, the algorithm is in the convergence stage, where u becomes smaller and the LM algorithm is approximated to Gaussian Newton method to accelerate convergence [11]. By using LM algorithm, the problems of low precision and slow convergence near the extreme point in deep neural network can be solved, and the minimum error can be approximated faster and more accurately [12].

3.3 Wavelet Analysis

Wavelet analysis is developed in view of the shortcomings of Fourier transform. In the field of signal processing, Fourier transform is one of the most widely used analytical methods. In engineering applications, however, there are a large number of non-steady-state signals, and the Fourier transform does not function as a time-domain analysis. Wavelet transform replaces infinite trigonometric function basis with attenuated wavelet basis, processes the data with different resolutions, and realizes the approximation of fitting function. It is a time-frequency domain localization analysis method in which the time window and frequency window can be changed, which overcome the disadvantage that Fourier analysis cannot obtain both time domain and frequency domain at the same time.

In the traditional DNN, the hidden layer selects the Sigmoid function as the activation function for nonlinear transformation. However, for the nonlinear component of the pressure sensor, the Sigmoid function mapping ability is poor, and the correction cannot be completed accurately. In this paper, the wavelet function is used to replace the original Sigmoid function as the activation function of the hidden layer node, and a series of wavelet generating functions are combined to approximate the measured values, so as to achieve the purpose of pressure sensor correction.

At present, the main wavelet functions are Harr wavelet, Db wavelet, Morlet wavelet and Mexican Hat wavelet. Morlet wavelet has good nonlinear mapping ability, and has achieved remarkable results in precipitation analysis [13], atmospheric environment prediction [14], laser calibration [15-18] and so on. The expression of the Morlet wavelet function is:

$$h(x) = C * \cos(ux) * exp\left(-\frac{x^2}{2}\right) \#(8)$$

In the formula, C is the normalization constant of reconstruction, and the value is 1. u controls the shape of the wavelet function. The shape comparison diagram of Morlet wavelet function corresponding to different values is shown in Fig. 4.The u value is determined by experiments, and the shape of Morlet wavelet function is determined in order to achieve the best correction effect.

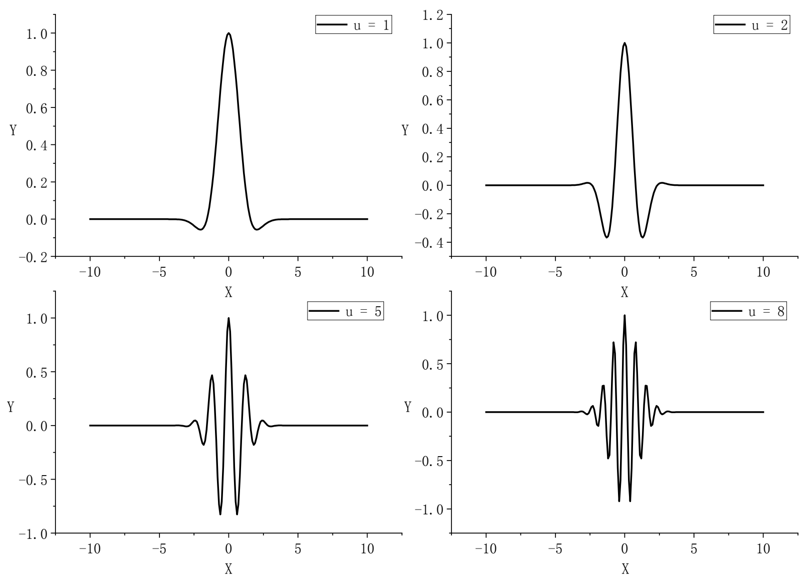

Figure 4: The comparison of the *u* value and the Morlet function

4 Depth Neural Network Model and Improved Algorithm

4.1 Deep Neural Network Structure

In order to test the nonlinear correction effect of the neural network on the air pressure sensor, the training sample data should be obtained first. Therefore, it is necessary to use the standard equipment to carry out the calibration experiment on the air pressure sensor, and the measured value of the air pressure sensor is not only related to the atmospheric pressure but also related to the temperature, and the calibration can be carried out by using the control variable method.

The measurement error is less than 1hPa at the range of 1100 hPa to 500 hPa and the measurement error is less than 0.7 hPa in the range of 500 hPa to 5 hPa according to the high-altitude weather detection specification. Therefore, the calibration pressure range is 5hPa~1100 hPa. According to the needs of high altitude detection, the calibration temperature range is -30°C~+40°C. At 35°C, some of the collected data are shown in Tab. 1.

Table 1: Data collected by pressure sensor

Measuring temperature /ºC	Measurement pressure /hPa	Standard Pressure /hPa	Measurement Error /hPa
35	1103.2	1100	3.2
35	906.27	900	6.27
35	806.31	800	6.31
35	702.44	700	2.44
35	601.73	600	1.73
35	401.68	400	1.68
35	302.58	300	2.58
35	103.78	100	3.78
35	10.55	5	5.55

Fig. 5 shows the measurement error distribution of pressure sensors at different temperatures. It can be seen from the diagram that the pressure sensor has a large temperature drift effect, and the temperature has a great influence on the measurement results of the sensor. After correction by neural network, the influence of temperature on the pressure sensor can be overcome, and the measured value can be closer to the real value.

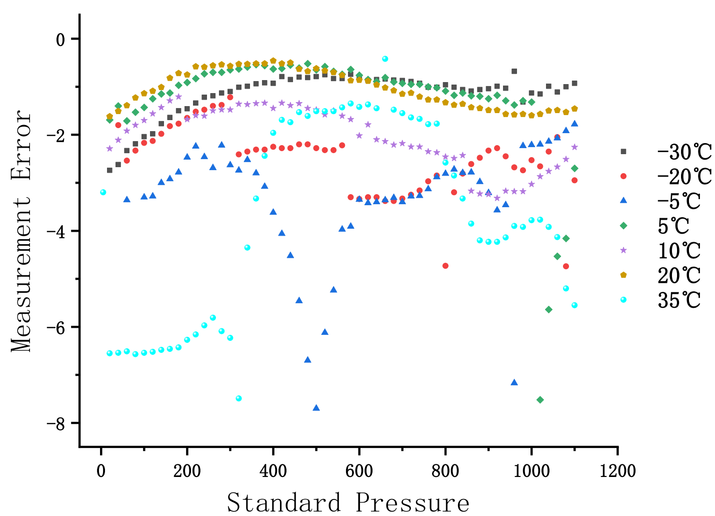

Figure 5: Distribution of sensor measurement error at different temperatures

4.2 Network Parameter Setting

According to the basic structure of deep neural network, a six-layer network is selected to construct the model, which includes one input layer, four hidden layers and one output layer. From the data measured by the pressure sensor, it can be seen that the influencing factors are temperature and air pressure, so there are two neurons in the input layer. In order to prevent the occurrence of overfitting, the number of neurons in the hidden layer was 5-10-10-5.After the network calculation, it outputs the corresponding standard pressure, so there is a neuron in the output layer, that is, the network structure is 2-5-10-10-5-1.The measuring pressure and temperature of the air pressure sensor are input into the depth neural network, and the corresponding standard pressure is output by the network calculation, so as to achieve the purpose of sensor correction.

For the different temperature ranges and different pressure ranges collected in Tab. 1, there are 800 pieces of data. In order to make the training results correctly reflect the inherent law of the sample, and in order to avoid overfitting, all the data are divided into training set and test set according to 8:2.The network is trained by the training set data, so that the network model parameters are optimized, and the final network is tested by the test set to detect the generalization ability of the model.

The initial weight value of each layer network in the range of [0–1] is generated by random function, the offset value is set to 0, and the other parameters are set as shown in Tab. 2.

Table 2: Network training parameter setting

Learning Rate	0.0001
Epochs	10000
Dropout	0.5
Loss Function	Mean Square Error (MSE)
Optimization Algorithm	Gradient Descent LM Algorithm
Activation Function	Sigmoid Morlet Wavelet

5 Correction Results and Performance Comparison

5.1Convergence Rate Comparison

In order to compare the influence of LM algorithm and gradient descent method on the convergence speed of the network, the hidden layer function adopts Sigmoid function to randomly generate 10 groups of initial weights. Two kinds of network parameter optimization algorithms are used to train, and the training period is recorded when the MSE is less than 0.7 in the training process. The experimental results are shown in Tab. 3.

In the training process, the change of the loss value of the gradient descent method is shown in Fig. 6, and the LM algorithm is shown in Fig. 7.

Table 3: Convergence rate performance comparison

Number	Gradient Descent	LM Algorithm
1	3825	5
2	2022	5
3	2460	8
4	4041	5
5	7092	8
6	3034	10
7	5923	4
8	4423	4
9	1095	7
10	7431	4
Average	4135	6

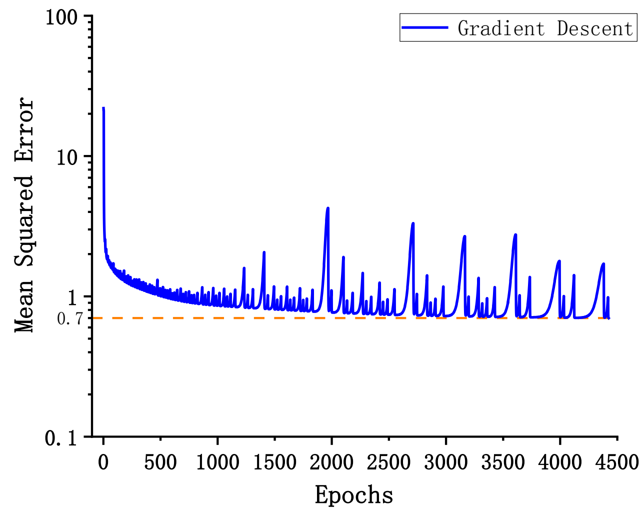

Figure 6: Gradient descent algorithm

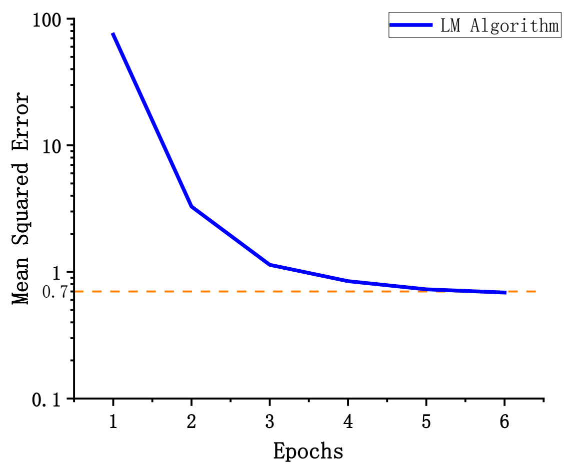

Figure 7: LM algorithm

As can be obtained from Tab. 3, for random network weight initial values, the gradient descent method requires a large difference in the training period and is sensitive to the weight initial value. It can be seen from Fig. 6 that there is jitter phenomenon in the process of convergence by using gradient descent method to train the network, and the minimum value cannot be approximated directly. In contrast, LM algorithm can overcome the shortcomings of gradient reduction method and complete convergence quickly and accurately. The average training period based on LM algorithm is about 6 times, which is much faster than that of gradient drop method. It can be seen that the LM algorithm can overcome the shortcomings of the gradient subtraction method, converge more quickly, and improve the stability of the network.

5.2 Wavelet Function Shape Comparison

It can be seen from Fig. 4 that for Morlet wavelet function, different n values correspond to different wavelet shapes, and the influence of different n values on the final calibration results is tested by experiments to determine the optimal activation function. The same test data are input into the network, and the network is trained to achieve the final convergence. The MSE between the corrected data and the standard measured value is calculated. The experimental results are shown in Tab. 4.

Table 4: n value and calibration error

n	MSE	n	MSE
1	0.413	6	0.432
2	**0.335**	7	0.509
3	0.431	8	0.401
4	0.506	9	0.522
5	0.430	10	0.513

As can be seen from the experimental results, in the vicinity of n = 2, the calibration error has a minimum value. For the accurate experiment of n = 2, it is found that when n = 1.5, the MSE of the data reaches the minimum value of 0.307. The best correction effect can be obtained by setting the *n* value of wavelet function to 1.5.

5.3Comparison of Calibration Accuracy

The prediction accuracy of the network is an important index to evaluate the performance of the network. In order to compare the effect of the Simoid function and the wavelet function on the result of the final calibration, the network is trained by the gradient descent method, and the results of the partial calibration are shown in Tab. 5.

Table 1: Comparison of calibration accuracy

Standard pressure	Pre-calibration pressure	Post-calibration pressure	
		Simoid	Morlet Wavelet
1100	1103.2	1097.96	1097.42
1000	1006.54	1001.78	1000.61
900	906.27	902.05	900.63
700	702.44	698.44	699.63
600	601.61	599.41	599.66
500	501.35	498.46	500.01
400	401.48	399.39	400.05
200	204.23	200.91	200.64
100	103.78	101.15	99.45
5	10.55	6.74	5.87
MSE	2.10	0.63	0.31

In order to further analyze the effect of the Simoid function and the wavelet function on the calibration result of the pressure sensor, the measurement error curve of pressure sensor shown in Fig. 8 is drawn. It can be seen from Fig. 8 that compared with Simoid function, using wavelet function as activation function has better approximation ability, can compensate error more accurately, improve measurement accuracy and realize pressure sensor correction.

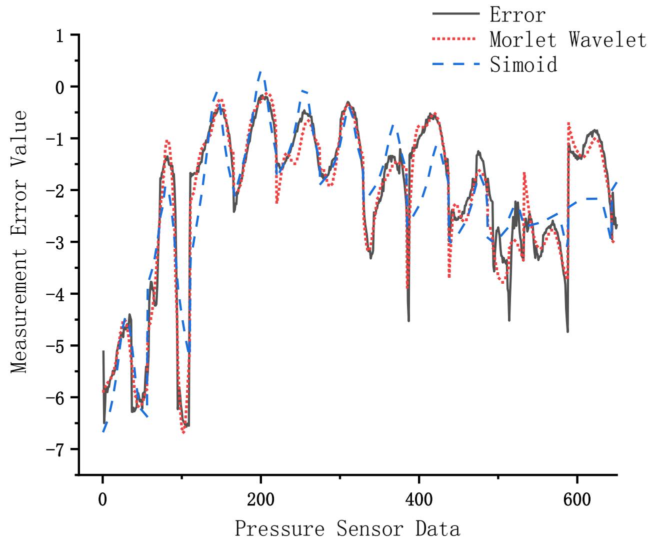

Figure 8: Error compensation contrast diagram

5.4 Prediction Capability Comparison

In order to test the generalization ability of the established model and whether the network is over-fitting, the different air pressure values are selected as test set data for model test at different temperatures. The partial test results are shown in Tab. 6.

Table 2: Comparison of calibration accuracy of the test set

Standard pressure	Pre-calibration pressure	Post-calibration pressure	
		Simoid	Morlet Wavelet
1100	1101.58	1099.67	1099.78
1000	1003.03	1000.92	1000.06
900	903.31	900.83	900.09
700	701.29	700.45	699.82
600	602.02	600.63	600.05
500	500.47	498.66	499.82
200	200.75	200.53	200.14
100	101.76	99.04	99.95
5	10.67	4.39	4.58
MSE	2.10	0.66	0.31

According to Tab. 6, both the traditional depth neural network and the depth neural network based on wavelet function have been corrected by neural network, and the measurement accuracy of the sensor has been significantly improved. From the experimental results, it can be seen that the average error of the test set is close to that of the training set, and there is no over-fitting phenomenon. The correction value error of neural network based on wavelet function is smaller, which is closer to the actual value, and can realize the nonlinear correction of pressure sensor more accurately, and has higher accuracy and generalization ability.

6 Conclusion

Aiming at the nonlinearity of the input and output of the pressure sensor, the error compensation is realized by introducing Depth Neural Network correction. In view of the shortcomings of the traditional neural network, LM algorithm is introduced to speed up the training speed of the network. By using the Morlet wavelet function, the measurement accuracy is further improved, and the nonlinear output error of the pressure sensor can be more accurately compensated. The experimental results show that, after the correction, the average error of the air pressure sensor is 0.31 hPa, and the accuracy requirement of high altitude detection is fully satisfied. The method has good generalization ability and can be extended to nonlinear correction of similar sensors.

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