Prediction of Aircraft Optimal Slip Rate Based on IFABP Neural Network

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Abstract

In view of the nonlinear property of aircraft braking process and the complexity of on-line estimation, a prediction method of optimal slip rate based on improved firefly BP neural network (IFABP) is proposed. By improving the cross factor of the firefly algorithm, the operation speed of the firefly algorithm is enhanced. The global optimization ability of firefly algorithm is used to optimize the weights and thresholds of BP neural network, and the prediction ability of BP neural network is improved. The improved BP neural network prediction model of firefly is constructed based on the slip rate-coefficient data under different working conditions, and the optimal slip rate identification system is constructed. The simulation results in the aircraft brake system verify the feasibility and effectiveness of the proposed optimal slip rate identification method.

Key Words: Prediction of Aircraft Optimal Slip Rate, BP Neural Network, Improved Firefly Algorithm

1. Introduction

The anti-lock braking system (ABS) control method with slip rate as the control target can keep the optimal slip rate during the braking process of the aircraft, so as to maximize the stability and maneuverability of the aircraft. This is an ideal braking mode, and the difficulty is that the optimal slip rate under various runway conditions is not a fixed value. Because of the non-linearity of tire and the non-linearity of contact between tire and ground, there is a non-linear relationship between the wheel slip rate and adhesion coefficient. At the same time, the optimal slip rate is also related to the type of runway, and its value varies from 5% to 30% with the road condition. Therefore, real-time identification of pavement characteristics and determination of the optimal slip rate under various road conditions become the key to the design of aircraft ABS system based on slip rate.

At present, many literatures have studied this. In [1], a backstepping sliding mode control scheme with the barrier Lyapunov function was proposed and implemented on braking systems using electromechanical actuator for aircraft. The Lyapunov stability analysis shows that the asymptotic output tracking has been ensured. The effectiveness of the proposed approach is assessed on a hardware-in-the-loop experimental facility. In [2], an adaptive sliding mode control (ASMC) algorithm is proposed. The results from simulation that ASMC strategy, compared with the traditional SMC strategy, makes the ABS obtain the maximum friction coefficient in a shorter time. Additionally it is shown that the system works under optimal slip ratio and shortens the braking time. Reference [3] based on the force analysis of aircraft ground taxiing, a nonlinear dynamic mathematical model of aircraft is established, and a fuzzy control law of aircraft braking system based on optimal slip rate is proposed. The results show that fuzzy control with EKF estimation algorithm can estimate the aircraft velocity and realize air-

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craft ABS optimal slip ratio control. The slip ratio is ameliorated in lower velocity; brake performance and efficiency is improved. In [4], for overcoming the higher order nonlinearity and parameters variability in the model of the antiskid braking system (ABS) of aircraft, a dynamic surface control approach based on the barrier Lyapunov function (BLF) is proposed to design the slip ratio tracking control with an output upper constraint. Reference [5] in order to deal with the high nonlinearity of aircraft braking system, we design a fuzzy sliding-mode variable structure controller. Based on sliding-mode variable structure control, additional control is realized through adjustment with fuzzy logic, which can make the control signal smooth, weaken the chattering and improve the quality of control. The simulation results and their analysis indicate preliminarily that the anti-skid braking system can track the optimal slip ratio well and the control method is reasonable and effective. In [6], aiming at the nonlinearity, time-varying and uncertainty of the aircraft antiskid braking system, the model of the antiskid braking system based on the closed-loop PI iterative learning control algorithm is derived from the relative slip rate. It proves the correctness and superiority of this method in control performance, and provides a good theoretical basis for the optimization design of aircraft brake system.

The method of approximating the mu-s curve or the method of approximating the mu-s curve adopted in the above literature keeps the optimal slip rate basically unchanged and non-optimal control; or although it can identify the pavement characteristics in real time, it takes too much time to estimate the parameters on-line, which is difficult to meet the real-time requirements of the online control braking system. Based on the above problems, this paper proposes a method for predicting the optimal slip rate based on improved firefly algorithm optimization BP neural network (IFABP). By improving the cross factor of the firefly algorithm, the operation speed of the firefly algorithm is enhanced. The global optimization ability of firefly algorithm is used to optimize the weights and thresholds of BP neural network, and the prediction ability of BP neural network is improved. The improved BP neural network prediction model of firefly is constructed with the slip rate-coefficient data under different working conditions, and the optimal slip rate identification system is constructed.

2. BP Neural Network

The neural network uses a physically achievable device or computer to simulate certain structures and functions of a neural network in an organism and apply it to a project. The neural network has a strong fault tolerance function. It can relatively easily implement a non-linear mapping process and has a large-scale computing capability, so it has wide applicability in the fields of automation, computers, and artificial intelligence.

Back propagation (BP) network [7–9] was proposed by a group of scientists headed by Rumelhart and McClelland in 1986. It is a multi-layer feedforward network trained by error back propagation algorithm and is one of the most widely used neural network models. BP network can learn and store a large number of input-output pattern mapping relations without revealing the mathematical equations describing the mapping relations beforehand. Its learning rule is to use the steepest descent method to adjust the weights and thresholds of the network by back propagation, so as to minimize the sum of squares of errors of the network. The topological structure of BP neural network includes input layer, hidden layer and output layer.

3. Firefly Algorithm

The principle of firefly algorithm [10–12]: the space points as fireflies, the use of luminous fireflies will attract the characteristics of glowing fireflies. In the process of moving the glowing firefly to the glowing firefly, the iteration of the position is completed to find the best position, that is, the optimization process is completed.

The search process is related to two important parameters of the firefly: the glow brightness and mutual attraction of the firefly. Glowing and bright fireflies will attract light and weak fireflies to move towards it. The brighter the light is, the better the position is. The brightest fireflies represent the optimal solution of the function. The more luminous the firefly is, the more attractive it is to the surrounding fireflies. If the luminous brightness is the same, the firefly does random movement. Both of these important parameters are inversely proportional
to the distance, and the greater the distance is, the smaller the attraction is.

Firefly algorithm is an optimization algorithm based on the social characteristics of fireflies. Like most evolutionary algorithms, it is based on population to optimize the target. The difference is that the evolutionary operator is not used in the algorithm. In recent years, experts and scholars have found that compared with particle swarm optimization [13–15] and genetic algorithm [16–18], firefly algorithm has higher efficiency, faster search speed, and is not easy to fall into local optimum.

In firefly algorithm, the attraction of a firefly to another firefly will decrease as the distance between two fireflies increases. The mathematical formula of the attraction between fireflies can be expressed as:

\[ \beta(r) = \beta_0 \times \exp(-r^m), \quad m \geq 1 \]  

(1)

In the formula, \( r \) represents the distance between any two fireflies. \( \beta_0 \) represents the initial attraction of \( r = 0 \), and \( \gamma \) is the absorption coefficient of light intensity.

Any firefly and firefly meet the following mathematical formula:

\[ r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{d}(x_{ik} - x_{jk})^2} \]  

(2)

\[ X_i = [x_{i1}, x_{i2}, \ldots, x_{id}] \]  

(3)

\[ X_j = [x_{j1}, x_{j2}, \ldots, x_{jd}] \]  

(4)

In the formula, \( r_{ij} \) stands for the distance between two fireflies, and \( d \) represents the dimension.

It is assumed that the firefly \( i \) and \( j \) are two random fireflies in the population, and the light intensity of the firefly \( i \) is higher than that of the firefly \( j \), so the position change formula of the firefly \( j \) can be expressed as:

\[ X_j = X_j + \beta_0 \times \exp(-r^m) \times (X_i - X_j) + U_j \]  

(5)

\[ U_j = \alpha \left(\text{rand} - \frac{1}{2}\right) \]  

(6)

In the formula, \( \alpha \) is a random number between \((0, 1)\).

According to formula (5), the above equations are mainly composed of three parts: 1) current location \( X_j \); 2) the attraction of firefly \( i \) to firefly \( j \); 3) random motion. When firefly \( i \) can not see the brightness of the firefly \( j \), the third cases have the greatest influence on the location of fireflies.

The efficiency of the firefly algorithm is derived from its random step length. If the random step length is always large, the algorithm has a strong search ability, but it can not obtain the high precision global optimal solution. If the random step length is always smaller, the algorithm will pay more iterations when the target accuracy is reached.

Aiming at the shortcomings of slow convergence rate and low precision of the standard firefly algorithm, this paper proposes an adaptive random step firefly algorithm. The improved algorithm has a large step factor in the initial stage of optimization, thus enlarging the search space in the early stage of the algorithm and improving the global search ability. In the process of optimization, the step length is reduced and the local search performance of the algorithm is improved.

\[ \alpha_{k+1} = \left(\frac{1}{2k_{\text{max}}}\right)^{\frac{r_{\text{max}}}{k}} \alpha_k \]  

(7)

In the formula, \( k \) represents the number of iterations, and \( k_{\text{max}} \) represents the maximum number of iterations.

Therefore, the location update based on improved firefly algorithm can be changed to:

\[ X_j = X_j + \beta_0 \times \exp(-r^m) \times (X_i - X_j) + \left(\frac{1}{2k_{\text{max}}}\right)^{\frac{r_{\text{max}}}{k}} \alpha_k \left(\text{rand} - \frac{1}{2}\right) \]  

(8)

4. Online Identification System for Optimal Slip Rate

4.1 The Basic Principle of Best Slip Rate Recognition

After landing, pilots step on the brakes and apply a certain amount of braking pressure to the brakes by connecting pipes. The resulting friction gives the aircraft a backward force, that is, braking force. In braking system, it is called binding force, and the combined torque is composed of the product of the force and the rolling radius of the wheel. When the combined torque is greater than the braking torque, the wheel speed is accelerated, and the
relative slip rate of the wheel decreases. When the combined torque is less than the braking torque, the wheel speed decelerates, and the relative slip rate of the wheel increases. When the combined torque equals to the braking torque, the wheel rotates at a constant speed, and the relative slip rate of the wheel can be considered to be basically constant in a relatively short time.

When the slip ratio is small, the braking pressure is relatively small, and the friction coefficient of the wheel supplied by the ground is also relatively small, so the braking force is not very large. With the increase of braking pressure, the slip rate and friction coefficient increase gradually. The braking force provided by the ground increases and the braking efficiency increases gradually. When the brake pressure increases to the slip rate corresponding to the maximum adhesion coefficient at the peak, the brake efficiency of the system increases to 100%. However, if the brake pressure continues to increase and the slip rate exceeds the slip rate corresponding to the peak value of the binding coefficient, the friction coefficient will rapidly decay. If the brake can not be released in time, the wheel will soon die and drag. The control of the braking process is to change the control law and adjust the parameters of the control system so that the binding torque produced by the friction coefficient between the tire and the ground can reach or approach the maximum value to improve the braking efficiency. From the above analysis, it can be seen that the aircraft braking mainly depends on the tire and ground braking force. The relationship between slip rate and binding coefficient of aircraft at landing stage (under different runways) is shown in Figure 1.

At present, the following two methods are commonly used to estimate the optimal slip rate $s_p$. One method is based on the shape of the longitudinal adhesion coefficient-slip rate curve ($\mu$-$s$), i.e. at the optimum slip rate $s_p$, there is $\partial \mu / \partial s = 0$.

The model expression of tire longitudinal adhesion coefficient and slip rate is as follows [19]:

$$\mu = f(s, F, \delta, v, \sigma) \quad (9)$$

In the formula, $\mu$ is the binding coefficient, $s$ is the slip rate, $F$ is the normal load acting on the tire, $\delta$ is the sideslip angle, $v$ is the aircraft speed, $\sigma$ is the runway surface condition factor.

Professor Pacejka of Delft University of Technology in the Netherlands has proposed a commonly used method to fit the shape of longitudinal adhesion coefficient-slip rate curve ($\mu$-$s$) curve: Pacejka magic formula. A set of tire model formulas which can express longitudinal force, transverse force and return torque in the same form are obtained by fitting the experimental tire data with the combination formula of trigonometric function, so they are called “magic formula”. Its general expression is:

$$Y = D \sin(C \arctan(B\varphi)) + \Delta S_i \quad (10)$$

$$\varphi = (1 - E)(X + \Delta S_i) + (E / B) \arctan(B(X + \Delta S_i)) \quad (11)$$

In the formula, $D$ is the peak factor: the maximum value of the curve, $B$ is the stiffness factor, $E$ is the curvature factor of the curve: the shape near the maximum value of the curve, $C$ is the curve shape factor: the curve represents the transverse force, longitudinal force or self-return moment, $S_i$ is the horizontal direction of the curve, $S_v$ is the vertical direction of the curve.

The running model based on the Pacejka magic formula can be expressed as follows:

$$\mu = D \sin \left( C \arctan \left[ B(1 - E)\sigma + E / B ~ \arctan(B\sigma) \right] \right) \quad (12)$$

In the formula, $B, C, D$ are all greater than 0. By limiting the range of parameters, the number of iterations can be
reduced, the workload can be reduced, and the application can be convenient.

Another way is to express the \( \mu_s \) curve with an analytic function containing parameters \[20\]. The parameters under real-time operating conditions are identified, and the maximum longitudinal adhesion coefficient and the optimal slip rate are obtained indirectly by calculating the maximum value of the function. In this paper, the first method is used to predict the optimal slip rate online.

4.2 Aircraft Taxiing Dynamics Model

When the aircraft is running and braking, it is assumed that there is no crosswind or crosswind speed is very small, so the effect on the whole model is very small, so it can be neglected.

The acceleration of the aircraft in the direction of running (X) and the binding force between the wheel and the runway are as follows:

\[
(G / g) \cdot X = T - Q - n_1 F_1 - n_2 F_2 \quad (13)
\]

\[
F_1 = \mu_1 N_1 \quad (14)
\]

\[
F_2 = \mu_2 N_2 \quad (15)
\]

\[
n_2 N_2 a - n_1 N_1 b - (n_1 F_1 + n_2 F_2) h = 0 \quad (16)
\]

In the formula, \( T \) is the residual thrust of the aircraft engine, \( F_1 \) is the binding force of the single brake wheel of the aircraft, and \( F_2 \) is the binding force of the single free wheel of the aircraft. \( X \) is the acceleration of the aircraft, \( Q \) is the windward resistance of the aircraft, and \( \mu_1 \) is the combination coefficient of the aircraft brake wheel and the surface of the runway, and \( \mu_2 \) is the combination coefficient of the aircraft’s free wheel and the runway surface. \( N_1 \) is the reaction force of the runway to a single brake wheel. \( N_2 \) is the reaction force of the runway to a single free wheel. \( n_1 \) is the number of the brake wheels, and the number of \( n_2 \) is the number of the free wheel. The \( G \) is the weight of the aircraft, the \( g \) is the gravity acceleration, the \( a \) is the distance from the free machine to the center of gravity of the aircraft, and the distance between the \( b \) is the center line of the aircraft and the \( h \) is the height of the center of gravity from the center of the plane.

4.3 Wheel and Tire Model

\[
i \frac{d\omega}{dt} = M_f - M_s \quad (17)
\]

\[
M_f = F_s R_s \quad (18)
\]

\[
R_s = R - \frac{1}{n} NK_s \quad (19)
\]

In the formula, \( R \) is the brake wheel radius, \( R_s \) is the dynamic rolling radius of the brake wheel, and \( \omega \) is the angular speed of the wheel. \( M_s \) is the braking torque of a single wheel, \( M_f \) is the combined torque of a single wheel, \( I \) is the moment of inertia of a single wheel, and the \( K_s \) is the compression coefficient of the tire, \( F \) is the binding force of the single brake wheel of the aircraft, and \( N \) is the reaction force of the runway to a single brake wheel.

The model of aircraft dynamics, wheel and tire is the basis of the whole simulation model of the brake system, and it is ready for the simulation of the whole brake system.

4.4 Sample Data of Slip Rate Recognition

In order to ensure the randomness and practicability of the data, this paper uses 500 groups of data (slip rate, combination coefficient, optimal slip rate) under three different runway conditions as training data and sample data (50% training data and 50% sample data respectively) according to NASA statistics.

4.5 Optimal Slip Rate Recognition Algorithm Based on IFABP

The IFABP aircraft slip rate identification model is shown in Figure 2. The weights and thresholds of BP neural network are optimized by IFA, then the optimized results are applied to system modeling. Based on the optimized slip rate identification algorithm is as follows:

(1) Determination of BP neural network structure.

The BP neural network adopts a three-layer structure. The number of neurons at the input layer and output layer is 1, and when the number of hidden layer neurons is determined, the number of neurons in the optimal hidden layer is determined by comparing the errors. The
mapping function from the input layer to the hidden layer is tansig () function. Tansig () is the node transfer function of BP neural network, which is expressed as tangent S-type transfer function. The purelin () function is used from the hidden layer to the output layer. Purelin () is a linear function commonly used in BP neural networks. Its mathematical formula is as follows:

\[ y = x \] (20)

The traingdm () function is used to the training function, it means the gradient descent method with momentum term. The learning rate is 0.1. This paper selects the random number between the weight of the initial value (-1, 1) and the threshold. At the same time, the samples were normalized.

The purpose of normalization algorithm is to map large input and large signal into a small range, and then improve the accuracy of operation. The training data and prediction data should be processed from 0.5 to 1 before they are input into BP neural network. This normalization process can not only avoid the operation error caused by the large fluctuation of data, but also improve the convergence speed of the neural network. The data processing expression is as follows:

\[ x = \frac{1}{2} \times \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} + \frac{1}{2} \] (21)

In the formula, \( x_{\text{min}} \) represents the minimum value in the data, and \( x_{\text{max}} \) represents the maximum value in the data.

1. Initialization of firefly population: the random step length is 0.18, the maximum iteration is 150, the optical absorption factor is 1, the population number is 50, and the preset error is 0.001.

2. The location vector element of the firefly \( i \) is assigned to the set of connection weights, and the training sample is input into the network to get the output, and the fitness value of each firefly is determined by the training error. The fitness function of individuals is calculated based on the mean square deviation of neural network.

3. In order to evaluate the prediction accuracy and training speed of the model, the actual output of the BP neural network and the mean variance mse generated by the target output and the number of network training iterations are used as the model evaluation indexes.

\[ \text{mse} = \frac{1}{N} \sum_{i=1}^{N} (e_i)^2 = \frac{1}{N} \sum_{i=1}^{N} (y_i - h_i)^2 \] (22)

4. A new round of updating is carried out through the
(5) If the training error of the individual with the light intensity in the population is lower than the preset error value or the maximum number of iterations, skip to the next step, otherwise skip to step (3).
(6) The maximum brightness of fireflies is the initial weight of BP neural network.
(7) BP neural network update weights.
(8) If the BP neural network training error value is lower than the preset error value or the maximum number of iterations, skip to the next step. Otherwise, skip to step (7).
(9) End of training, enter test samples and get test results.

5. Experimental Simulation

5.1 Simulation Tools and Software Description
The simulation tool used in this paper is the Simulink toolbox in Matlab. Simulink is a platform for multidomain simulation and model-based dynamic system design. It provides an interactive graphical environment and a customized module library, enabling developers to accurately design, simulate, apply, test and control the system. The emergence of Simulink tool platform makes the design and simulation of control system simple and intuitive. In this paper, Simulink simulation environment is used to facilitate the modeling of the whole aircraft anti-skid control system.

5.2 Simulation Model and Structure of Aircraft Braking System
The simulation model of aircraft braking system is established according to document [21,22] as shown in Figure 3.

The working principle of the brake system in the real aircraft environment can be seen in Figure 3. The rotational speed of the wheel is converted into AC signal by the speed sensor and transmitted to the control box. The control box outputs anti-skid control current to control the brake pressure of the servo valve according to the change of speed. When the pressure reaches the brake device, the pressure between the brake discs is adjusted and the brake torque is changed. This torque controls the speed of the wheel together with the combined torque between the tire and the runway. At the same time, the combined torque also affects the motion of the aircraft in three degrees of freedom directions, making the aircraft speed, load, rolling radius of the wheel constantly changing, the difference between the braking torque and the combined torque causes the wheel to slide in varying degrees, and ultimately controls the speed of the wheel. Thus a large closed-loop control process corresponds to the slip rate after the change, and there is a corresponding binding coefficient, the binding torque will change with the change, then the torque difference of the control wheel will change, so that the rotational state of the wheel will change.

5.3 Simulation Parameters
Simulation parameters setting is an important part of the simulation process, which directly affects the simulation time and simulation results. Parameters are set in the menu sub-menu, including the following typical parameters start time, end time, simulation step, maximum integration step, allowable error, simulation method, etc. After setting up the simulation parameters, we can use the software introduced by the section to simulate the whole system. The parameters used in the simulation are typical aircraft parameters. The typical aircraft simulation parameters are shown in Table 1.

6. Result Analysis
This paper mainly lists the braking simulation results of three different identification algorithms under wet runway. Figure 4 is the speed change curve of aircraft under different recognition algorithms. Figure 5 is the curve of wheel speed change under different recognition algo-
It can be seen from the plane/wheel speed curve contrast diagram that the braking time based on the IFABP neural network recognition algorithm is shorter than the FABP neural network recognition algorithm by 1s and is about 2s shorter than that of the BP neural network. From the brake distance curve, we can see that the braking distance based on the IFABP neural network recognition algorithm is shorter than the first two recognition algorithms.

Braking efficiency is defined as the ability to obtain the maximum effective friction coefficient between tire and runway. According to the US Military Standard MIL-B-8075D [23], the most commonly used method for evaluating and calculating braking efficiency is pressure efficiency method. The calculation formula is as follows:

\[
\eta = \frac{A}{A_0} \times 100\%
\]  

(23)

In the formula, \(\eta\) is the braking efficiency, \(A\) is the area between the braking pressure change trace and abscissa, \(A_0\) is the area between the envelope of the braking pressure change trace and abscissa. It can be seen from Table 2–4 that, although the braking distance is very different under different runways, the braking performance of the IFABP recognition algorithm is always better than the latter two algorithms under the same running condition.

7. Conclusions and Discussion

(1) An optimal slip rate prediction method based on improved firefly BP neural network algorithm is proposed.
(2) Simulation of aircraft braking system based on Simulink system verifies the effectiveness and feasibility of the optimal slip rate identification system.
Therefore, the method presented in this paper has a wide application prospect, and the generated Simulink module can provide great convenience for system modeling.

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