Nonlinear Correction and Temperature Compensation Method of Turbine Flowmeter Based on Neural Network

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Abstract. For the nonlinear characteristics of turbine flow sensor and the influence of medium temperature, the traditional compensation method is difficult to apply. This paper uses BP neural network based method to improve measurement accuracy. Firstly, the reason of nonlinearity and the influence of temperature on flow measurement are analyzed theoretically. Then the nonlinear correction and temperature compensation scheme based on neural network is proposed, and different optimization algorithms are used for training. After simulation experiments and analysis, the results show that neural network the maximum reference error of the sensor after compensation is 0.683%. Compared with the traditional least square fitting, the accuracy is greatly improved, which can effectively solve the influence of nonlinearity and temperature change on flow measurement, expand the measurement range of turbine flow meter, and improve the measurement accuracy so as to meet the requirements of industrial use.

1. Introduction
Turbine flowmeter is a kind of flow measuring instrument widely used in industrial production. It measures the volumetric flow rate of the measured medium according to the angular velocity of the impeller in the sensor. The calculation formula of the conventional flowmeter is: \( Q = f/K \).

In general, the traditional turbine flowmeter takes the average value of the sensor flow coefficient as the instrument coefficient. However, the theoretical characteristics of the turbine flowmeter are nonlinear in the small flow range, which is the main source of nonlinear error of the flowmeter. Secondly, the change of the medium temperature also interferes with the flow sensor, which affects the measurement accuracy and measurement range. In order to reduce the sensor error and improve the stability and accuracy of the sensor, many scholars put forward error correction schemes, such as piecewise linear correction and nonlinear fitting in the flow interval, which can effectively improve the measurement accuracy; however, there are also related problems. If the segmentation interval is small,
more calibration points are needed; secondly, other interference factors such as the influence of temperature on the flow measurement cannot be solved.

With the deepening of the research on the turbine flow sensor, higher requirements are put forward for the measurement accuracy, measurement range and linearity of the sensor. It is more and more important to improve the accuracy and nonlinear correction of the sensor. Relevant advanced algorithms and theories are introduced into the application of sensor nonlinear correction, such as neural network and wavelet analysis [1-2]. Among them, neural network has strong nonlinear adaptability, good data generalization performance, and can consider the influence of multiple factors such as temperature at the same time, which can achieve some functions that other compensation methods cannot achieve. Therefore, this paper will apply BP neural network, using gradient descent, Adam, AdaGrad and other optimization algorithms to realize the nonlinear correction and temperature compensation of the turbine flowmeter, so that the sensor test results are more accurate and better in the test process.

2. Theoretical Model and Nonlinear Characteristics of Turbine Flowmeter
Before applying the BP neural network compensation, we first analyze the measurement principle and the nonlinear characteristics of the turbine flowmeter. For the convenience of analysis, the actual simulation model of the axial turbine is shown as fig. 1. When the fluid passes through the pipeline, the impeller is pushed to generate the active torque. The torque that hinders the rotation of the impeller is the mechanical friction torque in the bearing and the frictional torque between the fluid and the turbine [3]. When analyzing the working principle of the axial turbine, it is usually analyzed by the turbine force process according to the momentum conservation theory [4]. The theoretical model of the turbine flowmeter can be obtained as (1):

\[
\omega = C_3 \frac{t \theta}{\gamma A} Q - C_4 \frac{T_{rm}}{\gamma^2 \rho q} - C_4 \frac{T_{rf}}{\gamma^2 \rho q}
\]

where \( \theta \) is the angle between fluid flow direction and the blade of the impeller, \( \rho \) is the fluid density, \( \gamma \) is the average radius of rotation of the turbine, \( C \) is the proportional constant, \( A \) is the flow path area, \( T_{rm} \) is the mechanical resistance torque, and \( T_{rf} \) is the fluid friction torque, \( \omega \) is the angular frequency of the sensor, \( Q \) is the measured flow rate.

Figure 1. Simulation model of the axial turbine.

It can be seen from (1) that the relationship between the angular frequency of the turbine sensor and the measured flow rate \( Q \) is nonlinear. Only when the flow rate is large, the mechanical reacting torque \( T_{rm} \) is relatively small, and the reactive torque generated by the fluid becomes the dominant factor. For example, in the turbulent zone, \( T_{rm}=0 \), and \( T_{rf} \) is as (2):
Then there are:

\[ \omega = C_3 \frac{tg\theta}{\gamma A} Q - K \]  

At this time, the angular frequency of the turbine is linear with the measured flow rate. Therefore, the flow calculation formula (3) used in the conventional turbine flowmeter can be established only when the flow rate is large, and the meter characteristics are poor when the flow rate is small. Therefore, the introduced measurement error is large.

According to the theoretical model of the turbine, the nonlinearity of the meter coefficient is the main factor affecting the measurement accuracy of the turbine flowmeter when the viscosity of the medium does not change much [5]. Therefore, when the measurement condition cannot meet the flow range specified by the turbine flowmeter, especially when the turbine flowmeter is used as a meter for frequent starting and intermittent measurement of the fluid volume, there would be large measurement errors if the average flow coefficient method is still used.

In addition, temperature changes can also affect the instrument coefficient of the turbine flowmeter. When the temperature of the measured fluid in the sensor changes greatly, it will cause changes in the internal dimensions and fluid volume of the sensor, resulting in a change in the sensor meter factor. Therefore, it is necessary to add a correction coefficient of the sensor size change and a correction coefficient of the fluid volume change in the calculation. In general, the turbine speed will vary linearly with temperature differences, and the effects of temperature should be considered when high measurement accuracy is required.

In order to improve the measurement accuracy and measurement range during the measurement process, it is necessary to correct the nonlinear characteristics of the turbine flowmeter and compensate for the temperature change.

3. Nonlinear Correction and Compensation Principle

3.1. Nonlinear Correction and Temperature Compensation Based on Neural Network

The principle of neural network based nonlinear correction and temperature compensation adopts the structure shown in Fig. 2. The measurement background of the scheme is as follows. The flow sensor used is TMR, which is integrated in self-developed secondary instruments and can be installed on the flow calibration device. After the flow value Q and the medium temperature T are set on the calibration device, the secondary frequency meter can be used to measure the rotational frequency F and the temperature T of the turbine. Then the corresponding flow rate \( Q' = F/K \) can be calculated according to the meter coefficient K. However, there are nonlinear errors in the method. Therefore, the neural network is used for compensation. The frequency and temperature measured by the flowmeter are used as the input of the neural network, and the inverse model of the sensor obtained by the neural network can be used to compensate the flow [6]. It is guaranteed that for any measurement frequency F and different temperature T at any time, the ideal output flow value corresponding to the input flow Q in the ideal input-output characteristic curve can be found as \( Q' \) through the neural network, thereby realizing nonlinear correction and temperature compensation.
In order to achieve the above functions, the neural network must be trained first, and it is divided into two stages: offline training and online testing. In the offline training phase, the flow rate Q and temperature T of the calibration test equipment are changed as several sets of different flow calibration points to obtain a set of samples of frequency F. Then the F and T of the sample sets are used as the input of the training neural networks, and measured Q as the desired output. Then use the above sample data to train the neural network to obtain the neural network weight parameters that meet certain error requirements. In the test phase, according to the measured different frequency and temperature values, the parameters of the neural network weights in the previous training phase are used to calculate and obtain the corresponding flow output values, thereby realizing effective compensation for the current flowmeter.

3.2. BP Neural Network

In this paper, a $2 \times n \times 1$ neural network is established, as shown in Fig. 3. Two neurons are used as the input layer, which are the frequency $f$ measured by the sensor and the oil temperature $T$; one neuron is used as the output layer, which takes the nominal flow as the expected output of the neural network, and there are N hidden nodes. Leaky and tanh functions are the excitation functions of neurons. The flow compensation value $Q'$ is obtained by training the sample data, and then the flow compensation value $Q'$ is compared with the expected value $Q$ to obtain an error $e$. Then different optimization algorithms are used to update the weight $w$ of each layer, and the flow compensation value and error are calculated again until the output flow value reaches the required accuracy requirement [7].

According to the sample data $(x_t, f(x_t))$, $t=1, 2, ..., s$ ($x_t$ is the input parameter, $f(x_t)$ is the expected output under the parameter, $s$ is the sample point), the error between the network output $y$ and the target value $f(x_t)$ is recorded as follows: $e_t = f(t) - y_t$, $t=1, 2, ..., s$. The training error of the network is defined as (4):

$$ E = (e_1^2 + \cdots + e_t^2 + \cdots + e_s^2)/2 \quad (4) $$

The weight update formula of the network is (5):

$$ \begin{cases} \omega_{ij} = \omega_{ij} + \eta H_j (1 - H_j) x_i \sum_{k=1}^{m} \omega_{jk} e_k \\ \omega_{jk} = \omega_{jk} + \eta H_j e_k \end{cases} \quad (5) $$

Where $H_j$ is the output of the hidden layer; $e_k$ is the training error; $\eta$ is the learning rate.
Figure 3. $2 \times n \times 1$ BP neural network.

a) Initialize the weight $w_i$ and $w_o$ of each layer in the neural network, randomly select the initial weight $W(0)$, the learning rate $0 < \eta < 1$, and define the training sample set $(x_i, f(x_i))$; $t=1, 2, \ldots, s$, and let $E=0$, $t=1$, $k=0$;

b) Calculate the output value $y_t(k)$ of the output layer and the training error $E$:

$$y_t(k) = w_o(k)T_o(x_t) + \cdots + w_i(k)T_i(x_t) + \cdots + w_n(k)T_n(x_t)$$ (6)

$$Y_t(k) = \text{sigmoid}(y_t(k))$$ (7)

$$e_t = f(x_t) - Y_t(k)$$ (8)

$$E = E + 0.5e_t^2$$ (9)

c) The weight update formula adjusts the weight;

d) $t=t+1$, if $t<s$, the input parameters are not calculated, then jump back to b), otherwise to e);

e) If $E \leq \varepsilon$, the error satisfies the requirement and the training ends; otherwise, $E=0$, $t=1$, $k=k+1$, re-iteratively calculate the weight, and jump back to b).

Through the above iterative process, until the global optimal value of the neural network input and output weights under the given error requirement is obtained, and the network training is completed [8]. At the same time, the weight parameters of the network are saved for online test.

4. Compensation Experiment

The experimental platform consists of a transmitter, the S064 flow tester and a self-developed flowmeter, as shown in Fig. 4. The test platform can measure the frequency of the turbine transmitter, the temperature of the hydraulic oil and the outlet pressure of the oil; the tester can test different types of flow transmitters, different types of flow transmitters have slightly different measuring ranges, and the experiment takes one of the models CL-06 as an example.

Figure 4. Calibration test platform.
4.1. Sample Data Collection and Training

In the range of 0-5L/min of the transmitter, three groups of corresponding measurement frequency and nominal flow data under different temperatures are collected, and 16 different calibration flow points are collected in each group. Considering the nonlinear characteristics of the small flow range, the flow measurement range is set as 0.1L/min in the low frequency range and 0.5L/min in the high frequency range. The measurement process starts from 5L/min, and the nominal flow to be measured is input in order from large to small, and the measured frequency value of the flow meter is recorded. In order to ensure the accuracy of the data, the same flow point is averaged by multiple measurements, and the Grubbs outliers and sliding filtering are performed on the data, thus forming a set of training data samples composed of three parameters, namely nominal flow, measurement frequency and temperature, as shown in TABLE 1.

| Temperature 20℃ | Frequency (Hz) | Q L/min | Temperature 30℃ | Frequency (Hz) | Q L/min | Temperature 40℃ | Frequency (Hz) | Q L/min |
|-----------------|----------------|--------|-----------------|----------------|--------|-----------------|----------------|--------|
| 12.855          | 0.1            | 8.654  | 0.1             | 4.35           | 0.1    |                 |                 |        |
| 33.136          | 0.2            | 28.836 | 0.2             | 24.636         | 0.2    |                 |                 |        |
| 49.472          | 0.25           | 45.17  | 0.25            | 40.87          | 0.25   |                 |                 |        |
| 65.14           | 0.3            | 60.14  | 0.3             | 55.64          | 0.3    |                 |                 |        |
| 88.87           | 0.4            | 84.37  | 0.4             | 79.87          | 0.4    |                 |                 |        |
| 114.047         | 0.5            | 109.35 | 0.5             | 104.55         | 0.5    |                 |                 |        |
| 158.467         | 0.7            | 153.467| 0.7             | 148.367        | 0.7    |                 |                 |        |
| 220.778         | 1.01           | 215.578| 1.01            | 210.38         | 1.01   |                 |                 |        |
| 305.192         | 1.51           | 299.192| 1.51            | 293.692        | 1.51   |                 |                 |        |
| 374.509         | 2.02           | 368.9  | 2.02            | 363.3          | 2.02   |                 |                 |        |
| 452.152         | 2.52           | 445.65 | 2.52            | 439.45         | 2.52   |                 |                 |        |
| 544.37          | 3.03           | 537.78 | 3.03            | 531.17         | 3.03   |                 |                 |        |
| 637.08          | 3.5            | 630.776| 3.5             | 624.276        | 3.5    |                 |                 |        |
| 728.28          | 4.04           | 721.68 | 4.04            | 715.18         | 4.04   |                 |                 |        |
| 821.085         | 4.5            | 814.085| 4.5             | 807.085        | 4.5    |                 |                 |        |
| 914.307         | 5.04           | 906.8  | 5.04            | 899.2          | 5.04   |                 |                 |        |

Take the data in TABLE 1 as the training sample set, and conduct normalization for each group of data. 80% of the data in TABLE 1 are sent to neural network as sample data for effective learning and training, and the rest are used as online test data. After the training is completed, the network is saved for the next use, and the performance comparison of each training optimization algorithm can be obtained as shown in TABLE 2.

The experiment found that the neural network with 4 hidden nodes is fast. As can be seen in TABLE 2, compared with the Gradient-Descent and Adagrad optimization algorithms, Adam has a faster network convergence speed with the same accuracy, and the error is smaller under the same number of iterations. Therefore, the training results of the Adam optimization algorithm are used in the experiment, and the training error curve is shown in Fig. 5.
### Table 2. Comparison of Training Performance of Each Optimization Algorithm

| Optimization algorithm | Number of hidden layer nodes | Iterations / time | Average response time / s |
|------------------------|-----------------------------|-------------------|--------------------------|
| Gradient-Descent       | 4                           | 4650              | 3.9                      |
| Adam                   | 4                           | 690               | 1.7                      |
| Adagrad                | 4                           | 1900              | 2.3                      |

**Figure 5.** Training error curve.

It can be seen from the error curve in Fig. 5: after 690 iterations, the error is 0.0000991 and the target is 0.0001. The network convergence speed is faster.

4.2. **Training Results and Tests**

After the neural network training is completed, the training result curves under different temperatures are made based on the sample data, and the corresponding data under the flow rate of 0.25, 0.5 and 3.5l/min of the test sample data are input into the neural network for testing. The test results are shown in Fig. 6.

**Figure 6.** Neural network training results curve.
Figure 7. Local amplification of training results.

It can be seen from Fig. 7 that the training result curve is very close to the actual measured value. In the input test sample, the maximum relative error of the network compensated flow value is 1.79% at a temperature of 30 °C. For the nonlinear part of the low frequency band, the neural network can also be well fitted. It is proved that the trained network has good fitting, generalization and process convergence, which can improve the nonlinear error of the sensor.

4.3. Comparison between Neural Network and Least Square Method
For the convenience of analysis, the compensation comparison of the two methods was carried out using samples and test data at a temperature of 30 °C. Fig. 8 shows the comparison between the neural network and the least square method. The lower half of the figure is the fitting curve of the two algorithms, and the upper half is the compensation error of the two algorithms at each traffic point. It can be calculated from the figure that the maximum reference error of the least square method is 2.15%, and the maximum reference error of the neural network is 0.683%. It can be seen that the compensation effect of the BP neural network is better than that of the least square method.

Figure 8. Comparison of compensation between neural network and least square method.
5. Conclusion
In this paper, BP neural network is introduced to fit the nonlinear characteristics of the turbine flow sensor. The nonlinear error of the flow measurement is corrected by the appropriate optimization algorithm. At the same time, the influence of medium temperature on the measurement is considered to realize the temperature compensation of flow sensor. The experimental results show that the maximum reference error of the flow sensor compensated by neural network is 0.683%. Compared with the traditional method of calculating the average instrument coefficient using the least square method, the accuracy is greatly improved, which can meet the requirements of industrial use. In the follow-up work, the trained neural network should be transplanted into the flowmeter instrument to realize online real-time nonlinear correction and temperature compensation, and the compensation method based on neural network has a wide range of applicability, which can be fully applied to the compensation and calibration of other sensors.

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References
[1] CASALICCHIO, NERI, PERRONE, “Non-contact low-cost fiber distance sensor with compensation of target reflectivity.”, Instrumentation and Measurement Technology Conference, IMTC 09. IEEE, 2009, pp. 1671-1675.
[2] JIANG X Y, BAO Y J, “Nonlinear errors correction of pressure sensor based on BP neural network,” J. Intelligent Systems and Applications, 2009. ISA 2009: 1-4.
[3] Ya-fei Gu, Yong Zhao, Ri-qing Lv, Yang Yang, “Theory and structure of a modified optical fiber turbine flowmeter,” J. Flow Measurement and Instrumentation, vol. 50, pp. 178-184, August 2016.
[4] Zoheir Saboohi, Shahrokh Sorkhkah, Hossein Shakeri, “Developing a model for prediction of helical turbine flowmeter performance using CFD,” J. Flow Measurement and Instrumentation, vol. 42, pp. 47-57, April 2015.
[5] Bin Wang, Nan Zhang, Qiwei Cao, Yihao Du, “Evaluation approach to dynamic characteristic of turbine flowmeters considering calibration system response,” J. Flow Measurement and Instrumentation, vol. 64, pp. 126-132, December 2018.
[6] Jun-Seong Kim, Do-Yeop Kim, You-Taek Kim, “Experiment on radial inflow turbines and performance prediction using deep neural network for the organic Rankine cycle,” J. Applied Thermal Engineering, vol 149, pp. 633-643, 25 February 2019.
[7] Wenjing Li, Meng Li, Junfei Qiao, Xun Guo, “A feature clustering-based adaptive modular neural network for nonlinear system modeling,” J. ISA Transactions, In press, journal pre-proof, November 2019.
[8] Krzysztof Patan, Maciej Patan, Damian Kowalów, “Neural networks in design of iterative learning control for nonlinear systems,” J. IFAC-PapersOnLine, vol 50, pp. 13402-13407, July 2017.