Prediction of engine total pressure distortion in improved cascaded forward network

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Abstract: In order to solve the problem of the result delay in the real-time calculation of engine inlet total pressure distortion index in flight test, the multi-step prediction of engine inlet total pressure distortion index in flight test is carried out. The average prediction error of traditional cascade forward neural network prediction model is higher than traditional autoregressive integrated moving average model. An improved algorithm is proposed. By establishing a time series dynamic level model, the time series of engine inlet total pressure distortion index is divided into low dynamic series and high dynamic series by using particle swarm optimization algorithm. The cascade forward neural network prediction model is used for training and prediction respectively. The results show that the average prediction error and maximum prediction error of the improved algorithm are reduced by 3.90%, 10.66% and 3.29% and 1.38% respectively compared with autoregressive integrated moving average model and traditional cascaded feedforward neural network.

1. Introduction

The total pressure distortion index of engine inlet refers to the comprehensive characteristic of uneven total pressure on the aerodynamic interface at the inlet of engine. When the comprehensive pressure distortion index is large, the engine performance and working stability will be significantly reduced [1]. In serious cases, the engine will enter into unstable working state, resulting in rotating stall or surge of engine and fan, affecting the flight test safety of the test machine [2]. It is very important to obtain the total pressure distortion index of engine inlet in real-time for flight test safety monitoring [3]. Limited by the existing flight test telemetry technology, the engine inlet total pressure distortion index can only be calculated in real-time on the airborne side. Time delay is inevitably introduced in the calculation process. Compared with other airborne test parameters, the calculation result is delayed by several time cycles, which is not conducive to real-time monitoring of flight test process [4].

The real-time monitoring of total pressure distortion index is of great significance to reduce the risk of inlet matching. In the flight test, the calculated total pressure distortion index is directly used as the monitoring basis, so it is difficult to detect the flight safety risk in advance without predicting the future state of total pressure distortion. At present, the domestic research on total pressure distortion mainly focus on the numerical calculation of total pressure distortion [5] and inlet optimization design [6], and rarely involves the prediction of total pressure distortion index in flight test, which can’t solve the influence of total pressure distortion calculation delay on safety monitoring.

In this paper, a dynamic level model is established and the attenuation coefficient of the model is obtained by using particle swarm optimization algorithm. The engine inlet total pressure distortion
index time series are divided into low dynamic series and high dynamic series. The forward neural network model is used to train them respectively, and the average prediction error and the maximum prediction error are used as evaluation indexes. The results show that, compared with the traditional autoregressive integrated moving average model and the traditional cascaded forward neural network prediction model, the improved algorithm proposed in this paper has a greater improvement in the prediction accuracy, and can better realize the real-time prediction of engine inlet total pressure distortion index time series.

2. Time series analysis of total pressure distortion index of engine inlet

In flight test, the total pressure distortion index of engine inlet is composed of circumferential total pressure distortion index and turbulence degree [7]. Through the calculation of total pressure and dynamic pressure data of engine inlet aerodynamic interface, the mathematical model is more complex and has the characteristics of fixed data update rate. In order to verify whether the historical series can be used to predict the current engine inlet total pressure distortion index, the autocorrelation analysis of the engine inlet total pressure distortion index time series is carried out. The autocorr function of MATLAB is used to analyze the autocorrelation of the total pressure distortion index time series of the engine inlet in a flight test. The results are shown in figure 1:

![Figure 1. Total pressure distortion time series autocorrelation diagram](image)

It can be seen from figure 1 that the maximum autocorrelation coefficient of the time series is 1, and the autocorrelation coefficient is gradually decreasing. Although the attenuation rate is slow, a large part of the autocorrelation coefficients are obviously greater than 0. Therefore, it can be judged that the time series of engine inlet total pressure distortion index is unstable. With the significant trend, it can use historical time series data for future time Value.

3. ARIMA prediction model

Autoregressive integrated moving average model (ARIMA) is a classical time series model. According to the study of the characteristics of time series in advance, this model can specify three parameters to analyze time series, that is, to describe the order of autoregression \((p)\) the number of difference \((d)\) and the order of moving average \((q)\). Usually, the model is written as \(ARIMA(p, d, q)\).

ARIMA model can be expressed as follows:
\[
\begin{align*}
\Phi(B)\nabla^d x_t &= \Theta(B)\varepsilon_t \\
E(\varepsilon_t) &= 0, \; \forall\ar(\varepsilon_t) = \sigma^2 \\
E(\varepsilon_t, \varepsilon_s) &= 0, \; s \neq t \\
E_{x'tx'_s} &= 0, \; \forall s < t
\end{align*}
\] (1)

Where \(\nabla^d = (1 - B)^d\), \(\{\varepsilon_t\}\) is a zero mean white noise sequence, and \(\Phi(B) = 1 - \varphi_1 B - \cdots - \varphi_p B^p\) is the autoregressive coefficient polynomial of stationary reversible ARMA\((p, q)\) model, \(\Theta(B) = 1 - \theta_1 B - \cdots - \theta_q B^q\) is the moving smoothing coefficient polynomial of stationary reversible ARMA\((p, q)\) model.

In practical work, most of the time series are non-stationary, but after a finite number of differences, they often show the nature of stationary series, which is called differential stationary series. The stationary series after difference can be analyzed by ARIMA model.

Unit root test is the most commonly used statistical test method for sequence stationarity. First, unit root test is carried out for the time series of engine inlet total pressure distortion index obtained from flight test to judge the stability of the sequence. The Augmented Dickey-Fuller (ADF) test is used to judge the stationarity of the time series by using MATLAB. Under the ADF test, the significance level of \(p\) value is 0.5185, which is greater than 0.01, indicating that the unit root of the time series of the comprehensive distortion index is non-stationary.

The first-order difference of the total pressure distortion index time series is carried out. The unit tracking test method of MATLAB ADF test is used to determine the stationarity of the time series. Under the ADF test, the \(p\) value value is less than 0.001, which shows that more than 99.9% of the series data meet the unit root test, which shows that the total pressure distortion index time series after the first-order difference is stable.

Therefore, the difference order of the model is \(d = 1\). In order to obtain the order \(p\) of autoregression and the order of moving average in ARIMA\((p, d, q)\) model, autocorrelation (AC) graph and partial autocorrelation (PAC) graph were used to determine the order of the model.

**Table 1. AC and PAC order determination method for time series**

| Model   | AC     | PAC     |
|---------|--------|---------|
| AR \((p)\) | Trailing | \(p\) order Truncation |
| MA \((q)\) | q order Truncation | Trailing |
| ARMA \((p, q)\) | Trailing | Trailing |

**Figure 2. First order differential AC graph**
The autocorrelation graph is tailed, and the partial autocorrelation graph is truncated at order 15. The model can be written as ARIMA (15,1,0). The results are shown in Table 2.

ARIMA model is constructed to predict the total pressure distortion index in multi steps. The results are shown in Table 2.

Table 2. Prediction results of ARIMA model

| Prediction steps | Average error | Maximum error |
|------------------|---------------|---------------|
|                  | Before prediction | ARIMA | Before prediction | ARIMA |
| 1                | 2.37×10^{-5}   | 1.98×10^{-5} | 4.88×10^{-4} | 4.73×10^{-4} |
| 2                | 4.33×10^{-5}   | 3.28×10^{-5} | 6.41×10^{-4} | 5.14×10^{-4} |
| 3                | 6.10×10^{-5}   | 4.24×10^{-5} | 9.92×10^{-4} | 5.26×10^{-4} |
| 4                | 7.75×10^{-5}   | 5.11×10^{-5} | 12.21×10^{-4} | 5.74×10^{-4} |
| 5                | 9.37×10^{-5}   | 5.72×10^{-5} | 15.11×10^{-4} | 6.47×10^{-4} |
| 6                | 10.96×10^{-5}  | 6.65×10^{-5} | 18.16×10^{-4} | 7.47×10^{-4} |

4. Prediction model of cascaded feedforward neural network

Cascaded forward neural network (CFN) is a kind of artificial neural network with multi-layer network structure. Based on back-propagation algorithm, layers are cascaded with each other, and information propagates forward step by step. Compared with the standard back propagation (BP) neural network, each layer of the cascaded feedforward neural network is connected with the input layer, and has stronger nonlinear fitting ability than the standard BP neural network. The general mathematical expression of cascaded feedforward neural network is as follows:

\[ a^n = f^n(W^n_1a^{n-1} + W^n_2p + b^n) \]  

Where: \( n \) is the number of neural network layers; \( W \) is the hidden layer weight matrix with the number of rows as the number of neurons in each layer and the number of columns as the number of input individuals; \( b \) is the partial value column vector of hidden layer with the same number of rows as \( W \); \( a \) is the output vector of each layer; \( p \) is the input vector; \( f \) is the activation function.

To solve the weights and biases of each layer of neural network, error back-propagation algorithm is the extension of the minimum variance algorithm. According to the chain rule of derivation, the mean square error is backpropagation, so the weight and bias value of each layer are modified, and the mean square error is minimized by continuous iteration. The formula of sensitivity back propagation
through network is as follows:
\[ s^M = -2F^M(n^m)(t - a) \]  
\[ s^m = F^m(n^m)(W^{m+1})^T s^{m+1}; m = M - 1, \ldots, 2, 1 \]  
(3)  
(4)

Where: \( n^m \) is the display function of weight and partial value.
\[ n^m(W, b^m) = \sum(W_1^m a^{m-1}) + \sum(W_2^m p) + b^m \]  
(5)

\( F \) is the approximate mean square error.
\[ F(x) = (t(k) - a(k))^T(t(k) - a(k)) = e^T(k)e(k) \]  
(6)

\( a \) is the learning rate; \( s^M \) is the sensitivity of the last layer; \( s^m \) is the sensitivity of the remaining layer; \( t \) is the actual output vector. The formula for modifying the bias value of the weight of the steepest descent method in each iteration is:
\[ w_{ij}^m(k+1) = w_{ij}^m(k) - a \cdot s_i^m a_j^{m-1} \]  
(7)
\[ b_i^m(k+1) = b_i^m(k) - a \cdot s_i^m \]  
(8)

Where: \( s_i^m \) is the sensitivity of each layer.

According to the Markov property, the conditional probability distribution of the future state of the parameter only depends on the previous finite states. When predicting the future time series, only the sequence which is closest to the point to be predicted has a great influence on it. Generally, a sliding window with the size of \( \omega \) is used to cut a segment of the sequence as the input of the prediction model. The 1-step prediction results of different length \( \omega \) sequences are shown in the figure below. It is shown in figure 4.

It can be seen from the figure 4 that when the length of the time series is greater than 14, the accuracy of the prediction results will not be improved basically. When the length of the time series is 15, that is, the values of the previous 15 moments are used to predict the values of the next time series.

![Figure 4. Relationship between average prediction error and sliding window \( \omega \)](image)

For neural network prediction, the number of hidden layers is generally no more than two [8]. After many experiments, the optimal structure of cascaded forward neural network is one input layer, two hidden layers and one output layer. The first hidden layer has 5 neurons, the second hidden layer has 2 neurons, and the output layer has 1 neuron. The structure of the network is 15-5-2-1 hierarchical structure, in which trainlm is selected as the activation function of hidden layer neurons, and linear function is selected as the output layer neuron activation function. The training results are shown in
As can be seen from Table 3, compared with the traditional Arima prediction model, the maximum prediction error of the cascaded forward neural network prediction model is smaller than that of the ARIMA model, but the average prediction error is larger than that of the ARIMA model. The first mock exam result is that the data size is huge and the fluctuation level of time series is different from each other in the training of neural network. It is very difficult for a single model to predict the time series of different fluctuation levels simultaneously.

Table 3. Comparison between CFN and ARIMA

| Prediction steps | Average error | Maximum error |
|------------------|--------------|--------------|
|                  | ARIMA        | CFN          | ARIMA        | CFN          |
| 1                | 1.98×10^5   | 2.10×10^5   | 4.73×10^4   | 4.64×10^4   |
| 2                | 3.28×10^5   | 3.49×10^5   | 5.14×10^4   | 4.90×10^4   |
| 3                | 4.24×10^5   | 4.58×10^5   | 5.26×10^4   | 5.19×10^4   |
| 4                | 5.11×10^5   | 5.48×10^5   | 5.74×10^4   | 5.62×10^4   |
| 5                | 5.72×10^5   | 6.32×10^5   | 6.47×10^4   | 5.97×10^4   |
| 6                | 6.65×10^5   | 7.16×10^5   | 7.47×10^4   | 6.77×10^4   |

5. Improved cascaded feedforward neural network prediction

The traditional neural network directly selects part of the time series data for training, without considering the influence of the characteristics of the time series on the training results. In this paper, the exponential attenuation model is used to describe the fluctuation level of engine inlet total pressure distortion index time series. The optimal attenuation coefficient is obtained by using particle swarm optimization algorithm. The fluctuation level of time series is divided into high dynamic series and low dynamic series. Different neural networks are used for training and prediction.

5.1. Time series volatility level description

In the flight test, the engine working state is mainly divided into steady state and dynamic state. Under the steady state, the flight speed, attitude and engine speed of the aircraft are basically stable, and the total pressure distortion value is relatively stable; in the dynamic working state, the flight state, engine throttle, speed and other changes are more severe, resulting in the total pressure distortion fast with time Speed change. In these two states, the volatility of total pressure distortion time series has significant difference. According to the Markov property, the closer the point is to the predicted point, the greater the influence is. For the time series samples of total pressure distortion in a flight test, the sliding window ω = 15 is selected and the exponential attenuation model is used to describe the dynamic level of the time series. As shown in equation (9):

\[ D_t = f(X_t) = d_t + a \cdot d_{t-1} + \cdots + a^{w-2} \cdot d_{t-\omega+2} \]  

Among them:
- \( t \) is the time;
- \( \omega \) is the sliding window size;
- \( X_t = \{x_{t-w+1}, \ldots, x_1, x_t\} \) is a time series sample;
- \( x_t \) is the value of time series at time \( t \);
- \( d_t = |x_t - x_{t-1}| \) is the absolute value of the difference between two adjacent time points;
- \( a \in [0,1] \) is the attenuation coefficient.

5.2. Attenuation model coefficient of particle swarm optimization

Particle swarm optimization algorithm (PSO) imitates the flight behavior of birds. The birds in the flock are particles, and each particle is called a solution. By updating the speed and position of particles, the optimal solution is obtained in the whole space. The principle is: suppose there are \( m \) particles with arbitrary velocity in the \( n \)-dimensional search space, and the position of each particle is: \( X_i = (x_{i1}, x_{i2}, \ldots, x_{in}) \), \( i = 1, 2, \ldots, m \). The velocity of each particle is: \( V_i = (v_{i1}, v_{i2}, \ldots, v_{in}) \), \( i = 1, 2, \ldots, m \).
1, 2, ..., m. The position of the i-th particle is: \( P_i = (p_{i1}, p_{i2}, ..., p_{in}) \), \( i = 1, 2, ..., m \). The optimal position of the whole particle swarm is: \( P_g = (p_{g1}, p_{g2}, ..., p_{gn}) \). The optimization principle of the algorithm is to initialize a group of particles with random velocity and position, and then through iterative search. In each iteration, the particle finds the optimal solution by tracking a single particle, that is, the individual extreme value \( P_{best} \). The global extremum \( G_{best} \) is the optimal solution found by best and population particles to update themselves, constantly adjust the particle speed and position, and finally, find the optimal value in the search space. The update formula is as follows:

\[
V_{id}^{k+1} = \omega(c_1) V_{id}^k + c_1 r_1(p_{id}^k - X_{id}^k) + c_2 r_2(p_{gd}^k - X_{id}^k)
\]

\[
X_{id}^{k+1} = X_{id}^k + V_{id}^{k+1}
\]

\[
\omega(k) = \omega_0 - \left(\frac{k}{k_m+k_n}\right)
\]

Where: \( \omega_0 \) is the initial inertia weight, \( \omega(e) \) is the inertia weight at the end of the algorithm, \( k_m \) is the current number of iterations, \( k_n \) is the maximum number of iterations, \( r_1 \) and \( r_2 \) is a random number between \([0,1]\), \( c_1 \) and \( c_2 \) is the acceleration factor and is a nonnegative constant if \( c_2 \) is too small, it is easy to fall into local optimum. If \( c_2 \) is too small, the particles will not get the ideal result due to the lack of experience communication.

The total pressure distortion index time series is a kind of complex time series. After the establishment of the time series volatility level description model, its dynamic horizontal attenuation model coefficient \( a \) and significance index \( D \) are difficult to be selected manually based on experience. Therefore, in order to improve the selection efficiency and adaptability of attenuation coefficient \( a \) and significance value \( D \) of the model, particle swarm optimization model is adopted in this paper. To the attenuation coefficient \( a \) and significance index \( D \) which are suitable for describing the dynamic level of the total pressure fluctuation distortion index time series, the particle swarm optimization process is as follows:

Step 1. Initializes the parameters of the PSO algorithm. The initial particle number \( m = 50 \), dimension \( d = 2 \), acceleration constant \( c_1 = c_2 = 1.5 \), particle velocity \( v_{min} = -0.5 \), \( v_{max} = 0.5 \), the maximum number of iterations \( k_m = 100 \);

Step 2. Calculates the fitness value of particles. The individual optimal solution and the global optimal solution are updated by the fitness update of each operation. The fitness value of the initial particle is calculated by fitness formula, and the fitness value of a single particle and its history \( P_{best} \) are calculated if it is better, it will be regarded as the current individual optimal solution; the fitness values of all particles in the population and their history \( G_{best} \) are calculated if it is better, and it will be regarded as the current global optimal solution. The first 60% sequence samples with the largest fluctuation are selected, and the average value of fluctuation level is recorded as the fluctuation significance value \( D \). The average value of one-step error is calculated as the fitness \( P \), and the larger the value, the better. The \( P \) value can describe the error proportion of this part of time series and ensure that the selected time series are high dynamic time series;

Step 3. Updates the particle state. The velocity and position of particles are updated by formulas (10) and (11). If the particle velocity is less than the minimum velocity of particle swarm, the current velocity is set as the minimum velocity of particle swarm, otherwise, it is set as the maximum velocity of particle swarm;

Step 4. Checks whether the end condition is met. When the set maximum number of operations is reached or the preset fitness is obtained, the operation is terminated. Otherwise, Step 2 is returned to continue the operation.

5.3. Algorithm verification

Using particle swarm optimization algorithm, the attenuation model coefficient \( a \) and time series fluctuation significance value \( D \) are obtained. When the algorithm is iterated to 52 times, the optimal
individual fitness value does not change. At this time, the attenuation model coefficient \( a = 0.4482 \) and time series fluctuation significance value \( D = 4.1681 \times 10^{-5} \) are obtained by the algorithm optimization.

Using the attenuation coefficient \( a \) of the model, the volatility value \( D \) of each time series sample is calculated. Taking the significance value \( D \) of time series fluctuation as reference standard, the time series samples are divided into low dynamic samples \( Y_L (D_L \leq D, \text{ accounting for 72\% of the total sample size}) \), and high dynamic sample \( Y_H (D_H > D, \text{ accounting for 28\% of the total sample size}) \). The first 50\% of the samples are selected as the training samples, and the cascaded feedforward neural network is used for training and prediction. The results are as follows:

### Table 4. Improved CFN prediction results

| Prediction steps | Average error | Maximum error |
|------------------|---------------|---------------|
|                  | \( Y_L \)     | \( Y_H \) | mean | \( Y_L \) | \( Y_H \) | max |
| 1                | 1.08\times10^{-5} | 3.86\times10^{-5} | 1.86\times10^{-5} | 2.34\times10^{-4} | 4.58\times10^{-4} | 4.58\times10^{-4} |
| 2                | 1.71\times10^{-5} | 6.64\times10^{-5} | 3.08\times10^{-5} | 2.63\times10^{-4} | 4.82\times10^{-4} | 4.82\times10^{-4} |
| 3                | 1.91\times10^{-5} | 9.34\times10^{-5} | 3.98\times10^{-5} | 2.89\times10^{-4} | 5.05\times10^{-4} | 5.05\times10^{-4} |
| 4                | 2.09\times10^{-5} | 11.9\times10^{-5} | 4.82\times10^{-5} | 3.22\times10^{-4} | 5.42\times10^{-4} | 5.42\times10^{-4} |
| 5                | 2.33\times10^{-5} | 13.6\times10^{-5} | 5.49\times10^{-5} | 3.47\times10^{-4} | 5.82\times10^{-4} | 5.82\times10^{-4} |
| 6                | 2.82\times10^{-5} | 15.5\times10^{-5} | 6.39\times10^{-5} | 3.9\times10^{-4} | 6.61\times10^{-4} | 6.61\times10^{-4} |

It can be seen from table 4 that the average prediction error of time series samples with strong volatility is larger than that of time series with low volatility. The average prediction error increases with the increase of the number of prediction steps, showing a linear trend, as shown in figure 5. The maximum prediction error increases slowly from 1 step to 5 step prediction, and increases obviously in 6-step prediction, as shown in figure 6.

![Figure 5. Relationship between average prediction error and prediction steps](image1)

![Figure 6. Relationship between maximum prediction error and prediction steps](image2)

It can be seen from the prediction results that the total average prediction error of the improved CFN model for the engine inlet total pressure distortion time series samples is reduced by more than 3.90\% and 10.66\% respectively compared with ARIMA model and traditional cascaded feedforward neural network, and the maximum prediction error is reduced by 3.29\% and 1.38\% respectively, as shown in Table 5.
Table 5. Comparison of prediction error of improved CFN model with ARIMA and CFN

| Prediction steps | Average error reduction (%) ARIMA | Maximum error reduction (%) ARIMA | Average error reduction (%) CFN | Maximum error reduction (%) CFN |
|------------------|----------------------------------|----------------------------------|--------------------------------|--------------------------------|
| 1                | 6.15                             | 3.29                             | 1.38                           |                                |
| 2                | 6.05                             | 6.20                             | 1.46                           |                                |
| 3                | 6.12                             | 4.06                             | 2.65                           |                                |
| 4                | 5.67                             | 5.60                             | 3.53                           |                                |
| 5                | 4.00                             | 9.98                             | 2.55                           |                                |
| 6                | 3.90                             | 11.42                            | 2.32                           |                                |

6. Conclusion

According to the characteristics of engine inlet total pressure distortion time series in flight test, an improved cascaded forward neural network prediction model is proposed in this paper. The attenuation model is used to describe the volatility level of the sample time series. The particle swarm optimization algorithm is used to search for the optimal model attenuation coefficient and fluctuation significance value. The sample time series is divided into low dynamic sample and high dynamic sample. In this paper, cascaded feedforward neural network is used to train and predict. The results show that the average prediction error and maximum prediction error of the improved algorithm are reduced by 3.90%, 10.66% and 3.29% and 1.38% respectively compared with autoregressive integrated moving average model and traditional cascaded feedforward neural network. The smaller average prediction error and the maximum prediction error make this method can accurately predict the total pressure distortion index, and cooperate with the command and monitoring, which has an important role in the timely detection of its abnormal changes, and can be better applied to the safety monitoring of the flight test subject of the match between the advance and the departure.

The time series prediction method only considers the influence of the past time of parameters on the current time result, and the prediction accuracy is limited in multi-step prediction. In the follow-up, we will study how to further improve the multi-step prediction accuracy of total pressure distortion based on the information of aircraft attitude, speed and engine working state in flight test.

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