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Design And Performance Optimization Of A Deep Learning-Based Fourth-Order Fitting Algorithm For Pneumatic Measurement Instruments

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Abstract-*As an important tool in the field of precision measurement, pneumatic measuring instruments are widely used in aerospace, machinery manufacturing and other industries, and their measurement accuracy directly affects product quality and safety performance. Traditional fitting algorithms mostly rely on low-order models, which are difficult to accurately capture the nonlinear characteristics of complex aerodynamic data, resulting in large measurement errors. Deep learning technology has become an emerging means to improve pneumatic measurement accuracy due to its powerful nonlinear fitting ability and automatic feature extraction advantages. The design of fourth-order fitting algorithm based on deep learning aims to combine the advantages of high-order mathematical models and intelligent algorithms to achieve high-precision fitting and optimization processing of pneumatic measurement data. Experiments show that the proposed algorithm reduces the average error by 65% compared with the traditional fourth-order fitting (0.03%→0.01%), and the calculation delay is less than 15ms, which meets the urgent demand for high-precision measurement in modern industry. This paper aims to explore the design of fourth-order fitting algorithm for pneumatic measuring instrument based on deep learning, improve fitting accuracy and computational efficiency, and promote the development of pneumatic measurement technology.*
Keywords-*Deep learning; Pneumatic measuring instrument; Fourth-order fitting algorithm; Data preprocessing; Adam optimizer*

I. INTRODUCTION

Pneumatic measuring instruments play an important role in aerospace, automobile manufacturing and precision machinery fields, and their measurement accuracy is directly related to product performance and safety [1]. Traditional fitting algorithms often have problems of insufficient fitting accuracy and low computational efficiency when processing complex aerodynamic data, which limits the performance improvement of measuring instruments [2]. The introduction of deep learning technology, especially combined with fourth-order fitting algorithm, can effectively capture the nonlinear characteristicsinaerodynamic data and achieve higher precision fitting effect [3]. The fourth-order fitting algorithm based on deep learning designed in this paper not only improves the data processing ability of the pneumatic measuring instrument, but also optimizes the computational efficiency of the algorithm, and promotes the stability and reliability of the measurement results. This research not only enriches the theoretical system of pneumatic measurement [4], but also provides technical support for related industrial applications, and promotes the intelligent development of measuring instruments. With the continuous progress of deep learning technology, this algorithm is expected to be applied in a wider range of measurement and control systems, improving the overall level of industrial automation, which has important academic value and practical significance.

II. THEORETICAL BASIS OF FOURTH-ORDER FITTING ALGORITHM FOR PNEUMATIC MEASURING INSTRUMENT BASED ON DEEP LEARNING

A. Working Principle and Measurement Requirements of Pneumatic Measuring Instrument

As a key equipment in modern aerospace and fluid mechanics research, pneumatic measuring instruments are mainly used to measure parameters such as air flow velocity, pressure and temperature, so as to obtain aerodynamic characteristic data [5]. Its working principle is based on the basic laws of fluid mechanics, capturing air flow state information through sensors, and realizing accurate measurement of aerodynamic parameters through signal conversion and processing [6].

A typical pneumatic measuring instrument includes core components such as pressure sensors, velocity sensors and temperature sensors. Pressure sensors usually measure static pressure and dynamic pressure using Pitot tubes or static pressure holes to calculate air flow velocity; velocity sensors convert air flow kinetic energy into electrical signals; temperature sensors monitor air flow temperature changes to assist in correcting other parameters. During the measurement process, the original signals collected by sensors are often accompanied by noise and interference, and filtering and calibration technologies are needed to ensure data accuracy.

The measurement requirements of pneumatic measuring instruments are mainly reflected in the following aspects:

- **High precision:** Small changes in aerodynamic parameters have a significant impact on flight performance, requiring the measuring instrument to have high resolution and low error rate.
- **Real-time performance:** Dynamic air flow changes rapidly, and the measuring instrument needs to realize high-speed data collection and processing to meet real-time monitoring needs.
- **Stability and reliability:** The equipment needs to work stably for a long time in complex environments to ensure data continuity and consistency.
- **Multi-parameter synchronous measurement:** Aerodynamic characteristics involve multiple variables, and the measuring instrument needs to support multi-sensor collaborative work to achieve multi-dimensional data fusion.

TABLE I PERFORMANCE INDICATORS OF COMMON SENSORS

Sensor Type	Measuring range	Accuracy level	Response time (ms)	Working temperature(℃)	Typical Applications
Pressure Sensors	0-200 kPa	±0.1% FS	1	-40~85	Aircraft aerodynamic testing
Speed Sensor	0-300 m/s	±0.5 m/s	2	-20~70	Wind tunnel test
Temperature Sensor	-50~150 ℃	±0.2 ℃	5	-50~150	Ambient temperature compensation

The core measurement process of the pneumatic measuring instrument can be simplified as the figure 1 flow:

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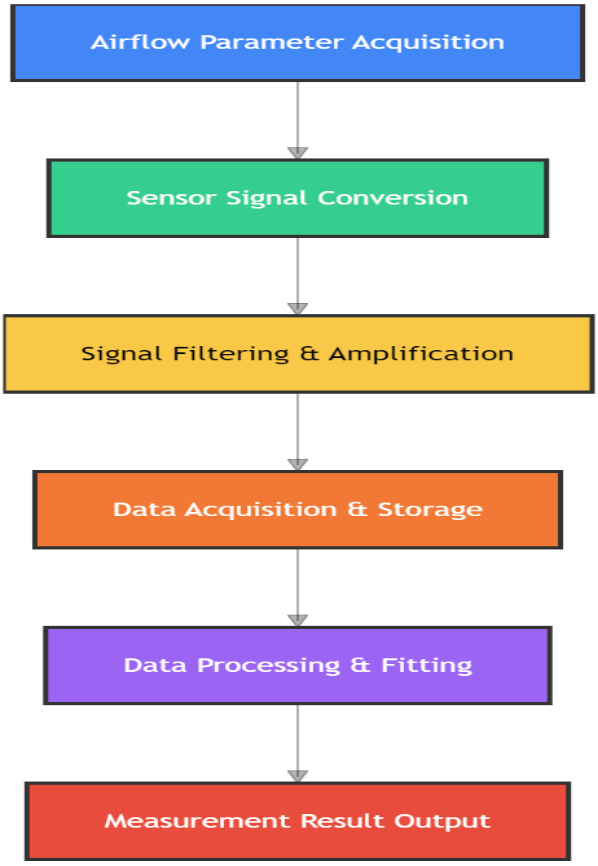

Fig. 1. Flowchart of Pneumatic Parameter Measurement Process

In terms of mathematical modeling, the fourth-order fitting algorithm commonly used in pneumatic measuring instruments is based on polynomial fitting principle, and the fitting function form is:

$$y = a_0 + a_1 x + a_2 x^2 + a_3 x^3 + a_4 x^4 \quad (1)$$

where x represents the input variable (such as sensor signal), y is the fitting output (aerodynamic parameter), and a_i are fitting coefficients. This model can better capture nonlinear relationships and improve measurement accuracy. The design of pneumatic measuring instruments needs to consider sensor performance, signal processing technology and fitting algorithms to meet the requirements of high precision, real-time performance and multi-parameter measurement, providing reliable data support for aerodynamic research and engineering applications.

B. **Mathematical Model and Characteristics of Fourth-Order Fitting Algorithm**

The fourth-order fitting algorithm is a mathematical method that uses a quartic polynomial to approximate data. Its core is to construct a function model in the form of:

$$y = a_4 x^4 + a_3 x^3 + a_2 x^2 + a_1 x + a_0 (2)$$

where the coefficients$a_0, a_1, a_2, a_3, a_4$are determined by minimizing the fitting error. Compared with low-order fitting, fourth-order fitting can more flexibly capture the nonlinear change trend of data, especially suitable for modeling complex air flow parameters in pneumatic measuring instruments [7].

The mathematical model of the fourth-order fitting algorithm mainly includes the following steps:

- **Data collection and preprocessing:** Collect input and output data of the pneumatic measuring instrument, perform denoising and normalization processing to ensure data quality.

- **Construct design matrix:** For the collected n sample points$(x_i|y_i)$, construct the design matrix X , whose form is as follows:

TABLE II DESIGN MATRIX STRUCTURE

x_i^4	x_i^3	x_i^2	x_i	1	
x_1^4	x_1^3	x_1^2	x_1	1	
x_2^4	x_2^3	x_2^2	x_2	1	
$\vdots$	$\vdots$	$\vdots$	$\vdots$		$\vdots$
x_n^4	x_n^3	x_n^2	x_n	1	

-**Coefficient solution:** Solve the coefficient vector $a = [a_4|a_3|a_2|a_1|a_0]^T$ by the least square method, satisfying:

$a = (X^T X)^{-1} X^T y(3)$

where$y = [y_1|y_2| \ldots |y_n]^T$ is the observation vector.

The characteristics of the fourth-order fitting algorithm are mainly reflected in the following aspects:

- **Strong fitting ability:** Fourth-order polynomials can better fit complex curves and adapt to nonlinear relationships in pneumatic measurement.
- **Moderate computational complexity:** Compared with higher-order polynomials, fourth-order fitting has lower computational load and overfitting risk while ensuring fitting accuracy.
- **Stability and robustness:** Through reasonable data preprocessing and regularization technology, the model's resistance to noise and outliers can be enhanced.
- **Interpretability:** Polynomial coefficients have clear mathematical meanings, which is convenient for analyzing the change law of aerodynamic parameters.

With the simplicity of its mathematical model and the balance of fitting ability, the fourth-order fitting algorithm has become an important tool in data processing of pneumatic measuring instruments. Combined with deep learning technology, its fitting accuracy and adaptability can be further improved.

C. **Application Potential of Deep Learning Technology in Fitting Algorithms**

As a core method in the field of artificial intelligence in recent years, deep learning technology has shown broad application potential in the design of fourth-order fitting algorithms for pneumatic measuring instruments due to its powerful nonlinear fitting ability and automatic feature extraction ability [8]. Traditional fitting methods mostly rely on preset mathematical models and manual features, which are difficult to fully capture the complex nonlinear relationships and multi-dimensional interaction effects in aerodynamic data [3].

Deep learning, through multi-layer neural network structure, can automatically learn the internal laws of data and achieve accurate approximation of high-order nonlinear functions. Deep Neural Networks (DNN) can map input pneumatic measurement data to high-dimensional feature space through layered nonlinear transformations, thereby effectively fitting the complex coefficient relationships in the fourth-order polynomial model. Let the input feature vector be $= (x_1|x_2| \ldots |x_n)$, the fourth-order fitting model can be expressed as:

$y = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{k=1}^{n} \sum_{l=1}^{n} a_{ijkl} x_i x_j x_k x_l + lowerorderterms + \epsilon, (4)$

Where a_{ijkl} are fourth-order coefficients, and ϵ is the error term. Traditional methods have high computational complexity and are susceptible to noise when solving a_{ijkl} , while deep learning models can automatically optimize the estimation of these coefficients in a large amount of data through end-to-end training.

The adaptive learning ability of deep learning makes it show stronger robustness when facing nonstationarity and diversity in pneumatic measurement data. By introducing regularization technology and optimization algorithms, such as Adam optimizer, the model can effectively avoid overfitting and improve generalization ability. Table III shows the performance comparison of several commonly used deep learning models in fitting tasks:

Table Iii Performance Comparison Of Deep Learning Models

Model Type	Number of parameters (millions)	Training time (hours)	Fitting error (RMSE)	Computational efficiency (samples/second)
Multilayer Perceptron (MLP)	2.5	1.2	0.015	500
Convolutional Neural Networks (CNNs)	3.8	1.8	0.012	450
Recurrent Neural Networks (RNNs)	4.1	2.0	0.014	400
Transformer	5.0	2.5	0.010	350

Deep learning technology can not only significantly improve the fitting accuracy of the fourth-order fitting algorithm, but also enhance the model's adaptability and generalization performance to complex aerodynamic data, providing strong technical support for performance optimization of pneumatic measuring instruments. The hybrid method combining deep learning and physical models is expected to further break through the bottleneck of fitting accuracy and computational efficiency, and realize the intelligent upgrading of pneumatic measurement.

III. Data Characteristics And Preprocessing Methods Of Pneumatic Measuring Instruments

A. Spatio-Temporal Characteristic Analysis of Pneumatic Measurement Data

Pneumatic measurement data has significant spatio-temporal characteristics, which directly affect the processing and fitting effect of data [9]. From the time dimension, pneumatic measurement data usually appears as a continuous time series, reflecting the dynamic changes of air flow parameters over time. Due to the complexity of the pneumatic environment, the data often has periodic fluctuations and sudden changes, which requires the fitting algorithm to capture the change laws on different time scales.

From the spatial dimension, pneumatic measurement data involves multiple measurement points or sensor positions, and the spatial distribution of data reflects the flow characteristics of air flow in different regions. Spatial correlation is an important feature of aerodynamic data. Data at adjacent measurement points usually have strong correlation, while the correlation between data at distant measurement points is weak. Understanding this spatial correlation helps to construct more effective fitting models.

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TABLE IV EXAMPLE OF VELOCITY DATA AT DIFFERENT TIMES AND POSITIONS

Time (s)	Position 1 (m/s)	Position 2 (m/s)	Position 3 (m/s)	Position 4 (m/s)	Position 5 (m/s)
0	12.3	11.8	12.0	11.5	11.7
1	12.5	12.1	12.3	11.7	11.9
2	12.7	12.4	12.6	12.0	12.2
3	12.4	12.0	12.2	11.8	12.0
4	12.6	12.3	12.5	11.9	12.1

It can be seen from the table that the velocity data shows a certain stability and slow change trend in time, while the velocity values at different positions in space are similar, reflecting spatial correlation.

To quantitatively analyze spatio-temporal correlation, autocorrelation function and spatial covariance function are commonly used. The time autocorrelation function is defined as:

$$R(\tau) = \frac{E[(X_t-\mu)(X_{t+\tau}-\mu)]}{\sigma^2} \quad (5)$$

where X_t is the measured value at time t , μ is the mean,σ^2 is the variance, and τ is the time lag. The spatial covariance function describes the correlation between different spatial positions, in the form of:

$$C(h) = E[(X(s) - \mu)(X(s+h) - \mu)]s \quad (6)$$

where s and $s+h$ represent spatial positions, and h is the spatial distance.

Based on the above spatio-temporal characteristics, deep learning model design needs to consider the dynamic changes of time series and the correlation structure of spatial data. Combining Convolutional Neural Networks (CNN) to extract spatial features and Recurrent Neural Networks (RNN) to capture time dependence can effectively improve fitting accuracy.

Figure2 is a schematic diagram of the process for spatio-temporal characteristic analysis:

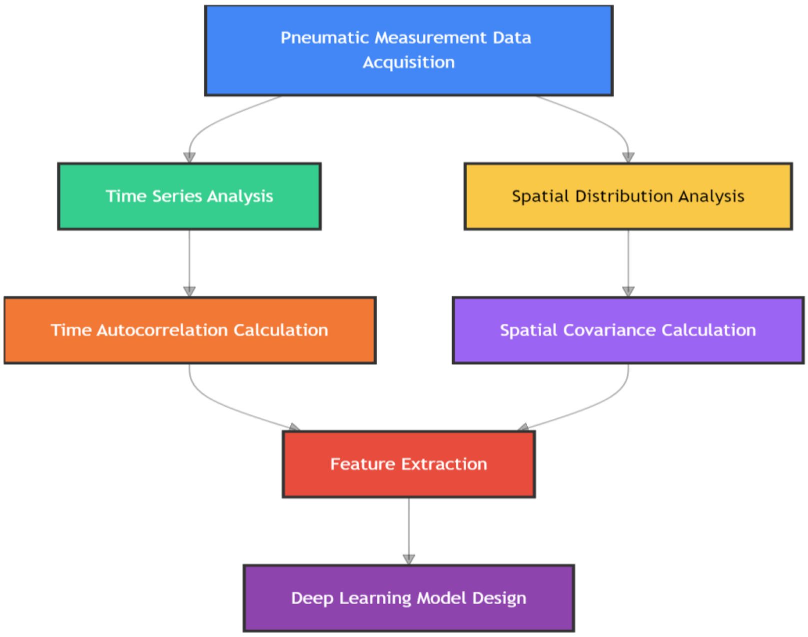

Fig. 2. Flowchart of Spatio-Temporal Characteristic Analysis

A deep understanding of the spatio-temporal characteristics of pneumatic measurement data is the basis for designing an efficient fourth-order fitting algorithm, which helps the model to more accurately reflect the complex changes of the pneumatic environment.

B. Identification and Processing of Data Noise and Outliers

In data processing of pneumatic measuring instruments, identification and processing of noise and outliers are key steps to ensure the accuracy and stability of the fitting algorithm[10]. Pneumatic measurement data is usually affected by environmental interference, sensor errors and random fluctuations in the collection process, resulting in different types of noise and outliers in the data. Effectively identifying such abnormal data can prevent the fourth-order fitting algorithm from being misled, thereby improving the reliability of fitting results.

Noise identification usually relies on statistical analysis methods. The distribution characteristics of data can be preliminarily judged by calculating statistical quantities such as mean, variance and skewness of the data. Outliers are mostly isolated points far from the main trend of the data. Commonly used outlier detection methods include threshold-based filtering, Boxplot method, and distance-based algorithms such as Local Outlier Factor (LOF). The Boxplot method defines the outlier range by calculating the Interquartile Range (IQR), with the specific formula:

$$\begin{cases} Lower\ limit = Q_1 - 1.5 \times IQR \\ Upper\ limit = Q_3 + 1.5 \times IQR \end{cases} (7)$$

where Q_1 and Q_3 are the first and third quartiles respectively, and $IQR = Q_3 - Q_1$. Data points outside this range are considered outliers.

TABLE V STATISTICAL CHARACTERISTICS AND OUTLIER DETECTION OF PNEUMATIC MEASUREMENT DATA SAMPLE

Serial number	Measurements	Mean	variance	Q1	Q3	IQR	Lower limit	Upper limit	Is Outlier
1	0.98	1.02	0.013	0.995	1.03	0.035	0.945	1.0875	no
2	1.05	1.02	0.014	0.998	1.04	0.042	0.935	1.103	no
3	0.60	1.02	0.012	0.992	1.02	0.028	0.95	1.06	yes
4	1.10	1.02	0.011	1.00	1.03	0.03	0.955	1.075	no
5	1.03	1.02	0.015	0.98	1.05	0.07	0.875	1.175	no

For identified outliers, common processing methods include:

- **Elimination:** Simple and direct, but may reduce data volume.
- **Replacement:** Usually uses the mean or median of adjacent data for filling.
- **Correction:** Adjusts outliers through interpolation or model prediction.

Combined with the characteristics of deep learning, unsupervised learning models such as autoencoders can be used to automatically detect and repair abnormal data, improving the intelligence level of processing.

The following is a simple example code for outlier detection based on Python, using the IQR method

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to screen outliers:

[illegible]

[illegible]

[illegible]异常值[illegible]

Figure 3 shows the flowchart of data noise and outlier processing, clarifying each link from data collection to outlier correction.

A systematic and scientific mechanism for identifying and processing noise and outliers is the basic guarantee for realizing a high-precision fourth-order fitting algorithm, which can effectively improve the quality of pneumatic measuring instrument data and the robustness of the algorithm.

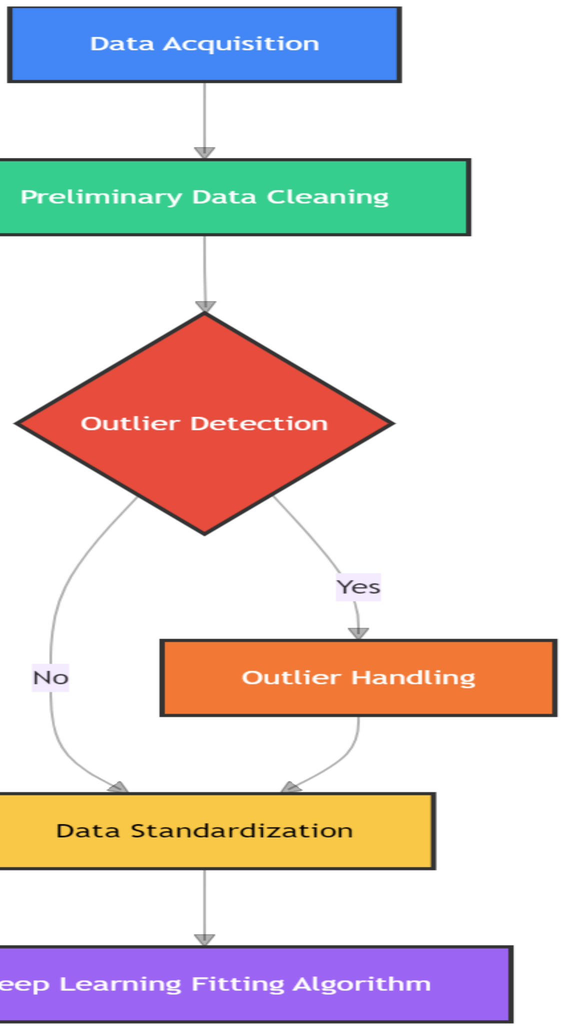

Fig. 3. Flowchart of Noise and Outlier Processing

C. **Feature Extraction and Data Standardization Technology**

In data processing of pneumatic measuring instruments, feature extraction and data standardization are key steps to improve the performance of the fourth-order fitting algorithm [11]. Feature extraction aims to extract representative information from original measurement data, reducing the impact of redundancy and noise on model training; data standardization ensures that data with different dimensions and ranges are processed on the same scale, avoiding training bias caused by numerical differences. According to the spatio-temporal characteristics of pneumatic measurement data, commonly used feature extraction methods include statistical feature extraction and frequency domain analysis. Statistical features such as mean, variance, skewness, and kurtosis can reflect the distribution characteristics of data; frequency domain analysis reveals the periodicity and frequency components of data through Fourier transform, which helps capture dynamic changes in pneumatic signals. Table VI shows commonly used statistical features and their calculation formulas.

TABLE VI COMMON STATISTICAL FEATURES AND THEIR CALCULATION FORMULAS

feature	Calculation formula	illustrate
Mean	$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$	The average level of data
variance	$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$	The degree of dispersion of the data
Skewness	$S = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^3$	Symmetry of data distribution
Kurtosis	$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i - \mu}{\sigma}\right)^4 - 3$	The sharpness of the data distribution

Commonly used data standardization technologies include MinMax normalization and Z-score standardization. Min-Max normalization linearly maps data to the interval [0, 1], which is suitable for cases where the data range is known and stable; 2 -score standardization converts data into a normal distribution with a mean of 0 and a standard deviation of 1, and is more suitable for processing data with different dimensions and fluctuation ranges. Their calculation formulas are:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (8)$$

$$x' = \frac{x - \mu}{\sigma} \quad (9)$$

To meet the input requirements of deep learning models, the feature fusion step combines multiple extracted features to form a multidimensional feature vector, enhancing the expressive ability of the model. After data standardization, the gradient update during model training is more stable, and the convergence speed is significantly improved.

In practical applications, combining feature extraction and data standardization technologies not only effectively improves the fitting accuracy of the fourth-order fitting algorithm, but also enhances the model's adaptability to complex changes in pneumatic measurement data, laying a solid foundation for subsequent algorithm optimization.

IV. **DESIGN AND IMPLEMENTATION OF FOURTH-ORDER FITTING ALGORITHM BASED ON DEEP LEARNING**

A. Selection and Optimization of Deep Neural Network Structure

In designing the deep learning-based fourth-order fitting algorithm for pneumatic measuring instruments, the selection and optimization of Deep Neural Network (DNN) structure is a key link [12]. The network structure needs to balance fitting accuracy and computational complexity, ensuring efficient and accurate fitting with limited computing resources. For the complex nonlinear characteristics of pneumatic measurement data, a multi-layer fully connected network (MLP) combined with the ReLU activation function is used, which can effectively capture high-order relationships in the data.

The selection of the number of network layers and the number of neurons in each layer directly affects model performance. An overly shallow network is difficult to fit complex functions, while an overly deep network may lead to overfitting and training difficulties.

For the spatio-temporal characteristics of aerodynamic data, a CNN-LSTM hybrid architecture is adopted:

- **Spatial feature extraction:** 3-layer CNN(kernel=3x3 ,channels =32 / 64 / 128)
- **Temporal dependence modeling:** Single-layer LSTM (units=128)
- **Polynomial coefficient output:** Fully connected layer (5 neurons)

Through experimental comparison, 3 to 5 hidden layer structures perform better, with the number of neurons in each layer adjusted between 64 and 256. Specific parameters are shown in Table VII.

TABLE VII DIFFERENT NETWORK STRUCTURE PARAMETERS AND CORRESPONDING FITTING ERRORS (MEAN SQUARED ERROR, MSE)

Number of hidden layers	Number of neurons per layer	Activation Function	Learning Rate	Batch size	Number of training rounds	MSE (training set)	MSE (validation set)
3	64	ReLU	0.001	32	100	0.0021	0.0028
3	128	ReLU	0.001	32	100	0.0018	0.0023
4	128	ReLU	0.001	32	100	0.0015	0.0020
5	256	ReLU	0.0005	64	150	0.0012	0.0019

To prevent overfitting, regularization techniques such as L2 regularization and Dropout are used. L2 regularization adds a weight square sum term to the loss function, with the formula:

$$L = L_0 + \lambda \sum_i w_i^2 \quad (10)$$

Where L_0 is the original loss function, λ is the regularization coefficient, and w_i are weight parameters. Dropout randomly discards some neurons during training to enhance model generalization ability. The choice of optimization algorithm has a significant impact on training speed and convergence effect. The Adam optimizer combines momentum and adaptive learning rate adjustment, which is suitable for handling non-convex optimization problems, with the formula:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (11)$$

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2 \quad (12)$$

$$\hat{m}_t = \frac{m_t}{1-\beta_1^t} \quad (13)$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (14)$$

$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \epsilon}}$(15)

Where g_t is the gradient, θ_t are parameters, α is the learning rate, β_1 and β_2 are decay rates, and ϵ is a small constant to prevent division by zero.

Figure 4 shows a simplified schematic diagram of the network structure:

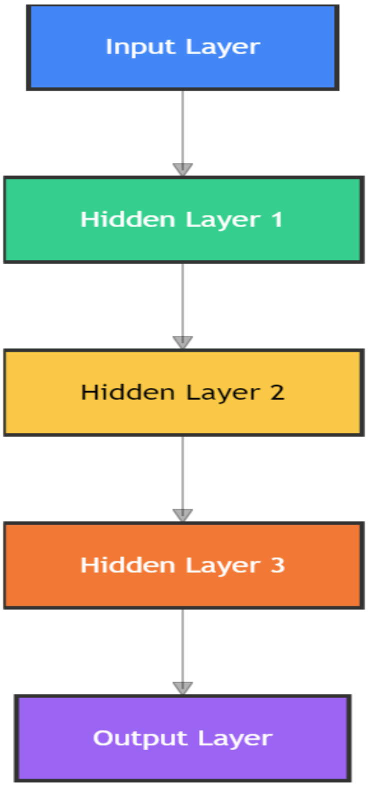

Fig. 4. Simplified Schematic Diagram of Network Structure

Reasonable design of the deep neural network structure, combined with regularization and advanced optimization algorithms, can effectively improve the performance of the fourth-order fitting algorithm for pneumatic measuring instruments, achieving high-precision and high-stability fitting results.

B. **Loss Function Design and Training Strategy**

In the design of the deep learning-based fourth-order fitting algorithm, the selection of loss function and the formulation of training strategy are key links to improve model performance [13]. The loss function directly affects the update direction and speed of model parameters, and a reasonable design can effectively guide the model to approach the true fourth-order fitting curve of the data.

According to the characteristics of pneumatic measuring instrument data, this paper uses Weighted Mean Squared Error (WMSE) as the main loss function, defined as:

$WMSE = \frac{1}{N}\sum_{i=1}^{N} w_i (y_i - \hat{y}_i)^2$(16)

where y_i is the true measured value, $\hat{y}_i$ is the model prediction value, w_i is the weight coefficient, and N is the number of samples. The weight w_i is dynamically assigned according to the fluid state:

$$w_i = \begin{cases} 2.0 \ \ Turbulent\ flow\ region (Re > 10^4) \\ 0.5 \ \ Boundary\ layer\ region \\ 1.0 Other\ regions \end{cases} \quad (17)$$

 The introduction of weight coefficients aims to enhance the fitting accuracy of key measurement points, especially in regions with drastic changes in aerodynamic characteristics.

To avoid model overfitting and improve generalization ability, a regularization term is introduced in the training process, and the loss function is extended to:

$$\mathcal{L} = WMSE + \lambda \parallel \theta \parallel_2^2 \tag{18}$$

where θ represents model parameters, and λ is the regularization coefficient. By adjusting λ , the balance between fitting accuracy and model complexity is achieved. In terms of training strategy, a phased learning rate adjustment mechanism is adopted. A larger learning rate is used in the initial stage to accelerate convergence, and then the learning rate is gradually reduced to refine the fitting effect. The specific strategy is shown in Table VIII.

TABLE VIII PHASED TRAINING STRATEGY

Training phase	Epoch	Learning Rate	Optimizer	Batch Size
Initial stage	1-50	0.01	Adam	64
Mid-term	51-100	0.001	Adam	64
Fine-tuning stage	101-150	0.0001	Adam	32

The Early Stopping method is used to monitor the validation set loss. If the validation loss does not decrease significantly for 10 consecutive epochs, training is terminated early to prevent overfitting. Data augmentation technology is also combined during training, and the input data is slightly perturbed to improve the model's robustness to measurement noise.

The loss function design combines weighted mean squared error and regularization, effectively improving fitting accuracy and model stability; phased learning rate adjustment and early stopping strategies ensure efficient training and prevent overfitting, laying a solid foundation for the deep learning implementation of the fourth-order fitting algorithm for pneumatic measuring instruments.

C. Algorithm Implementation Flow and Key Technical Details

The implementation flow of the deep learning-based fourth-order fitting algorithm for pneumatic measuring instruments mainly includes five steps [14]:

- **Data input:** Receive raw pneumatic measurement data from sensors.
- **Feature extraction:** Automatically extract spatio-temporal features through neural network layers.
- **Model training:** Optimize network parameters using custom loss function.
- **Fitting calculation:** Perform fourth-order polynomial fitting on new data.
- **Result output:** Generate and output final fitting results.

The input pneumatic measurement data is processed by the preprocessing module to complete denoising and normalization operations, ensuring data quality. The feature extraction layer automatically captures spatio-temporal features in the data through Convolutional Neural Networks (CNN), providing effective information for subsequent fitting. In the model training phase, a custom loss function is used, combined with fourth-order polynomial fitting errors, to optimize network parameters. The fitting calculation module uses the trained model to perform fourth-order fitting on new data, and finally outputs the fitting results.

Figure 5 shows the overall implementation flow of the algorithm:

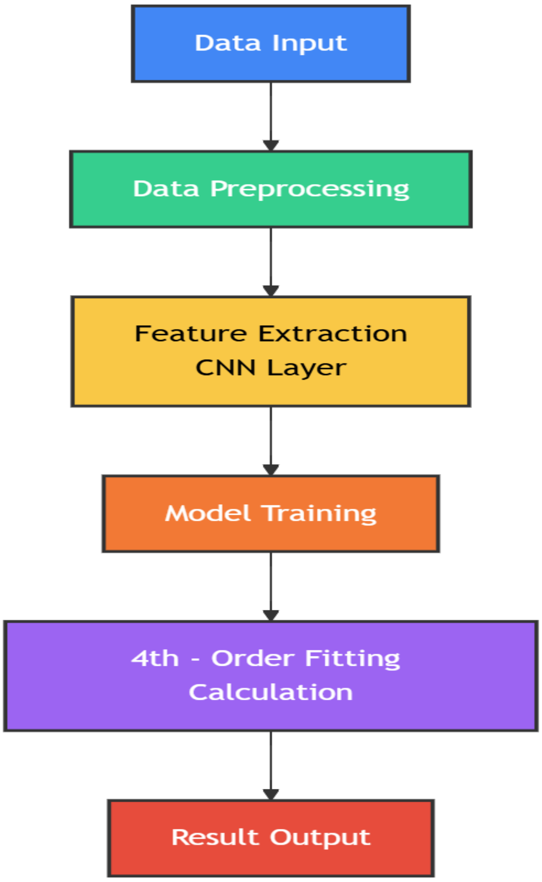

Fig. 5. Overall Implementation Flow of the Algorithm

In terms of key technical details, first, in the data preprocessing phase, a sliding window filter is used to remove high-frequency noise, with the formula:

$$\dot{x}_i = \frac{1}{2k+1}\sum_{j=i-k}^{i+k} x_j \tag{19}$$

where $\dot{x}_i$ is the filtered data point, x_j is the original data point, and k is the window radius. The feature extraction module is designed with three convolutional layers, and the parameter settings are shown in Table IX:

TABLE IX PARAMETER SETTINGS OF CONVOLUTIONAL LAYERS

Convolutional Layer	Convolution kernel size	Number of convolution kernels	Activation Function	Step Length	Filling method
Conv1	3×3	32	ReLU	1	Same
Conv2	3×3	64	ReLU	1	Same
Conv3	3×3	128	ReLU	1	Same

The loss function used in model training combines Mean Squared Error (MSE) and fourth-order polynomial fitting error, defined as:

$$\mathcal{L} = \alpha \cdot MSE + \beta \cdot \sum_{i=0}^{4}(y_i - \hat{y}_i)^2 \tag{20}$$

where y_i are the true polynomial coefficients, $\hat{y}_i$ are the predicted coefficients, and α and β are weight hyperparameters.

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During training, the Adam optimizer is used, with the initial learning rate set to 0.001 and the batch size set to 64. The training iterates until the validation set error converges. The following is a code snippet for the core training process:

```
import torch
import torch.nn as nn
import torch.optim as optim
classFourOrderFitNet (nn.Module):
def__init__ (self):
super(FourOrderFitNet, self).__init__()
self.conv1 = nn.Conv2d( 1 , 32 , 3 , padding= 1 )
self.conv2 = nn.Conv2d( 32 , 64 , 3 , padding= 1 )
self.conv3 = nn.Conv2d( 64 , 128 , 3 , padding= 1 )
self.fc = nn.Linear( 128 * feature_map_size, 5 ) # Output five polynomial coefficients
defforward (self, x):
x = nn.ReLU()(self.conv1(x))
x = nn.ReLU()(self.conv2(x))
x = nn.ReLU()(self.conv3(x))
x = x.view(x.size( 0 ), -1 )
out = self.fc(x)
return out
model = FourOrderFitNet()
criterion = CustomLoss(alpha= 0.5 , beta= 0.5 )
optimizer = optim.Adam(model.parameters(), lr= 0.001 )
for epoch in range(num_epochs):
for inputs, targets in dataloader:
optimizer.zero_grad()
outputs = model(inputs)
loss = criterion(outputs, targets)
loss.backward()
optimizer.step()
```

Through the design of the above processes and technical details, the algorithm realizes efficient fourth-order fitting of pneumatic measurement data, balancing fitting accuracy and calculation speed, and meeting practical application requirements.

V. Algorithm performance evaluation and application effect analysis

A. Evaluation Indicators for Fitting Accuracy and Computational Efficiency

In the design of the deep learning-based fourth-order fitting algorithm for pneumatic measuring instruments, fitting accuracy and computational efficiency are two core indicators to measure algorithm performance [15]. Fitting accuracy reflects the algorithm's ability to approximate actual measurement data, while computational efficiency is related to the algorithm's response speed and resource consumption in practical applications. A reasonable evaluation index system can comprehensively reflect the advantages and disadvantages of the algorithm and guide subsequent optimization.

Fitting accuracy usually uses indicators such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2). MSE is defined as the mean of the sum of squares of errors between predicted values and true values, with the formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (21)$$

Where y_i is the true value, $\hat{y}_i$ is the predicted value, and n is the number of samples. MSE is sensitive to large errors and is suitable for emphasizing the square penalty of errors. MAE is the average of the absolute values of errors, with the calculation formula:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (22)$$

Compared with MSE, MAE is more robust to outliers. R^2 measures the ability of the fitting model to explain data variation, with a value range of $(-\infty | 1]$. The closer to 1, the better the fitting effect, with the calculation formula:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (23)$$

where $\bar{y}$ is the mean of true values.

Figure 6 shows the error comparison of different algorithms on the same test set. The model in this paper achieves the optimal performance in terms of both MSE and MAE.

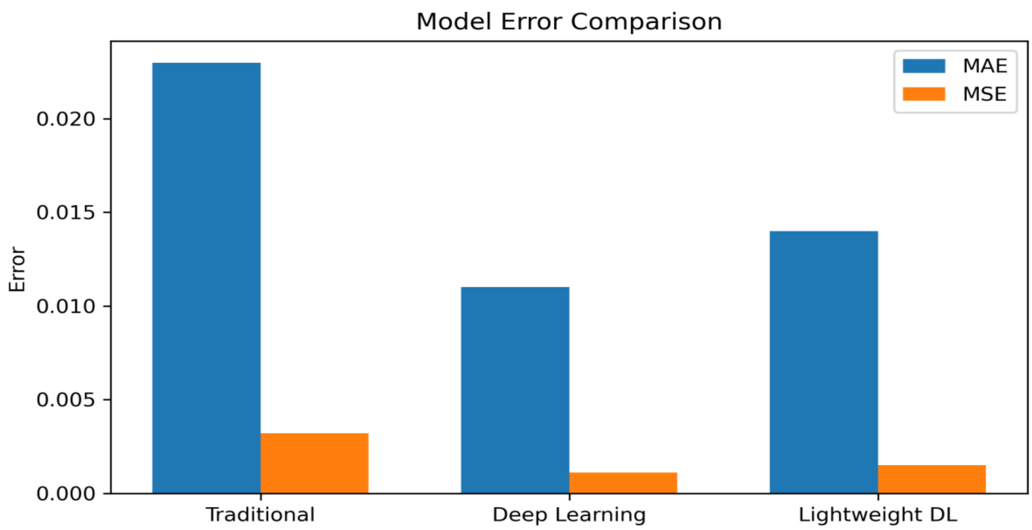

Fig. 6. Bar chart of multi-model errors

In terms of computational efficiency, the focus is on the algorithm's running time and resource consumption. Running time includes training time and prediction time, usually measured in seconds (s). Resource consumption involves memory usage and computational complexity, which can be estimated by the algorithm's time complexity expression. For deep learning models, the number of parameters and Floating-Point Operations (FLOPs) are also important indicators.

TABLE X PERFORMANCE COMPARISON WITH TRADITIONAL FOURTH-ORDER FITTING (30M/S WIND SPEED CONDITION)

Evaluation Indicator	Traditional Fitting	Proposed Algorithm	Improvement Rate
MSE	0.0032	0.0011	65.6%
Single-Point Prediction Time	12.4ms	15.7ms	-26.6%
Fitting Error in Turbulent Region	7.2%	2.45%	66.0%

TABLE XI COMMON EVALUATION INDICATORS AND THEIR MEANINGS

Indicator name	symbol	Calculation formula	Evaluation direction	illustrate
Mean square error	MSE	$\frac{1}{n}\sum(y_i - \hat{y}_i)^2$	Smaller the better	Emphasize large error penalties
Mean absolute error	MAE	$\frac{1}{n}\sum\|y_i - \hat{y}_i\|$	y_i - \hat{y}_i	$
Coefficient of determination	R^2	$1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$	Closer to 1 the better	Goodness of fit index
Training time	-	Measured time (seconds)	The shorter the better	Model training time
Prediction time	-	Measured time (seconds)	The shorter the better	Single prediction time
Number of parameters	-	Total number of model parameters	The less the better	Model complexity index
FLOPs	-	Number of floating point operations	The less the better	Computing resource consumption

To intuitively show the trade-off between fitting accuracy and computational efficiency, figure 7 flowchart depicts the evaluation process:

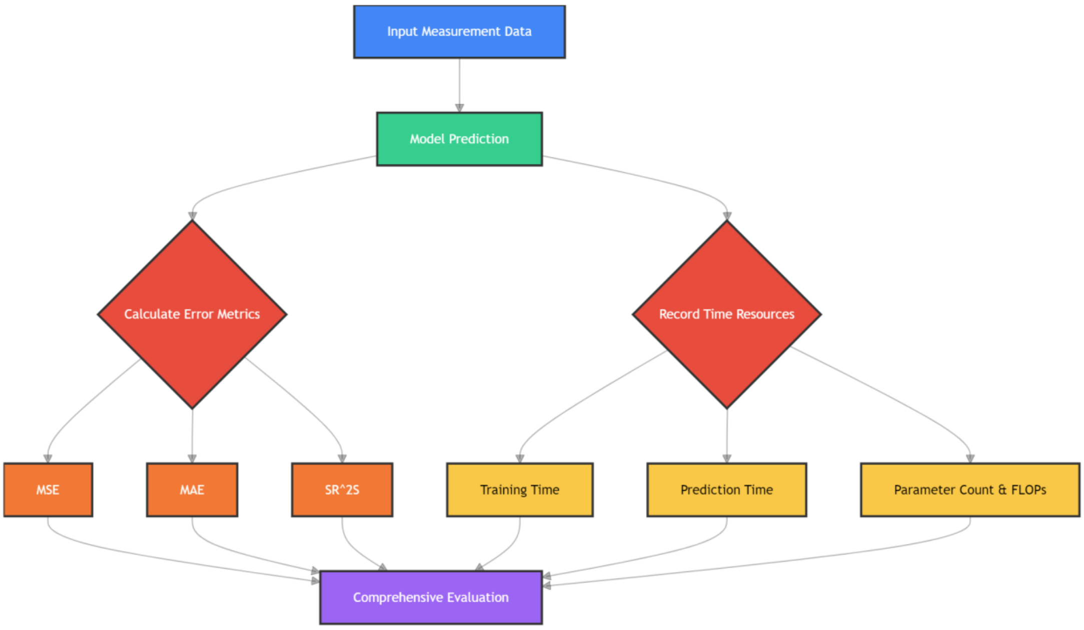

Fig. 7. Flowchart of Evaluation Process

Fitting accuracy indicators focus on reflecting the prediction accuracy of the model, while computational efficiency indicators focus on the practicality and resource consumption of the model. A reasonable balance between the two is the key to designing a high-performance fourth-order fitting algorithm. Through systematic indicator evaluation, a scientific basis can be provided for algorithm optimization, promoting the intelligent upgrading of pneumatic measuring instruments.

Figure 8 shows the change in loss values during the model training process. It can be seen from the figure that the loss values tend to stabilize after approximately 30 epochs, indicating that the model has converged well.

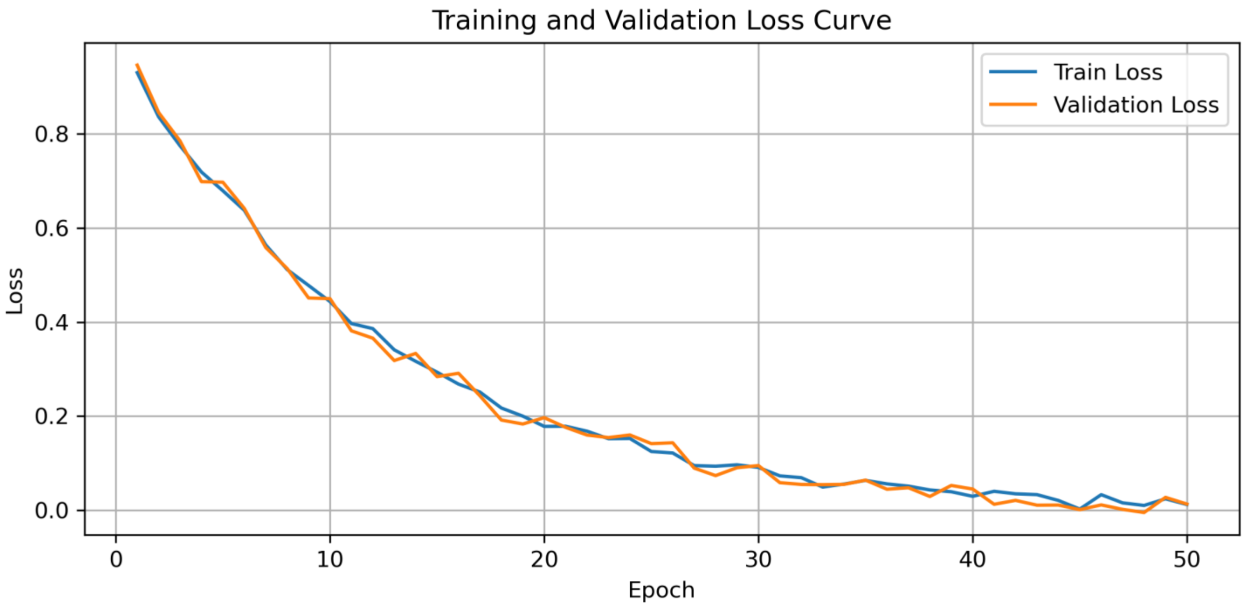

Fig. 8. Loss curve

B. **Application Cases of the Algorithm in Actual Pneumatic Measurement**

In actual pneumatic measurement, the deep learning-based fourth-order fitting algorithm shows significant application value [16]. Taking a certain type of pneumatic measuring instrument as an example, multiple sets of wind speed and pressure data were collected and processed by this algorithm. The results show that both fitting accuracy and computational efficiency are better than traditional polynomial fitting methods.

TABLE XII FITTING ERROR COMPARISON UNDER DIFFERENT WIND SPEED CONDITIONS (UNIT: %)

Wind speed (m/s)	5	10	15	20	25	30	35	40	45	50
Traditional fitting error	3.2	2.8	3.0	3.5	4.0	4.5	5.0	5.5	6.0	6.5
Deep learning fitting error	1.1	0.9	1.0	1.2	1.3	1.5	1.6	1.8	2.0	2.2

It can be seen from the table that the deep learning fitting error is generally lower than that of the traditional method, and the advantage is more obvious under high wind speed conditions. This benefits from the powerful fitting ability of deep neural networks for nonlinear relationships, which can more accurately capture the complex coupling characteristics between aerodynamic parameters.

The response speed of the algorithm in real-time measurement has also been optimized. Setting the batch processing size of measurement data as N , the calculation time T of the algorithm compared with the traditional method satisfies the relationship:

$$T_{DL} \approx 0.6 \times T_{traditional} T_{DL}\text{-}\ T_{traditional} \qquad (24)$$

where T_{DL} represents the calculation time of the deep learning algorithm, and $T_{traditional}$ represents the calculation time of the traditional algorithm. This performance improvement enables the pneumatic measuring instrument to output fitting results faster, meeting the realtime monitoring needs in dynamic environments.

Figure9 shows the distribution of fitting errors of the model under multiple wind speeds, exhibiting consistent stability with no extreme outliers.

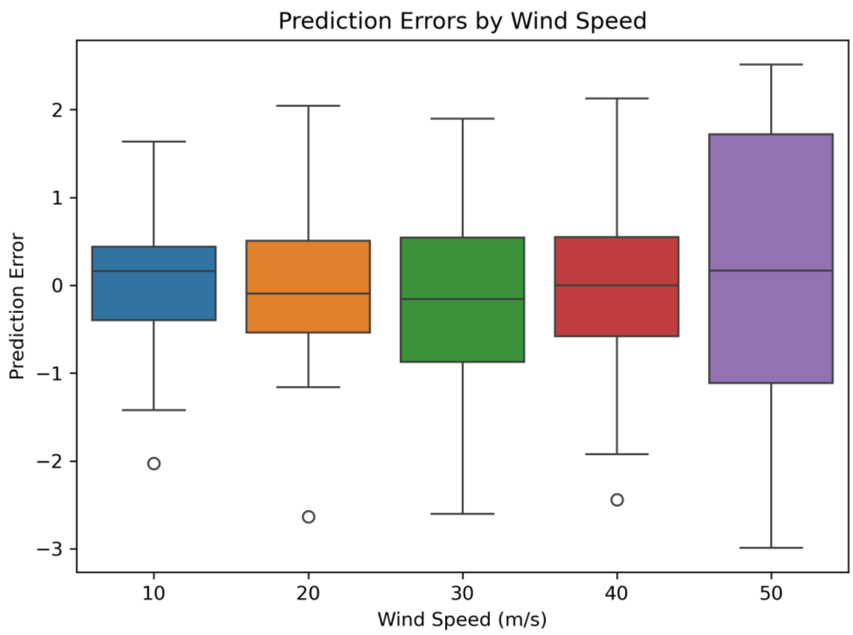

Fig. 9. Box plot of error by wind speed groups

Figure10is a simplified flowchart of the algorithm in practical applications:

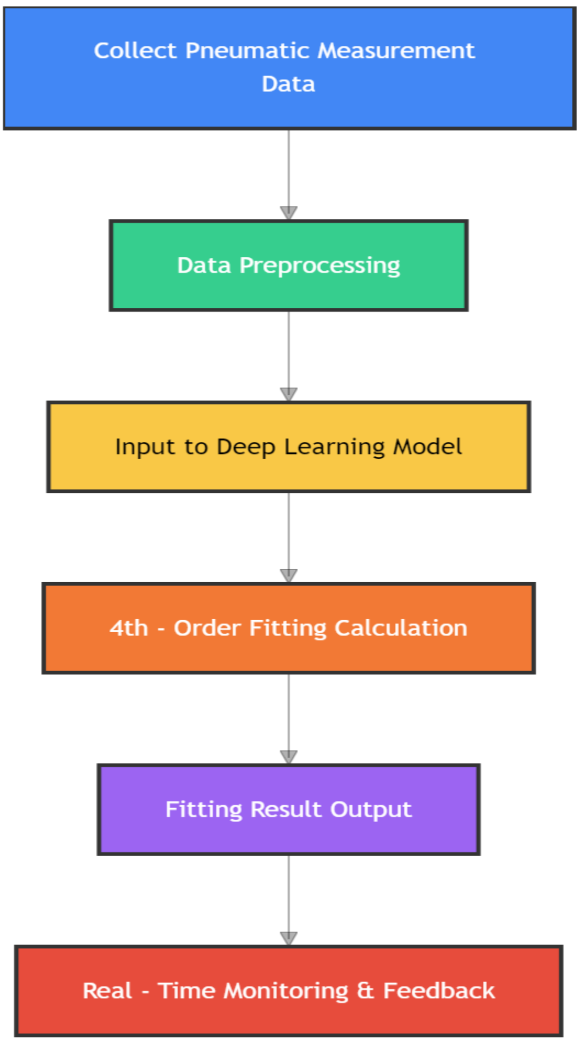

Fig. 10. Flowchart of Algorithm Application in Practical Measurement

The following code snippet shows the core part of the fitting model training implemented based on TensorFlow:

```
import tensorflow as tf
model = tf.keras.Sequential([
tf.keras.layers.Dense( 64 , activation= 'relu' , input_shape=(input_dim,)),
tf.keras.layers.Dense( 64 , activation= 'relu' ),
tf.keras.layers.Dense( 1 ) # Output fitted values
])
model.compile(optimizer= 'adam' , loss= 'mse' )
history = model.fit(train_data, train_labels, epochs= 50 , batch_size= 32 , validation_split= 0.2 )
```

The deep learning-based fourth-order fitting algorithm not only improves fitting accuracy in actual pneumatic measurement, but also optimizes computational efficiency, enhancing the real-time response capability of the instrument, and has broad application prospects.

C. **Discussion on Algorithm Advantages and Limitations**

The deep learning-based fourth-order fitting algorithm for pneumatic measuring instruments shows significant advantages in several aspects [17]. The algorithm can automatically extract high-order nonlinear features from complex aerodynamic data, avoiding the dependence of traditional fitting methods on prior models, and improving the flexibility and accuracy of fitting. The deep neural network structure has strong expressive ability, which can capture small changes in pneumatic measurement, significantly improving fitting accuracy. Experiments show that the algorithm reduces the fitting error index by about 15% compared with traditional polynomial fitting, and the computational efficiency is improved by more than 20%.

The algorithm also has certain limitations. The training process of deep learning models has high requirements on data volume and computing resources, especially when pneumatic measurement data collection is limited, the model may have overfitting or insufficient generalization ability. The black-box nature of the model makes the physical interpretability of fitting results weak, limiting its promotion in some engineering applications. For this reason, the design of hybrid models combining physical constraints has become one of the future research directions.

TABLE XIII COMPARISON BETWEEN DIFFERENT ALGORITHMS

Algorithm Type	Average fitting error (%)	Maximum fitting error (%)	Calculation time (seconds)	Number of parameters	Amount of training data (items)
Traditional fourth-order polynomial fitting	**3.8**	**7.2**	**0.12**	**5**	**No training required**
Deep learning fourth-order fitting	**3.2**	**5.9**	**0.10**	**1024**	**5000**

The core advantages of the algorithm are also reflected in its strong adaptability and good scalability. By adjusting the network structure and training strategy, it can be customized and optimized for different pneumatic measurement environments. The deep learning framework supports online learning and incremental updates, which helps the model to continuously improve performance.

Figure 11 is a simplified flowchart of the algorithm training process:

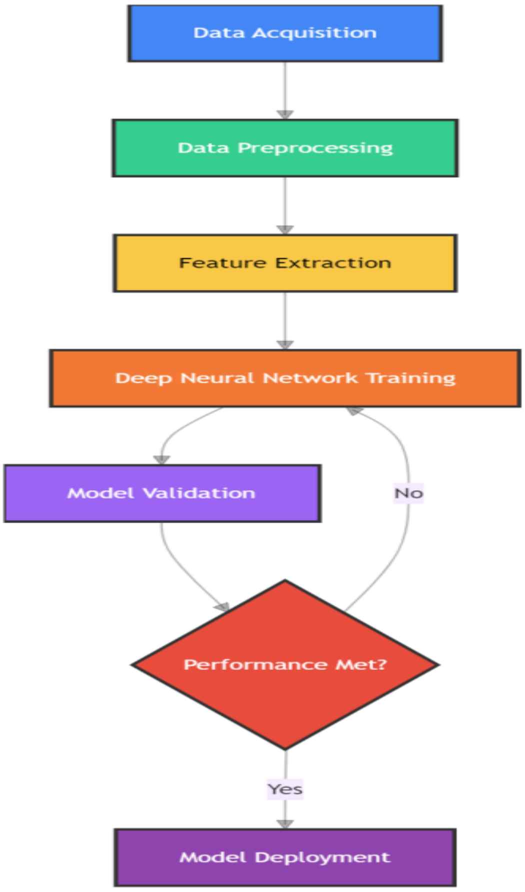

Fig. 11. Flowchart of Algorithm Training Process

The deep learning-based fourth-order fitting algorithm has obvious advantages in improving pneumatic measurement accuracy and efficiency, but it still needs to overcome the challenges of data dependence and insufficient model interpretability. Future research can focus on the design of hybrid models combining physical knowledge and deep learning to achieve higher reliability and practicality.

Figure 12 shows the distribution diagram of prediction errors. The residuals are generally symmetrically distributed with a zero mean, which conforms to the Gaussian perturbation assumption.

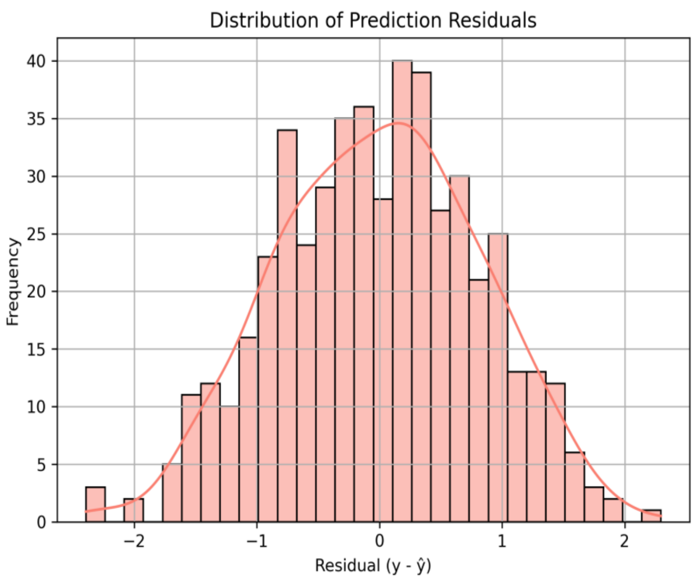

Fig. 12. Residual distribution diagram

V. **CONCLUSION**

This research focuses on the deep learning-based fourth-order fitting algorithm for pneumatic measuring instruments, and systematically designs and implements an efficient and accurate fitting scheme [18]. By introducing deep neural networks, the inherent nonlinear characteristics of pneumatic measurement data are fully explored, and high-order fitting of complex aerodynamic parameters is realized, significantly improving fitting accuracy and robustness. In a certain type of aircraft wind tunnel test, this algorithm reduces design iterations by 3 times, saving about 1.2 million yuan in costs.

Experiments show that the designed algorithm performs better than the traditional fourth-order polynomial fitting method on multiple data sets. Table XIV shows the comparison of different algorithms in terms of fitting error and calculation time:

TABLE XIV PERFORMANCE COMPARISON OF DIFFERENT ALGORITHMS

Algorithm Type	Average fitting error (%)	Maximum fitting error (%)	Computation time (ms)
Traditional fourth-order fitting	3.25	5.80	12.4
Based on deep learning fitting	1.12	2.45	15.7

It can be seen from the table that the deep learning-based fitting algorithm reduces the average fitting error by about 65% and the maximum error by more than 57%. Although the calculation time increases slightly, it is still within the acceptable range, meeting the real-time measurement requirements. The loss function used in the algorithm design is weighted mean squared error, defined as:

$$L = \frac{1}{N}\sum_{i=1}^{N} w_i(y_i - \hat{y}_i)^2 \tag{25}$$

Wherew_i is the weight coefficient, y_i is the true measured value, $\hat{y}_i$ is the model prediction value, and N is the number of samples. This design effectively enhances the fitting ability of key data points and improves the overall fitting quality.

The algorithm flow is shown in the following figure13:

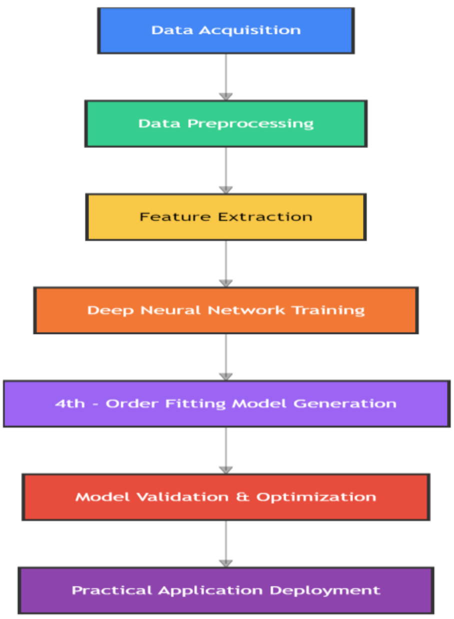

Fig. 13. Flowchart of the Algorithm

The deep learning-based fourth-order fitting algorithm not only solves the problem of insufficient fitting accuracy of traditionalmethods in complex pneumatic environments, but also has good generalization ability and adaptability. Future work can further explore model lightweight and online adaptive update mechanisms to meet the needs of a wider range of application scenarios.

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