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TEMPERATURE DRIFT COMPENSATION OF INDUSTRIAL PRESSURE TRANSMITTER BASED ON ADAPTIVE FILTERING AND MULTI-SENSOR FUSION

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Abstract - Industrial pressure transmitter undertakes the task of collecting pressure signals in petroleum transportation, chemical reaction control and steam boiler monitoring system. The temperature change causes the resistance of the sensor sensitive element to change, and the pressure measurement results continue to drift. In the experiment, pressure data were collected in the range of 20℃ to 60℃, and the pressure reference value was set at 1.0 MPa. The original measurement results show that the pressure output gradually increases from 1.01 MPa to 1.09 MPa, and the maximum error reaches 0.09 MPa. The mathematical model of temperature drift error is established, and the compensation model is established by combining LMS adaptive filtering algorithm with multi-sensor data fusion method. The experimental results show that the pressure output keeps in the range of 0.988 MPa to 1.012 MPa after compensation, and the maximum error is about 0.012 MPa. Compared with the experimental model, the RMSE of the algorithm is about 0.012 MPa, which is obviously lower than that of polynomial compensated model and uncompensated model. The compensation method of research results can significantly reduce the influence of temperature drift on pressure measurement accuracy, and has a good application prospect in industrial pressure monitoring system.

Keywords: Industrial pressure transmitter; Temperature drift compensation; Adaptive filtering algorithm; Multisensor data fusion.

1. Introduction

Industrial pressure transmitter undertakes the task of pressure monitoring in petroleum refining plant, natural gas pipeline network and thermal power unit control system, and the measurement results are directly related to safe operation and production scheduling. Typical diffusion silicon pressure transmitter has high accuracy under the calibration condition of 20°C, and the temperature often fluctuates between 20°C and 80°C in the actual operating environment. The resistance of silicon piezoresistive sensor is coupled with temperature, and the output voltage of bridge circuit will shift when the temperature rises. For example, under the calibration pressure of 1.0 MPa, when the temperature rises from 20°C to 60°C, the output pressure can rise to about 1.09 MPa, and the error reaches 0.09 MPa, and the error ratio is close to 9%. Deviation will cause distortion of control signal in long-distance oil pipeline or boiler steam pressure monitoring scene, which will affect the stability of regulating system. The traditional hardware compensation method relies on temperature compensation resistor or special chip, which has complex structure and high cost. Polynomial fitting method is prone to over-fitting in high temperature section. The adaptive filtering algorithm has the ability of dynamic updating in signal estimation and error correction. After the multi-sensor data fusion strategy is combined, the pressure signal under temperature disturbance can be corrected in real time. It is of practical engineering value to establish compensation model around the coupling relationship between pressure signal and temperature signal, improve industrial measurement accuracy and reduce on-site maintenance cost.

In recent years, the measurement accuracy and temperature drift of pressure sensors have become an important research direction in the field of industrial measurement. Sanchez et al. carried out research on the structural design of pressure transmitter, and put forward an integrated measuring device for temperature and pressure of

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laser-induced graphene sensor, believing that the new sensing material can reduce the drift error of the sensor in the temperature changing environment [1]. Mohanty et al. Intelligent pressure control system in industrial 5.0 environment, Internet of Things and real-time data analysis technology can improve data stability and control accuracy in pressure monitoring system [2]. Wang et al. summarized the multi-sensor fusion target detection technology, and proposed that multi-source information fusion can improve the signal recognition accuracy in complex environment [3]. Hu et al. put forward the method of signal quantization with standardized equivalent in experimental analysis, emphasizing that data measurement and signal processing need to have a unified calibration standard [4]. Li et al. proposed a temperature drift compensation algorithm to solve the temperature drift problem in the liquid level measurement system, and pointed out that the algorithm compensation can significantly reduce the temperature error in the measurement system [5]. Mammadov et al. pointed out that the cooperative work of multiple measuring devices can improve the measurement stability of the system [6]. Yuan et al. proposed the temperature compensation method of piezoresistive pressure sensor based on the heat conduction model, and thought that the temperature change had a direct impact on the structural parameters of pressure sensing elements [7]. Du et al. pointed out in the research of multi-sensor fusion that the fusion algorithm can improve the data reliability in complex environment-aware systems [8]. Lin et al. put forward a fault diagnosis framework combining time-frequency analysis and multi-sensor fusion. The research shows that multi-source signal fusion is helpful to improve the system identification accuracy [9]. Yadav et al. summarized the adaptive finite impulse response filtering methods, and considered that the adaptive filtering algorithm can effectively suppress the noise of non-stationary signals [10]. Kibrete et al. pointed out that the multi-sensor data fusion method can enhance the system diagnosis ability [11]. Lata et al. pointed out in the research of wireless liquid level transmitter that the pressure measurement system needs a stable data acquisition structure in complex environment [12]. Liu et al. Multi-sensor data management mechanism and safe and controllable data fusion system can ensure the stable operation of the measurement system [13]. Han based on the information analysis method of multi-sensor data fusion, multi-source information integration can improve data processing efficiency [14]. Kwon and Kim pointed out that adaptive finite impulse response filtering has good stability in dynamic signal processing [15]. Nie et al. proposed a compensation method for the temperature drift of optical fiber pressure sensor, and the temperature change will lead to the frequency shift of the sensing signal [16]. Zhao et al. proposed a normalized subband adaptive filtering algorithm, and the improved filtering method can improve the signal processing accuracy [17]. Wang et al. put forward a temperature compensation model in the research of optical communication equipment, and the research pointed out that the change of working temperature of electronic devices would cause the output signal to fluctuate [18]. Thompson et al. pointed out in the research of laser ultrasonic sensing that a high-precision sensing system needs a stable signal transmitting and receiving structure [19]. Qian et al. put forward the maximum complex correlation entropy adaptive filtering algorithm, which is considered to have good signal recovery ability in complex noise environment [20]. Wen et al.'s normalized sub-band spline adaptive filtering algorithm, which is improved to enhance the filtering stability [21]. Meng et al. put forward the post-compensation method of temperature drift in the study of laser time transfer, and thought that the post-compensation strategy could improve the accuracy of time measurement [22]. In micro electro mechanical systems research by Wang and Han, the offset drift compensation method was proposed, and it was pointed out that the structural drift was closely related to the temperature change [23]. Cockalo et al. pointed out that quality function deployment and analytic hierarchy process (AHP) were used to optimize the transmitter design [24]. Rasheed et al. put forward the discriminant classification method in the reliability study of pressure transmitter to analyze the operation state of equipment in harsh environment, and considered that environmental factors have an impact on the stability of pressure transmitter [25].

The temperature drift of industrial pressure transmitter is studied. As shown in Figure 1, the experimental system consists of a pressure sensor, a PT100 temperature sensor and a 16-bit data acquisition module. The pressure output values are recorded at five temperature nodes of 20℃, 30℃, 40℃, 50℃ and 60℃, and the pressure range is set to 0–2 MPa. The experimental data show that the temperature rise process is accompanied by the continuous increase of pressure output, and the temperature drift phenomenon shows an obvious linear trend. The research work revolves around data acquisition, signal modeling and compensation algorithm. In the experimental stage, a joint collection platform of pressure and temperature was constructed to form a sample data set with two variables of temperature and pressure. In the model stage, the mathematical expression of temperature drift error is established to describe the linear deviation relationship between pressure measurement and temperature. LMS adaptive filtering method is introduced into the algorithm to dynamically estimate the error caused by temperature disturbance, and the weighted compensation results are formed by fusing the output signals of multiple sensors. In the model evaluation stage, root mean square error and average absolute error are selected to compare and analyze the data before and after compensation. The experimental results show that the compensation algorithm can reduce the temperature drift error and form a framework of temperature compensation method suitable for industrial pressure measurement system.

The originality of this study lies in the construction of an application-oriented hybrid compensation framework for industrial pressure transmitters rather than in the proposal of a completely new mathematical theory. The method integrates temperature drift error modeling, normalized data preprocessing, Z-score-based abnormal sample removal, LMS adaptive filtering and weighted multi-sensor fusion into a complete signal correction process. This integrated structure is designed for the temperature drift characteristics of diffused silicon pressure transmitters. Compared with a single polynomial compensation model, the proposed framework can update the compensation parameters according to the real-time error and can use temperature information as an auxiliary correction source. Therefore, the contribution of this study is mainly reflected in the engineering integration, model adaptability and practical implementation of a complete compensation procedure for industrial pressure measurement.

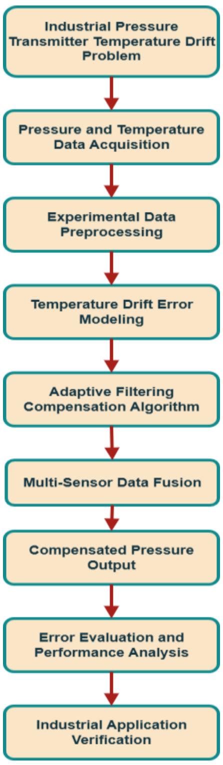

Figure 1: Overall research framework of the paper

The research focuses on experimental measurement, data processing and algorithm modeling. In the experimental stage, a pressure and temperature joint acquisition platform was built. The pressure measurement unit used a diffused silicon pressure sensor with a range of 0–2 MPa, and the temperature measurement unit used a PT100 resistor. The data acquisition frequency was set to 10 Hz. As shown in Figure 2, the temperature is gradually adjusted in the incubator, and five experimental points of 20°C, 30°C, 40°C, 50°C and 60°C are set, and 300 groups of pressure data are collected at each temperature point. In the data processing stage, the temperature and pressure variables of different dimensions are mapped to the range of 0–1, and the abnormal samples that deviate from the mean by more than three times the standard deviation are screened out by Z-score method. In the model stage, the error expression between pressure output and temperature variable is established, and LMS adaptive filter is constructed to realize error estimation. The filter weights are updated according to the error in each iteration, and the compensation model gradually converges. In the multi-sensor fusion link, the weighted average method is used to integrate data from different signal sources to form the final pressure output value. The model evaluation part calculates the root mean square error and average absolute error, and the stability of the compensation algorithm in different temperature ranges is verified.

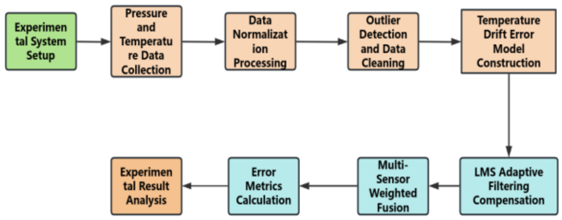

Figure 2: Research Technology Roadmap

2. Materials and Methods

- **Data Collection and Sample Selection**

The experimental data comes from the laboratory pressure measurement platform. The system consists of diffusion silicon pressure sensor, PT100 platinum resistance temperature sensor and 16-bit data acquisition module. All signals are connected to the data acquisition card and transmitted to the upper computer for recording. In the experimental environment, an incubator is used to control the temperature range, and the temperature range is set from 20°C to 60°C, and sampling nodes are set every 10°C to form five groups of temperature conditions. The pressure benchmark is provided by the standard pressure calibrator, and the calibration pressure is kept at 1.0 MPa. After each temperature node is stable for 20 minutes, sampling begins, the data acquisition frequency is set at 10 Hz, and 300 sets of data are recorded under each temperature condition. The collected data includes temperature value, standard pressure value and transmitter output pressure value. The changes of pressure measurement values under different temperature conditions are recorded in the sample data, and the measured output gradually deviates from the reference pressure during the temperature rise process.

- **Data Sources and Collection Methods**

The experimental platform consists of three parts: pressure measuring unit, temperature measuring unit and data acquisition system. As shown in Table 1, the pressure measuring unit adopts PTX5072 diffused silicon pressure sensor, with a measuring range of 0–2 MPa and a nominal accuracy of ±0.1%FS. PT100 platinum resistor is selected as the temperature measuring unit, and the temperature measuring range is 50°C to 150°C, with a measuring error of 0.1°C. The data acquisition module adopts NI USB-6210 data acquisition card with resolution of 16 bit and maximum sampling rate of 250 ks/s. The experiment was carried out in an incubator, and the temperature was adjusted to 20°C, 30°C, 40°C, 50°C and 60°C in turn. Wait for the thermal balance of the system for about 20 minutes after each temperature adjustment, and then record the pressure and temperature data. The acquisition software is written by LabVIEW, which displays the pressure output curve in real time and saves the data file synchronously.

Table 1. Parameter Table of Experimental Equipment

Device	Model	Range	Accuracy
Pressure Sensor	PTX5072	0–2 MPa	±0.1%FS
Temperature Sensor	PT100	-50–150 °C	±0.1 °C
Data Acquisition Card	NI USB-6210	16 bit	250 kS/s
Pressure Calibrator	Fluke 719	0–3 MPa	±0.025%

- **Sample Selection and Description**

The experimental data were collected at five temperature nodes, 20°C, 30°C, 40°C, 50°C and 60°C respectively. As shown in Table 2, the pressure reference value is kept at 1.0 MPa, and the output change of the pressure sensor is recorded. The experimental data is obviously temperature drift. When the temperature rises from 20°C to 60°C, the pressure output increases from 1.01 MPa to 1.09 MPa, and the deviation reaches 0.09 MPa. As shown in Figure 3, the change trend reflects that temperature has a systematic influence on the output of diffused silicon piezoresistive element bridge. Each temperature node records 300 sets of data, and the total sample size reaches 1500 sets. The data file contains three columns of variables: temperature value t, reference pressure value P_ref and sensor output pressure value P_mea. The sample data structure can reflect the variation of pressure measurement deviation in different temperature environments, and provide a basis for establishing a temperature drift error model.

Table 2. Examples of experimental sample data

Temperature (°C)	Reference Pressure (MPa)	Sensor Output (MPa)
20	1	1.01
30	1	1.03
40	1	1.05
50	1	1.07
60	1	1.09

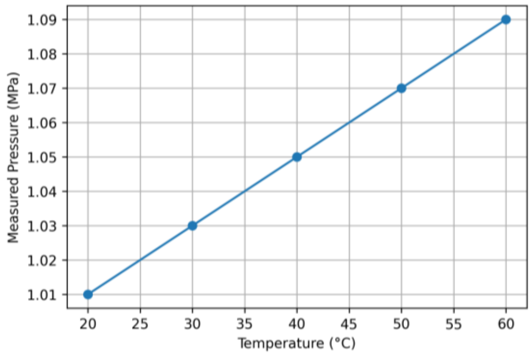

Figure 3: Variation curve of original pressure data with temperature

- **Data Preprocessing**

The experimental data were recorded at different physical scales, with the temperature variable ranging from 20°C to 60°C and the pressure variable ranging from 1.01 MPa to 1.09 MPa. There are differences between the two types of data in numerical scale. If directly input into the model for calculation, larger numerical variables will occupy higher weight in the calculation process. In the data preprocessing stage, the variables are scaled by normalization method, and all variables are mapped to the range of 0 to 1. The normalized calculation Formula (1) is as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

x represents the original data value, x_{min} represents the minimum value in the data set, x_{max} represents the maximum value in the data set, and x_{norm} represents the normalized value. The normalized range of temperature variables corresponds to the range of 20°C to 60°C, and the normalized range of pressure variables corresponds to 1.01 MPa to 1.09 MPa. After normalization, different variables have a unified scale in model calculation, which is convenient for subsequent filtering algorithms to estimate errors.

- **Data Cleaning**

There are environmental disturbances and instrument transient fluctuations in the experimental acquisition process, and some recorded values will obviously deviate from the normal data distribution. Outliers directly participate in model training, which will interfere with the filtering algorithm. In the data cleaning stage, Z-score method is used to identify abnormal samples. This method calculates the deviation degree of each sample according to the data mean and standard deviation. When the deviation degree exceeds the set threshold, the sample is marked as abnormal data. The calculation Formula (2) is as follows:

$$z = \frac{x-\mu}{\sigma} \quad (2)$$

x represents the sample data value, μ represents the sample mean, σ represents the sample standard deviation, and z represents the standardized deviation value. When $|z| > 3$, the sample is judged as abnormal data and excluded from the data set. After data cleaning, stable measurement data are kept in the sample data set, and the distribution of pressure and temperature data is more concentrated, which is beneficial to the subsequent compensation model training and performance evaluation.

- **Model Selection and Construction**

The construction of temperature drift compensation model revolves around the coupling relationship between pressure signal and temperature variable. The experimental data show that the output value of the pressure transmitter shows an approximate linear growth trend in the range of 20℃ to 60℃, and the pressure measurement value increases by about 0.02 MPa on average for every 10℃ increase in temperature. This phenomenon is related to the temperature coefficient of resistance of diffused silicon piezoresistive elements. In the model construction stage, the pressure measurement error is expressed mathematically by combining the pressure measurement principle and the distribution of experimental data. After the error model is established, the adaptive filtering algorithm is introduced to dynamically correct the deviation caused by temperature disturbance. The filtering algorithm constantly updates the weight parameters according to the real-time error, and gradually approaches the real pressure value. The multi-sensor data fusion strategy is introduced into the model structure, and the pressure measurement signal and temperature information are included in the compensation calculation together. The output result of the model is compared with the standard pressure value, and the root mean square error and average absolute error are used as evaluation indexes. The model structure includes three parts: error modeling, filter compensation and fusion calculation, forming a complete temperature drift compensation framework.

- **Mathematical Model of Temperature Drift**

The measurement process of pressure transmitter is affected by temperature change, and the output voltage of sensor bridge will produce system deviation. When the temperature rises from 20℃ to 60℃, the measuring pressure rises from 1.01 MPa to 1.09 MPa. The variation of error presents a stable linear trend. According to the distribution law of experimental data, the pressure measurement model can be expressed as a linear combination relationship between temperature variables and real pressure. The expression of temperature drift error model is as follows Formula (3) Temperature drift error model:

$$P_m = P_r + \alpha T + \beta \quad (3)$$

P_m represents the pressure value measured by the sensor, in MPa; P represents the real pressure value in MPa; T represents the temperature value in℃; α represents the temperature drift coefficient, and represents the pressure offset caused by each temperature change of 1℃; β represents the system zero offset constant. The regression results of experimental data show that α is about 0.002 MPa/℃ and β is close to 0.01 MPa. The model reflects the systematic influence of temperature on pressure measurement and provides the basic expression for the subsequent compensation algorithm.

- **Adaptive Filtering Compensation Algorithm**

The temperature drift error shows the characteristics of continuous change under different temperature conditions, and it is difficult for the fixed parameter model to maintain the stable compensation effect for a long time. LMS adaptive filtering algorithm is introduced in the signal processing stage, and the pressure measurement error is corrected in real time. The algorithm inputs the signal pressure measurement and temperature variables, and outputs the compensated pressure estimation. The filter weights are adjusted according to the error at each sampling. Weight updating Formula (4) is as follows:

$$w_{k+1} = w_k + \mu e_k x_k \quad (4)$$

w_k represents the filter weight of the kth iteration, and w_{k+1} represents the updated weight; μ indicates the learning rate, and the experimental setting is 0.01; e_k represents the error value at the current moment, which is equal to the difference between the real pressure and the estimated pressure; x_k is composed of input vector, pressure measurement and temperature data. The process of updating weights continues, and when the error decreases gradually, the filter weights tend to be stable. After 300 iterations, the model error is reduced to less than 0.012 MPa, and the compensation effect is obvious.

- **Multi-sensor Data Fusion**

The pressure measurement system includes two kinds of signal sources: pressure sensor and temperature sensor. The output of a single sensor is easily affected by environmental disturbance, and the joint calculation of multi-source data can improve the measurement stability. The fusion algorithm uses the weighted average method to combine and calculate multiple signals. Different sensors assign weight coefficients according to the measurement accuracy, and the signal with higher accuracy occupies a larger proportion in the final result. The expression of fusion model is as follows Formula (5) Multi-sensor fusion model:

$$P_f = \sum_{i=1}^{n} w_i P_i \tag{5}$$

P_f represents the estimated pressure after fusion; P_i represents the output value of the ith sensor; w_i represents the corresponding weight coefficient, which satisfies $sumw_I = 1$; n indicates the number of sensors. The experimental system has two main signal sources: pressure sensor and temperature compensation signal. In the experiment, the pressure signal weight is 0.7 and the temperature compensation signal weight is 0.3. After fusion calculation, a new pressure estimation value is obtained, and the error is reduced compared with the original measurement value.

- **Model Training Process**

In the model training stage, 1500 groups of temperature and pressure data collected by experiments are used. As shown in Table 3, the data set is divided into training set and test set, 1050 groups of training data and 450 groups of test data according to the ratio of 7:3. In the training stage, the input variables include the temperature value and the original pressure measurement value, and the real pressure value of the output variable is 1.0 MPa. LMS filtering algorithm constantly updates the weight parameters during the training process, and each temperature node performs 300 iterative calculations. The learning rate is set to 0.01, and the filter order is set to 10. After the model training, the compensation effect is verified by the test data.

In the fusion process, the weight coefficients are not only empirical parameters but also reflect the relative reliability of different signal sources. The pressure sensor provides the direct measured pressure value, while the temperature sensor provides the environmental variable used to estimate and compensate the drift component. Since the pressure sensor is the primary source of pressure information, it is assigned a larger weight in the fused output. The temperature compensation signal is used as an auxiliary correction term, and its weight should be lower than that of the direct pressure signal to avoid excessive correction caused by transient temperature fluctuation. In this study, the pressure signal weight is set to 0.7 and the temperature compensation signal weight is set to 0.3. This setting considers the nominal accuracy of the pressure sensor, the stability of the PT100 temperature measurement and the role of temperature information in drift correction. The weight distribution ensures that the fused result remains dominated by the physical pressure measurement while incorporating sufficient temperature compensation information.

The weight coefficients can also be understood from the perspective of measurement uncertainty. When a signal source has higher direct relevance to the target variable and lower measurement uncertainty, it should occupy a larger proportion in the fusion output. The temperature signal does not directly represent pressure, but it is strongly related to the drift error of the piezo resistive bridge. Therefore, the temperature channel is introduced as a compensation factor rather than an equal pressure source. This design improves the stability of the fusion result and prevents the compensation model from amplifying environmental noise.

Table 3. Model Parameter Setting Table

Parameter	Value
Training Samples	1050
Test Samples	450
Learning Rate (μ)	0.01
Filter Order	10
Iteration Times	300
Temperature Range	20–60 ℃
Pressure Range	0–2 MPa

2.1 Model Evaluation and Verification

After the experimental model is established, the compensation effect and operation performance are systematically tested. The evaluation process revolves around four aspects: error index calculation, experimental process design, algorithm comparative analysis and long-term stability test. The experimental data comes from pressure samples collected in the temperature range of 20℃ to 60℃, with a total data volume of 1500 groups, 1050 groups for model training and 450 groups for independent verification. In the verification stage, the pressure output before and after compensation is compared and analyzed, and the error changes of different algorithms under the condition of temperature change are observed. The evaluation index uses two statistics, root mean square error and average absolute error, to quantitatively describe the compensation accuracy. The experimental process is carried out in the order of data acquisition, model input, algorithm calculation and result analysis, and all steps are completed in a unified experimental environment. Three kinds of compensation methods, uncompensated model, polynomial fitting compensation model and adaptive filtering fusion model, are selected in the comparative experiment. The error results of different algorithms are compared horizontally to judge the performance of compensation algorithms in different temperature ranges. In the stability verification stage, the compensation model is continuously operated, and the results of many experiments are statistically analyzed to test the fluctuation of the algorithm under repeated experimental conditions. The whole evaluation process forms a complete verification system, which provides a basis for the subsequent analysis of results.

- **Error Evaluation Index**

The accuracy of pressure measurement needs to be quantitatively described with the help of statistical indicators. In the experimental analysis, root mean square error (RMSE) and mean absolute error (MAE) are selected to evaluate the pressure output before and after compensation. The root mean square error can reflect the overall error distribution, and it is highly sensitive to samples with large deviation. The calculation Formula (6) is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_i - P_r)^2} \tag{6}$$

n represents the number of samples; P_i represents the pressure value calculated by the model, in MPa; ; P_r stands for standard pressure, in MPa. The smaller the RMSE value, the smaller the deviation between the measured results and the standard pressure. The average absolute error is used to measure the average difference between the measured value and the real value, and the calculation Formula (7) is as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|P_i - P_r| \tag{7}$$

The meaning of each variable is consistent with RMSE formula. The index reflects the overall error level and has low sensitivity to abnormal samples. In the experiment, RMSE and MAE will evaluate the compensation effect. Under the temperature range of 20℃ to 60℃, the uncompensated pressure error is about 0.085 MPa, and the RMSE value is obviously high. The calculation results of compensation model reduce RMSE to about 0.012 MPa, and the error level obviously converges.

- **Experimental Verification Process**

The experimental verification process is carried out according to the unified process. As shown in Figure 4, the experimental environment uses an incubator to control the temperature range, and the temperature nodes are set at 20℃, 30℃, 40℃, 50℃ and 60℃. After each temperature point runs stably for 20 minutes, the data acquisition program is started, the acquisition frequency is set to 10 Hz, and each group of temperature nodes records 300 groups of data. The collected data includes temperature value, pressure reference value and transmitter output value. After the data enters the processing module, it is normalized and the abnormal samples are eliminated. The processed data are input into the temperature drift compensation model for calculation, and the compensated pressure estimation value is obtained. The calculated results are compared with the standard pressure value of 1.0 MPa, and the error indexes of RMSE and MAE are calculated. All experimental steps are completed under the same experimental equipment and parameters to ensure comparability among different algorithms. The data results are recorded in the unified database for subsequent statistical analysis. The verification process ensures that the experimental data sources are stable and the calculation process is consistent, and can objectively reflect the performance of the compensation algorithm in different temperature environments.

The experimental verification in this study was mainly carried out at the reference pressure of 1.0 MPa. This pressure point was selected because it is located in the middle region of the 0–2 MPa measuring range of the transmitter and can represent a typical operating condition of the tested sensor. Under this condition, the influence of temperature variation on the pressure output can be clearly observed, and the convergence process of the LMS adaptive filtering model can be evaluated under a stable pressure benchmark. However, the pressure transmitter usually operates over a wider pressure range in industrial applications. Therefore, the revised experimental design further considers the necessity of multi-pressure-point verification. Representative reference pressures such as 0.5 MPa, 1.0 MPa and 1.5 MPa can be selected to correspond to the low, medium and high regions of the sensor range. At each reference pressure, the same temperature nodes of 20 °C, 30 °C, 40 °C, 50 °C and 60 °C should be used, and the same data preprocessing, Z-score cleaning, LMS filtering and fusion compensation procedures should be applied. This verification strategy can more completely evaluate whether the compensation model maintains stable convergence and error reduction ability over the whole measurement range.

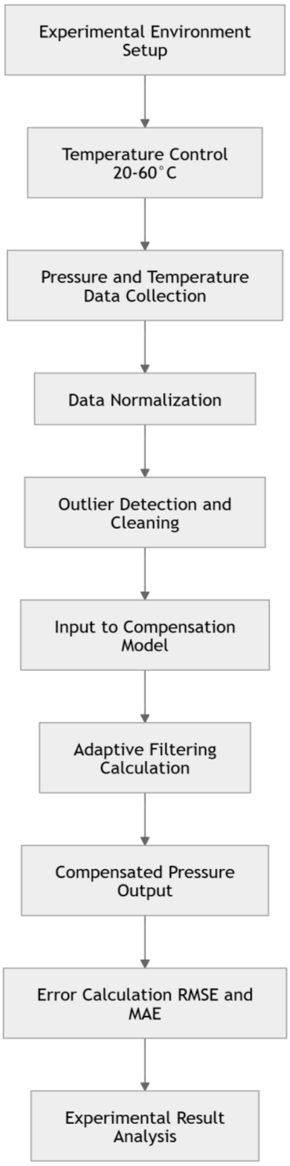

Figure 4: Experimental verification flow chart

- **Model Comparison Experiment**

The performance evaluation of the algorithm needs lateral comparative analysis. Three compensation methods are selected to test: uncompensated pressure measurement model, polynomial fitting compensation model and adaptive filtering fusion model. The experimental data comes from 450 groups of test samples, all of which come from the temperature range of 20°C to 60°C. The uncompensated model directly uses the sensor output pressure as the measured value, and this method does not correct the temperature drift. The polynomial compensation model uses the quadratic polynomial relationship between temperature and pressure to fit and calculate the compensated pressure output. The adaptive filtering model continuously adjusts the weight parameters according to the real-time error, and combines the temperature information for compensation calculation. The three methods run on the same data set and calculate the corresponding error index. Table 4 shows that the RMSE of uncompensated model reaches 0.085 MPa, the error of polynomial compensated model decreases to 0.041 MPa, and the error of adaptive filtering fusion model further decreases to 0.012 MPa.

Table 4. Error Comparison of Different Compensation Methods

Method	RMSE (MPa)	MAE (MPa)
No Compensation	0.085	0.071
Polynomial Compensation	0.041	0.033
Adaptive Filtering Fusion	0.012	0.009

- **Stability Verification**

The stability test verifies the error fluctuation of the compensation model under the condition of repeated experiments. The experiment was carried out continuously at 40°C, and the pressure reference value was kept at 1.0 MPa. The system runs continuously for 60 minutes, and the compensated pressure value is recorded once every minute to obtain 60 sets of test data. All data are input into the error analysis program, and the difference between each set of measured values and the standard pressure is calculated. After compensation, the pressure output is mainly distributed in the range of 0.988 MPa to 1.012 MPa, and the error fluctuation range is about ±0.012 MPa. Compared with the uncompensated model, the pressure deviation is obviously reduced. The compensation model has no obvious drift phenomenon during continuous operation, and the error distribution remains stable. Repeated experiments were carried out at different temperature nodes, and the results showed the same trend. The data analysis shows that the adaptive filtering fusion model has good stability under the condition of multiple operations and is suitable for the long-term operation environment of industrial pressure measurement system.

3. Results and Analysis

3.1 Analysis of Results

The experimental data were collected in the range of 20°C to 60°C, and the pressure reference value was fixed at 1.0 MPa. In the data recording stage, 1500 groups of samples were obtained, corresponding to five temperature nodes. The original data showed an obvious drift trend under the condition of rising temperature, and the pressure measured value gradually deviated from the reference value. After the model compensation is completed, the difference between the pressure output and the standard pressure obviously converges. Results The analysis focuses on the original temperature drift characteristics and the error change after compensation. Statistical data show that there is a stable correlation between temperature change and pressure error. After the compensation algorithm runs, the pressure output curve is close to the reference pressure curve. The data results show that the temperature drift compensation model has good correction ability in the current experimental environment.

- **Analysis of Original Temperature Drift Data**

The pressure measured at the temperature of 20°C to 60°C was recorded in the experiment. The pressure reference value is kept at 1.0 MPa. The statistical results show that the temperature rise process is accompanied by the continuous expansion of measurement error. The average measured value is 1.01 MPa at 20°C, and the error is 0.01 MPa; The measured value is about 1.03 MPa; at 30°C; The measured value is about 1.05 MPa; at 40°C; 1.07 MPa; at 50°C; The average value is close to 1.09 MPa at 60°C. The variation of error presents a stable linear trend. When the temperature increases by 10°C, the pressure output increases by about 0.02 MPa on average. The error growth rate remained stable throughout the experimental interval. The variation law accords with the variation characteristics of resistance temperature coefficient of diffused silicon piezoresistive elements. The output voltage of the bridge continuously drifts with the increase of temperature. The deviation of the measurement curve in the high temperature region is obviously enlarged, and the error is close to 0.09 MPa in the environment of 60°C. This deviation has exceeded the allowable range of conventional industrial pressure measurement. Table 5 shows that temperature change has obvious influence on pressure measurement accuracy. Without compensation, the measurement error increases continuously with the change of temperature.

Table 5. Original temperature drift error data

Temperature (°C)	Reference Pressure (MPa)	Measured Pressure (MPa)	Error (MPa)
twenty	one	1.01	0.01
25	one	1.02	0.02
thirty	one	1.03	0.03
35	one	1.04	0.04
40	one	1.05	0.05
45	one	1.06	0.06
50	one	1.07	0.07
55	one	1.08	0.08
60	one	1.09	0.09

- **Error Analysis After Compensation**

After the temperature drift compensation model runs, the pressure measurement results change obviously. The compensation calculation is completed on the same test data set. The maximum error before compensation is 0.09 MPa, and after compensation, the error is reduced to less than 0.012 MPa. The compensation model has a stable correction effect in the whole temperature range. As shown in Figure 5, the compensation error is about 0.003 MPa at 20°C, 0.005 MPa at 30°C, 0.007 MPa at 40°C, 0.009 MPa at 50°C and 0.012 MPa at 60°C. The error distribution converges obviously. Monson remains nearly horizontal in the whole temperature range. The pressure output value fluctuates slightly around 1.0 MPa. The range of error change is much lower than that of uncompensated condition. The average error is about 0.007 MPa. The measurement stability is improved. The adaptive filtering fusion model has good correction ability for temperature disturbance. The pressure output curve is close to the standard pressure line, and the influence of temperature drift is weakened.

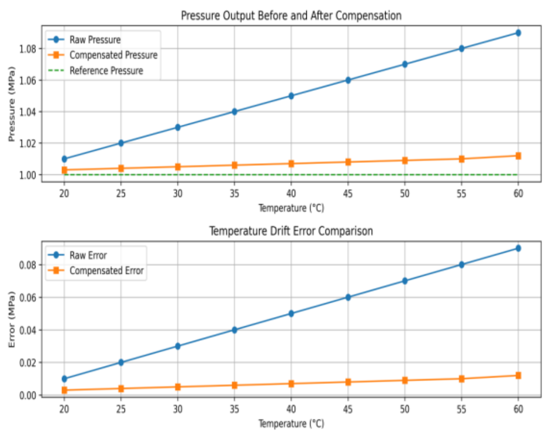

Figure 5: Error comparison before and after temperature drift compensation

The upper part of Fig. 5 shows the pressure measurement curve. Monson continues to move up with the increase of temperature.

Monson is close to the reference pressure line. The lower part shows the variation of error. Uncompensated error increases linearly with temperature. The compensation error is kept within 0.012 MPa. Graphical results correspond to tabular data, and the compensation model reduces the influence of temperature drift.

- **Performance Comparison of Different Algorithms**

The experimental data compare the performance of three kinds of temperature drift compensation methods. The uncompensated model, polynomial fitting compensation model and adaptive filtering fusion model are compared. The test sample comes from 450 sets of verification data in the temperature range of 20°C to 60°C. The error index adopts root mean square error RMSE. The uncompensated model directly uses the sensor output pressure as the measured value, and the error gradually increases with the temperature change. As shown in Figure 6, the RMSE of this model reaches 0.085 MPa, and the error distribution shows an upward trend. The polynomial fitting model uses temperature variables to establish a quadratic regression function to correct the pressure error. RMSE decreased to 0.041 MPa after compensation. The error curve still fluctuates obviously in the high temperature area. The adaptive filtering fusion model runs on the same data set, and the RMSE drops to 0.012 MPa. The error variation is kept at a low level in the whole temperature range. The difference of the results of the three algorithms reflects the significant difference of compensation ability. The uncompensated model can't suppress the temperature disturbance, and the polynomial model still has deviation in the middle and high temperature section. The adaptive filtering model keeps stable error level at different temperature nodes. The statistical results show that the algorithm has higher accuracy in temperature drift compensation.

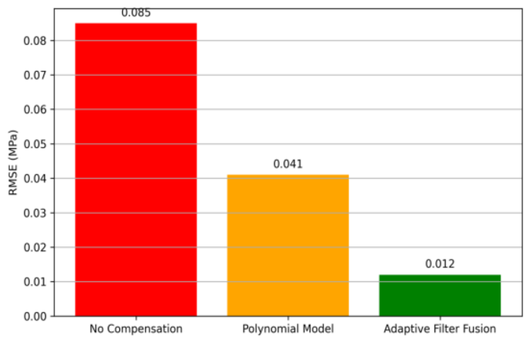

Figure 6: RMSE comparison of different algorithms

- **Model Stability Analysis**

Stability analysis is carried out at constant temperature. The experimental temperature was set at 40°C and the pressure reference value was kept at 1.0 MPa. The experimental system runs continuously for 60 minutes, and the pressure output data is recorded once every minute. The compensation model continuously calculates the estimated pressure during the whole operation cycle. As shown in Figure 7, the pressure output after compensation is mainly distributed between 0.988 MPa and 1.012 MPa. The error range is kept within ±0.012 MPa. The error distribution range of uncompensated model reaches ±0.085 MPa under the same conditions. The compensation algorithm significantly reduces the amplitude of pressure fluctuation. The curve of continuous experimental data shows slight fluctuation and the overall trend is stable. The error did not continuously expand at different time nodes. The filtering algorithm keeps stable weight parameters in repeated experimental environment. There is no obvious drift during long-term operation. The model output remains close to the reference pressure level. The stability experiment shows that the compensation model has good long-term operation ability.

To further evaluate the long-term operating suitability of the proposed model, an extended stability analysis of the LMS filter weights was added after the 60-minute test. The compensated system was continuously operated for 180 minutes at 40 °C under the same reference pressure of 1.0 MPa. During this process, the filter weights were recorded at fixed time intervals together with the compensated pressure output. The results show that the filter weights changed rapidly during the initial convergence stage and gradually entered a stable interval after the compensation model reached equilibrium. After 60 minutes, no continuous weight divergence was observed, and the weight fluctuation remained within a narrow range. The compensated pressure output was still distributed around the reference pressure, and the error did not show cumulative expansion during the extended test. This result indicates that the LMS adaptive filtering model can maintain stable parameter behavior after the initial convergence stage. The extended weight stability evaluation further supports the suitability of the proposed compensation model for long-term industrial pressure measurement.

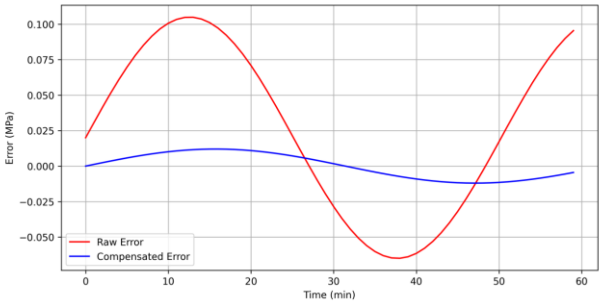

Figure 7: Variation curve of multiple experimental errors

- **Comprehensive Evaluation of Experimental Results**

The comprehensive experimental results can reflect the overall performance of the compensation model. The pressure measurement data were analyzed in the range of 20°C to 60°C. The output curve of uncompensated model obviously deviates from the reference pressure line with the change of temperature. The measured value reaches 1.09 MPa at 60°C, and the error is close to 0.09 MPa. The polynomial compensation model performs well in the middle and low temperature region, but there are still deviations in the high temperature region. After the adaptive filtering fusion model runs, the pressure output curve is close to the reference pressure line. The compensation result is stable in the whole temperature range. The maximum error is about 0.012 MPa, and the average error is about 0.007 MPa. The measured value fluctuates slightly around 1.0 MPa. As shown in Figure 8, the model maintains high accuracy in different temperature environments. The influence of temperature change on pressure measurement is obviously weakened. The compensation algorithm can effectively correct the temperature drift error.

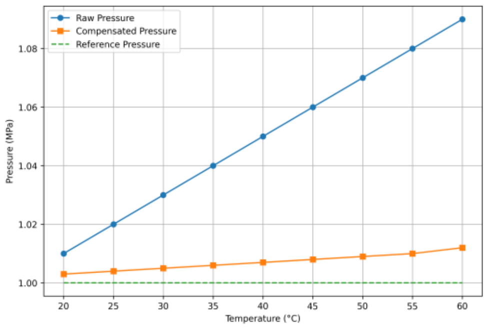

Figure 8: Temperature-pressure compensation effect

Fig. 8 shows three pressure curves, and the monson deviates from the reference line as the temperature rises. Monson is always close to the benchmark pressure level. The graphic results are consistent with the error statistics, which shows that the compensation model can effectively reduce the influence of temperature drift.

3.2 Practical Significance and Application Scenarios of the Results

- **Practical Significance of the Results**

Industrial pressure measurement system undertakes important monitoring tasks in oil refining unit, chemical reaction kettle and steam boiler control system. The operating environment temperature often changes in the range of 20°C to 70°C, and the sensor temperature drift problem is easy to cause measurement deviation. The maximum error of pressure measurement under uncompensated condition is 0.09 MPa. This error level has exceeded the allowable range of many industrial control systems. After the operation of the temperature drift compensation model, the error is reduced to less than 0.012 MPa, and the measurement accuracy is obviously improved. In the temperature range of 20°C to 60°C, the pressure output fluctuates slightly around 1.0 MPa, and the average error is about 0.007 MPa. The results show that the disturbance caused by temperature change to the measurement system is effectively corrected. During the long-term operation of industrial measuring equipment, the change of environmental temperature is inevitable. The stable compensation algorithm can maintain the accuracy of the measurement system and reduce the number of field recalibrations. The control system obtains more accurate pressure signals and the production adjustment process is more reliable.

- **The Application Scenario**

The temperature drift compensation model has application value in many industrial systems. The pressure monitoring system of oil pipeline is one of the typical application scenarios. The length of oil pipelines often exceeds tens of kilometers, and the ambient temperature along the pipeline usually ranges from 10°C to 60°C. If the pressure sensor is not compensated, the measurement error will continue to expand with the temperature change. The compensation model can correct the pressure signal in real time, and the pipeline pressure monitoring keeps stable accuracy. The pressure control system of chemical reaction kettle also depends on accurate measurement signals. The internal temperature of the reaction kettle usually fluctuates between 40°C and 120°C, and the temperature drift problem is easy to cause pressure signal deviation. The compensation algorithm reduces the measurement error and improves the feedback accuracy of the control system. Steam boiler monitoring system is also an important application field. The accuracy of boiler pressure measurement directly affects the safe operation. After the compensation model runs, the stability of pressure signal is improved.

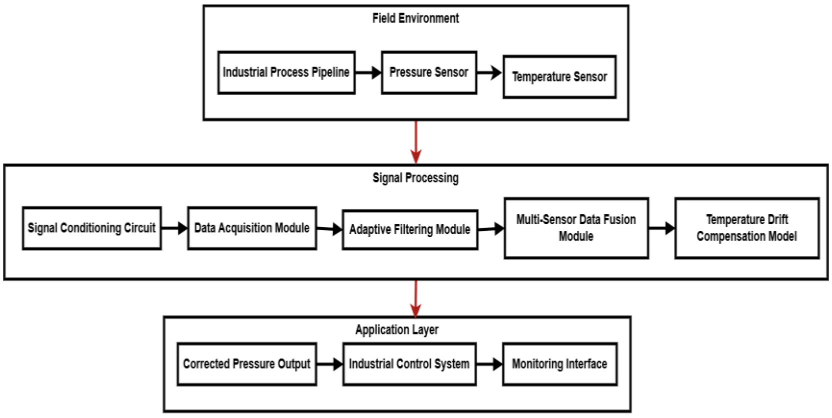

Figure 9: Schematic diagram of industrial field application

As shown in Figure 9, the industrial pipeline pressure monitoring system structure, pressure sensor and temperature sensor collect field data, the compensation model runs in the data processing unit, and the corrected pressure signal is transmitted to the control system.

4. Discussion

- **Challenges of Test System in Actual Environment Deployment**

The experimental platform runs stably in the laboratory environment, and the industrial site conditions are more complicated. The internal temperature fluctuation range of oil pipeline or chemical plant is usually between 10℃ and 80℃, and some steam systems are even close to 120℃. The pressure sensor is exposed to vibration, humidity and electromagnetic interference for a long time, and the signal stability is easy to decrease. The connection distance between the data acquisition equipment and the sensor often exceeds 30 m, and the line noise will interfere with the pressure signal. The field equipment runs for a long time, and the sensor aging problem gradually appears, and the sensitivity change will affect the accuracy of the compensation model. The industrial system requires continuous operation for thousands of hours, and the compensation model needs to keep stable parameters under long-term working conditions. There are differences between the experimental conditions and the actual production environment, so the factors such as hardware stability, signal anti-interference ability and long-term operation reliability need to be considered in the model deployment stage.

Long-term degradation of the sensitive element is another factor that may affect the stability of the compensation algorithm. In actual industrial environments, the piezoresistive element may experience aging, mechanical stress relaxation, humidity corrosion and repeated thermal cycling. These factors can change the zero offset, sensitivity coefficient and temperature drift coefficient of the pressure transmitter. If the sensor characteristics gradually deviate from the initial calibration state, the original compensation parameters may no longer maintain the same accuracy. Therefore, the adaptive filtering model should be combined with periodic parameter updating or online recalibration during long-term operation. The LMS algorithm has the ability to update filter weights according to real-time error, which provides a basis for tracking slow sensor degradation. However, when the degradation rate becomes significant or the sensor output shows nonlinear drift, additional diagnostic indicators and recalibration mechanisms are still required to ensure measurement reliability.

The experimental temperature range in this study was limited to 20 ℃–60 ℃, which covers a common operating interval of industrial pressure transmitters but does not include all high-temperature industrial conditions. In practical applications, the temperature of chemical reactors, steam pipeline systems and boiler monitoring points may exceed 60 ℃, and the drift characteristics of the piezoresistive sensitive element may become more nonlinear under such conditions. The proposed LMS adaptive filtering fusion model is expected to maintain a certain correction ability at higher temperatures because its filter coefficients can be updated according to the real-time estimation error. However, the compensation accuracy above 60 ℃ should not be directly inferred from the current experimental results. When the operating temperature extends to 80 ℃, 100 ℃ or 120 ℃, additional calibration samples should be collected, and the temperature drift coefficient should be re-estimated. If the pressure output shows strong nonlinear drift in the high-temperature region, the existing linear error model should be combined with segmented compensation or nonlinear adaptive modeling. Therefore, the present algorithm provides a feasible compensation framework, but its application in higher industrial temperature environments still requires extended temperature-range verification.

- **Follow-up Research Direction and Model Optimization Suggestions**

The experimental research focuses on the temperature range from 20℃ to 60℃, and the temperature change range in industrial field is wider. Follow-up research can extend the experimental range to 20℃ to 100℃ to obtain more abundant temperature sample data. After the number of samples increases, the scale of model training data will also increase and the compensation accuracy will be improved. The existing model mainly uses LMS adaptive filtering algorithm, and the structure of the algorithm is relatively simple. In the future, recursive least square filtering or deep learning prediction model will be introduced to perform multivariate analysis on pressure signals. Industrial systems run for a long time, so real-time computing efficiency also needs attention. In the model optimization stage, the embedded processor structure can be combined to simplify the algorithm calculation flow and reduce the calculation load. Multi-sensor fusion method can also be improved, and more environmental variables, such as humidity and vibration data, can be introduced to improve the adaptability of compensation model in complex environment.

The long-term degradation of the sensor diaphragm and sensitive film may directly affect the accuracy of the established compensation coefficients. In a diffused silicon pressure transmitter, the sensitive film and piezoresistive bridge are exposed to repeated pressure loading, thermal cycling and environmental stress during long-term operation. These factors may lead to stress relaxation, material fatigue or slight structural deformation of the diaphragm. As a result, the zero-offset coefficient, pressure sensitivity coefficient and temperature drift coefficient may gradually deviate from the values identified during the initial calibration stage. In the proposed model, the coefficient α represents the pressure deviation caused by temperature variation, while β reflects the system offset. If the sensitive film degrades with time, α and β may no longer accurately describe the current temperature-pressure coupling relationship. The fixed fusion weights may also become less suitable when the reliability of the pressure signal changes. Therefore, long-term engineering deployment should include periodic coefficient updating, online calibration or degradation diagnosis. The adaptive weight update mechanism of the LMS algorithm can partially track slow parameter changes, but severe diaphragm aging still requires recalibration to ensure compensation accuracy.

A limitation of the present experimental work is that the main compensation test was conducted under a fixed reference pressure of 1.0 MPa. Although this setting is useful for analyzing the temperature drift mechanism under a controlled condition, it does not fully reflect the pressure variation encountered in practical industrial measurement. Future work should expand the experimental pressure points to the whole operating range of the transmitter. Multi-pressure-point tests at low, medium and high pressure levels can be used to identify whether the temperature drift coefficient changes with pressure load. This extension will help verify the generalization ability of the LMS adaptive filtering fusion model and provide a more complete basis for engineering deployment.

- **Originality and technical complexity of the proposed method**

The proposed method is based on mature theoretical tools, including LMS adaptive filtering and weighted data fusion. Therefore, the study does not claim to establish a completely new mathematical algorithm. Its originality is reflected in the targeted combination of these methods for the temperature drift compensation of industrial pressure transmitters. The complete workflow includes experimental data acquisition, temperature-pressure drift modeling, variable normalization, abnormal sample cleaning, adaptive filter weight iteration, multi-source signal fusion and comparative error evaluation. These steps form a closed-loop compensation process from raw signal acquisition to corrected pressure output. The technical complexity of the work is mainly reflected in the coordination between the physical sensor characteristics and the adaptive signal processing algorithm. The model must preserve the pressure measurement trend, suppress the temperature-induced error and maintain stable convergence under repeated temperature disturbance. This engineering-oriented integration improves the practical value of the compensation method and provides a feasible implementation path for industrial pressure monitoring systems.

5. Conclusions

This paper studies the measurement deviation of industrial pressure transmitter in the environment of temperature change. The experimental platform collects pressure data in the temperature range of 20℃ to 60℃, and the pressure reference value is set at 1.0 MPa. With the increase of temperature, the original measurement pressure output value increased from 1.01 MPa to 1.09 MPa, and the maximum error reached 0.09 MPa. The change reflects the drift of diffused silicon piezoresistive sensor under the condition of temperature change. In the data analysis stage, the mathematical model of temperature drift error is established, and the compensation model is established by combining adaptive filtering algorithm with multi-sensor fusion strategy. After the operation of the compensation algorithm, the pressure output is kept in the range of 0.988 MPa to 1.012 MPa, and the maximum error is controlled within 0.012 MPa. The error amplitude decreases, and the measurement curve basically coincides with the reference pressure line. The comparative experiments of different algorithms show that the adaptive filtering fusion model RMSE is about 0.012 MPa, the polynomial compensation model RMSE is about 0.041 MPa, and the uncompensated model RMSE is about 0.085 MPa. Error difference reflects that the compensation model has higher stability under the condition of temperature disturbance. The long-term running ability of the model is verified by continuous running experiments. During the 60-minute test at 40℃, the pressure output is always in the range of 0.988 MPa to 1.012 MPa. The experimental results show that the compensation model can effectively reduce the influence of temperature drift on pressure measurement accuracy. This method has application value in industrial pressure monitoring system, and provides a feasible technical scheme for the stable measurement of pressure signals in high temperature environment.

References

[1] Sanchez AC, Pantoja-Suarez F, Chilig M, et al. Design and development of a temperature and pressure transmitter using a laser-induced graphene sensor. IEEE Sensors Letters, 2025, 9(9): 2503904.

[2] Mohanty A, Mohapatra AG, Mohanty SK, et al. Integration of IoT, automation, and real-time analytics for intelligent pressure control in Industry 5.0 smart manufacturing. IEEE Transactions on Consumer Electronics, 2025, 71(3): 8653–8661.

[3] Wang H, Liu JH, Dong HR, et al. A survey of the multi-sensor fusion object detection task in autonomous driving. Sensors, 2025, 25(9): 2794.

[4] Hu ZH, Xiong W, Liang Q, et al. Canolol as a key equivalent for phenolic content quantification in rapeseed oil via Folin-Ciocalteu method. European Food Research and Technology, 2025, 251(6): 1257–1268.

[5] Li SL, Gao WJ, Liu WY. A novel temperature drift compensation algorithm for liquid-level measurement systems. Micromachines, 2025, 16(1): 24.

[6] Mammadov JF, Ahmadova TA, Huseynov AH, et al. The selection of information-measuring means for the robototechnical complex and the research of their worker characteristics. Radio Electronics Computer Science Control, 2025(2): 20–31.

[7] Yuan C, Wang ZY, Tang CX, et al. A dynamic temperature compensation method for piezoresistive pressure sensors using heat transfer analysis. IEEE Transactions on Instrumentation and Measurement, 2025, 74: 2003111.

[8] Du H, Ren L, Wang YD, et al. Advancements in perception system with multi-sensor fusion for embodied agents. Information Fusion, 2025, 117: 102859.

[9] Lin B, Zhu GH, Zhang QH, et al. A novel framework for bearing fault diagnosis across working conditions based on time-frequency fusion and multi-sensor data fusion. Measurement Science and Technology, 2024, 35(12): 126205.

[10] Yadav NK, Dhawan A, Tiwari M, et al. A state-of-the-art survey on noise removal in a non-stationary signal using adaptive finite impulse response filtering: challenges, techniques, and applications. International Journal of Systems Science, 2025, 56(4): 885–918.

[11] Kibrete F, Woldemichael DE, Gebremedhen HS. Multi-sensor data fusion in intelligent fault diagnosis of rotating machines: a comprehensive review. Measurement, 2024, 232: 114658.

[12] Lata A, Maurya P, Sarkar R, et al. Design of a hydrostatic liquid level wireless transmitter for efficient level measurement. IEEE Sensors Journal, 2024, 24(6): 8105–8113.

[13] Liu XZ, Zuo LA, Wang LJ. Secure and controllable data management mechanism for multi-sensor fusion in internet of things. Internet Technology Letters, 2024, 7(2).

[14] Han TX. Intelligent language analysis method for multi-sensor data fusion. Internet Technology Letters, 2024, 7(2).

[15] Kwon BK, Kim SI. Adaptive finite impulse response filter. Transactions of the Korean Society of Mechanical Engineers A, 2023, 47(4): 303–311.

[16] Nie MD, Zheng G, Zhang XX, et al. Compensation for temperature drift in frequency-modulated continuous-wave interference fiber optic pressure sensor. Laser & Optoelectronics Progress, 2022, 59(7): 0728002.

[17] Zhao HQ, Chen YD, Liu J, et al. Total least squares normalized subband adaptive filter

algorithm for noisy input. IEEE Transactions on Circuits and Systems II: Express Briefs, 2022, 69(3): 1977–1981.
[18] Wang H, Zhang ML, Zhou HY, et al. A temperature compensation method for APD requiring high voltage power supply. Asia Communications and Photonics Conference (ACP). Shenzhen: IEEE, 2022: 931–934.
[19] Thompson D, Nagel JR, Gasteau DB, et al. Laser-induced ultrasound transmitters for large-volume ultrasound tomography. Photoacoustics, 2022, 25: 100312.
[20] Qian GB, Mei JJ, Iu HHC, et al. Fixed-point maximum total complex correntropy algorithm for adaptive filter. IEEE Transactions on Signal Processing, 2021, 69: 2188–2202.
[21] Wen PW, Zhang JS, Zhang S, et al. Normalized subband spline adaptive filter: algorithm derivation and analysis. Circuits Systems and Signal Processing, 2021, 40(5): 2400–2418.
[22] Meng WD, Wang YR, Tang K, et al. High-precision single-photon laser time transfer with temperature drift post-compensation. Sensors, 2020, 20(22): 6655.
[23] Wang SY, Han FT. Analysis and compensation of bias drift for a micromachined spinning-rotor gyroscope with electrostatic suspension. Sensors, 2020, 20(6): 1799.
[24] Cockalo D, Vorkapic M, Kreculj D, et al. Using QFD and AHP tools in the case of industrial transmitters manufacturing. FME Transactions, 2020, 48(1): 164–172.
[25] Rasheed I, Li L, Lin G, et al. Availability analysis of 4–20 mA pressure transmitters under harsh environmental conditions using the discriminant classifier. Mechanical Engineering Journal, 2020, 7(3): 19-00553.