Analysis and Prediction of Trough Track Superelevation Based on Big Data

Jiabin Huang, Zhichao He, Chen Li, Hongru Fan, Yi Yin, and Yongjun Xie

***Abstract*—The detection of the safety status of urban rail transit is an important part of ensuring the operation of the rail. Using the data detected by the rail to analyze and predict the quality of the rail is very important for the research of rail inspection. Based on the existing research, this paper uses big data to analyze the collected superelevation data, and builds a trough-track superelevation big data prediction model based on the combination of the stochastic oscillation sequence gray model and ALO-Elman network to analyze the historical superelevation data and mine information about superelevation trends. In this paper, the average value of superelevation data of the equal-spaced groove track in a certain interval is collected for verification. The experimental results show that the method can reasonably predict the change trend of the ultra-elevation. The change trend is basically in line with the original data change trend, and the deviation is controlled to be small within range.**

***Index Terms*—Antlion algorithm, Elman neural network, stochastic oscillation sequence grey Model, superelevation, urban traffic.**

I. Introduction

In the inspection process of the two types of tracks in my country, the inspected parameters include gauge, track direction, wear, superelevation, and torsion irregularity. After each test is completed, the amount of data obtained by the test is large, and the data utilization rate is low. How to analyze these data, comprehensively evaluate the quality of the track from the information reflected in the data, and use the existing historical inspection data to predict the trend of track quality changes is an important research direction of track inspection.

Nowadays, most scholars use TQI for data analysis of detection parameters, and at the same time construct a variety of big data prediction models for data analysis of historical detection TQI. The latest domestic research on orbital data prediction includes: the orbit TQI prediction method of the non-equidistant gray model and Elman neural network proposed by Ma Ziji et al.[1] , and the prediction based on wavelet transform and ARIMA model proposed by Zhao Jun et al. [2]and so on. At present, the direction of most researches is TQI, which is a comprehensive evaluation method for all detection parameters of the track, but as Chang Hui et al. proposed [3], there is no data analysis method and change trend prediction for a single detection parameter.

Manuscript received December 28, 2020; revised March 23, 2021.

The authors are with Jinan University, China (e-mail: 978671072@qq.com, 978553915@qq.com, 446231303@qq.com, 1921350530@qq.com, 528463264@qq.com, 528463264@qq.com).

In the existing researches, Li Shiyi et al. made gray predictions on the track irregularity index structure[4], and Bao Wenyan et al. made predictions on the high and low track irregularities of heavy haul railways[5]. Although their prediction models have high accuracy, the analysis of the data is still based on the index of track irregularity. The essence of the index of track irregularity is the root mean square of each parameter, which cannot well reflect the changes of the parameters at different positions.

Based on the existing research, this article aims to detect the data and predict the trend of the groove rail superelevation in a certain interval. Because tracked trains will produce level inclination errors during curve driving, this essay uses inertial elements to measure the raw data of groove rail superelevation through the quaternion attitude calculation algorithm, and converts the detected raw superelevation data into the superelevation average value in the interval, and proposes a prediction method combining the gray model of stochastic oscillation sequence with the ALO-Elman network, and finally verifies the method by historical superelevation average values. In this paper, the mean value is used to analyze the orbit data. The mean value can better reflect the overall changes of the orbit parameters in a certain section, and the big data prediction model used can well adapt to the random change of the mean value.

II. Superelevation Data Analysis

The superelevation data detected is the superelevation data of the entire track. The analysis of the superelevation data is mainly to compare the obtained superelevation data with the set superelevation limit. If the superelevation data exceeds the superelevation limit, it will lead to the risk of derailment of train operation. Since the laying of the grooved rail is connected by a fixed section of the grooved rail, this paper adopts the mean value method to deal with the superelevation of the grooved rail. If the average value exceeds the limit of superelevation, the grooved rail will be replaced.

III. Big Data Prediction Model

The track management department has a low utilization rate of the historical inspection data. The historical inspection data contains information about the track change trend. Through the data analysis of the historical inspection data, the track change trend is obtained, which is beneficial to the management department to better maintain the track.

A. Stochastic Oscillation Sequence Grey Model

Carrier coordinate system(b system) is transformed by the geographic coordinate system(a system), this process is

expressed as a quaternion:

$$\vec{Q} = cos\frac{\theta}{2} + \vec{u^E} sin\frac{\theta}{2} \tag{1}$$

In the above formula, $\vec{u^E}$ is the axis of rotation and the direction of rotation, θ is the rotation angle, then the transformation matrix from system b to system a is

$$C_b^a = \begin{bmatrix} 1-2(q2^2+q3^2) & 2(q1q2-q0q3) & 2(q0q2+q1q3) \\ 2(q0q3+q1q2) & 1-2(q1^2+q3^2) & 2(q2q3-q0q1) \\ 2(q1q3-q0q2) & 2(q0q1+q2q3) & 1-2(q2^2+q1^2) \end{bmatrix} \tag{2}$$

After obtaining the quaternion, the attitude angle formula of the carrier is solved by the quaternion as follows:

$$p = \text{-}\arctan\big(2(q1q3+q0q2)\big) \tag{3}$$

$$r = arctan\left(\frac{2(q0q1+q2q3)}{1-2(q1^2+q2^2)}\right) \tag{4}$$

$$y = -\,arctan\left(\frac{2(q1q2+q0q3)}{1-2(q1^2+q2^2)}\right) \tag{5}$$

In the above formula, p is the pitch angle, r is the roll angle, and y is the heading angle.

The specific detection method for super-elevation is to fix a gyroscope and an inclinometer on the inspection car. The gyroscope measures the inclination angle between the car and the horizontal plane as θ, and the inclinometer measures the inclination angle between the car and the track plane as β. The gauge is represented by d, and the superelevation is represented by h. The calculation formula is as follows:

$$h = \mathrm{d}\sin(\theta - \beta) \tag{6}$$

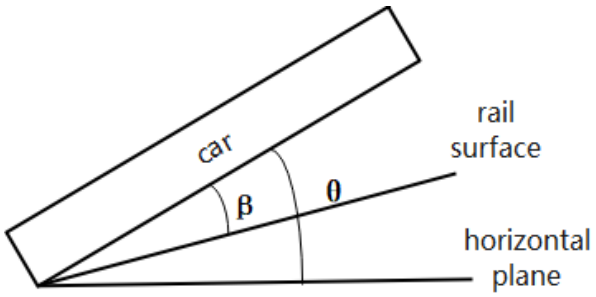

Fig. 1. Tilting diagram when running.

1) Stochastic oscillation sequence transformation

Set the original equal-spaced superelevation average value sequence as:

Since the superelevation average values are different in positive and negative, this essay first shifts the original superelevation average values to all positive value. $Max = max\{x^{(0)}(k)|k, k \in \{1,2,\cdots,n\}\}$, $Min = min\{x^{(0)}(k)|k, k \in \{1,2,\cdots,n\}$, $T = \frac{Max}{Min}$, the sequence obtained after accelerating exponential transformation of the original data is a monotonically increasing sequence[6]:

$$XD_1 = \{x(1)d_1, x(2)d_1, \cdots, x(n)d_1\} \tag{8}$$

in (8), $x(k)d_1 = x^{(0)}(k)T^{k-1}, k = 1,2,3\cdots,$ n.

Performing geometric average generation transformation on the XD_1 sequence to obtain a sequence that maintains a monotonous growth but decreases in growth rate:

$$XD_2 = \{x(1)d_2, x(2)d_2, \cdots, x(n)d_2\} \tag{9}$$

in (9), $x(k)d_2 = (\prod_{i=1}^{k} x(k)d_1)^{\frac{1}{k}}, k = 1, \cdots, n.$

Suppose, $k(i) = \frac{x(i-1)d_2}{x(i)d_2}$, i $= 2,3,\cdots,n$, if the stepwise ratio $k(i)$ in the interval $\left(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+1}}\right)$, the sequence can be directly used in the prediction model. If it is not satisfied, an appropriate z needs to be selected to translate the sequence as a whole：

$$x(i)d_2 = x(i)d_2 + z, i = 1,2,\cdots n \tag{10}$$

2) The establishment of grey model.

Accumulating the sequence XD_2 to $X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)\}$

Establishing a GM(1,1) model, in which the differential equation of the whitened form is

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = u \tag{11}$$

The discretized difference equation is

$$x(k)d_2 + az^{(1)}(k) = u. \tag{12}$$

in (12),

$$z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right), i = 2,3,\cdots,n. \tag{13}$$

Using the least square method to find a, u:

$$(a,u)^T = (B^TB)^{-1}B^TY \tag{14}$$

in (14),

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{15}$$

$$Y = \begin{bmatrix} x(2)d_2 \\ x(3)d_2 \\ \vdots \\ x(n)d_2 \end{bmatrix} \tag{16}$$

Substitute the parameters a and u into the differential equation to get

$$\hat{x}^{(1)}(i) = \left(x(1)d_2 - \frac{u}{a}\right)\mathrm{e}^{-a(i-1)} + \frac{u}{a}, i = 1,2.3.\cdots,n. \tag{17}$$

When $i > n$,

$$\hat{x}^{(1)}(i) = \left(x(1)d_2 - \frac{u}{a}\right)e^{-a(i-1)} + \frac{u}{a} \tag{18}$$

When $i < n$, subtracting $\hat{x}^{(1)}$ to obtain the predicted sequence, and the sequence is restored three times to obtain the true prediction $\hat{x}^{(0)} = \{\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \cdots, \hat{x}^{(0)}(n)\}$. When $i > n$, the first step of restoration has not changed, if $X^{(0)}(n+1) < X^{(0)}(n)$ then the second step of restoration is $\hat{x}^{(0)}(i) = \frac{x(i)d_1}{T^{n-1}}$, else if $X^{(0)}(n+1) > X^{(0)}(n)$, then the second step of restoration is $\hat{x}^{(0)}(i) = \frac{x(i)d_1}{T^n}$, finally, it is restored to the real forecast data.

B. Alo-Elman Residual Correction Model

JL Elman proposed the Elman neural network in 1990. Its structure includes an input layer, a hidden layer, a succeeding layer, and an output layer. The succeeding layer of the network has a memory function for the calculation results of the last hidden layer, and then feeds it back this time hidden layer calculation. This essay uses the network to correct the residual errors.

1) ALO-Elman residual correction model

Mirjalili observes the predation activities of ant lions and ants, and proposed a new simulation-based cluster intelligence algorithm in 2015 [7]——the ant lion algorithm. Antlion algorithm has the characteristics of diverse populations, strong optimization ability, few adjustment parameters, easy implementation, and good robust performance.

Because gray prediction cannot fully predict randomness, and the superelevation mean has randomness, this essay uses the ALO algorithm to optimize the Elman neural network. When the random mutation residual is corrected by the Elman neural network, the Elman neural network can fully learn the mutation residual and eliminate the interference of random factors preventing the residual correction results of the Elman neural network from showing a local optimal solution, and the residual correction results are more in line with superelevation randomness. The principle of the ALO-Elman neural network residual correction model is as follows:

a) Obtain the predicted value through the gray model and obtain the residual difference sequence:

$$\theta(t_i) = x^0(i) - \hat{x}^0(i), i = 1,2,\cdots,n \tag{19}$$

b) Normalize the residual sequence:

$$y = \frac{(y_{max}-y_{min})\times(\theta-\theta_{min})}{\theta_{max}-\theta_{min}} + y_{min} \tag{20}$$

in (20), $y_{max} = 1, y_{min} = -1$.

c) Elman neural network parameter setting

The number of hidden nodes of the neural network is set according to the empirical formula $n = \sqrt{n_i + n_o} + m$, where n_i is the number of input nodes, n_o is the number of output nodes, and m is any integer value from 1 to 10. After repeated training, the number of input layer nodes of the neural network in this paper is 2, the number of output nodes is 1, and the number of hidden layer nodes is set to 6, the neural network prediction result is relatively stable, and the learning rate is 0.05 to avoid falling into the local optimal solution. The additional momentum factor is 0.9, the hidden layer activation function is a hyperbolic tangent sigmoid function, which is consistent with the interval of the training data, and the output layer function is a linear transfer function. To ensure that the network can be fully trained, the number of iterations is 10000.

d) Antlion algorithm parameter initialization

In order to avoid local optimal values, the weights and thresholds of the Elman neural network are a number in (-3, 3), so the ant lion algorithm in this essay assigns the weights and thresholds to the neural network, and the training input simulation results are compared with the variance of the training output value is used as the fitness function, the ant colony scale is set in the (40,50) interval, and the number of iterations is in the range (50,100).

e) Encoded mode

In this essay, the initial weights and thresholds of the neural network are encoded with real number encoding. The encoding formula is

$$S = R \times S1 + S1 \times S1 + S1 \times S2 + S1 + S2 \tag{21}$$

in (21), R is the number of input nodes, S1 is the number of hidden layer nodes, and S2 is the number of output nodes.

f) Simulate ants walking randomly

The algorithm expresses the behavior of ants walking randomly looking for food as:

$$\begin{aligned} x(t) = [0, cumsum(2r(t_1) - 1), \\ cumsum(2r(t_2) - 1), \cdots, \\ cumsum(2r(t_n) - 1)] \end{aligned} \tag{22}$$

in (22), cumsum is the calculated cumulative sum, n is the maximum number of iterations, t is the step length of the random walk, r(t) is the random function:

$$r(t) = \begin{cases} 1 & if\ rand > 0.5 \\ 0 & if\ rand \le 0.5 \end{cases}, rand\epsilon(0,1) \tag{23}$$

g) Ant location update

$$x_i^t = \frac{(x_i^t - a_i)\cdot(d_i - c_i^t)}{(d_i^t - a_i)} + c_i \tag{24}$$

in (24), a_i, b_i are the minimum and maximum values of the i−th ant, C_i^t, d_i^t are the minimum and maximum values of the i-th ant's iteration t, where the expression of C_i^t 、d_i^t are

$$C_i^t = Antlion_i^t + C^t \tag{25}$$

$$d_i^t = Antlion_i^t + d^t \tag{26}$$

C^t,d^t are the minimum and maximum values in the t−th iteration, $Antlion_i^t$ is the t−th iteration position of the i−th ant lion.

$$C^t = \frac{C^t}{10^{\omega}\cdot\frac{t}{T}} \tag{27}$$

$$d^t = \frac{d^t}{10^{w}\cdot\frac{t}{T}} \tag{28}$$

t is the current number of iterations, and T is the maximum number of iterations. W is a constant, when $t > 0.1\,T$, w = 2; when $t > 0.5\,T$, w = 3; when $t > 0.75\,T$, w = 4; when $t > 0.9\,T$, w = 5; when $t > 0.95T$, w = 6.

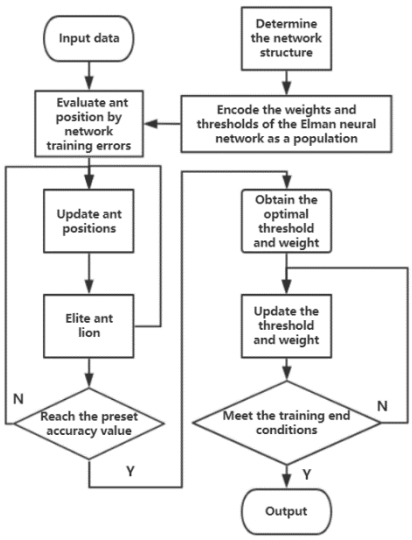

Fig. 2. The specific prediction process.

h) Antlion location update

After the ant lion captures the ant, the ant lion will move its position to increase the probability of capturing the ant again. The update operator in the algorithm is as follows:

$$Antliont_i^t = ant_i^t \tag{29}$$

$$if\ f(ant_i^t) > f(Antliont_i^t) \tag{30}$$

Each ant randomly walks around the selected ant lion and is affected by both roulette and elite individuals, expressed as follows:

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \tag{31}$$

in (31), R_A^t is the ants randomly walking around the ant lion selected in the *t-th* iteration of roulette; R_E^t is the ants randomly walking around the elite ant lion in the *t-th* iteration.

The specific process is shown in Fig. 2.

IV. Predictive Model Validation

In order to verify the feasibility of the combination of the stochastic oscillation sequence gray model and the ALO-Elman network, this essay collects the groove track superelevation data at the same detection time interval of 200m in a certain interval, and processes these data into the superelevation mean value of the segment:

TABLE I: Historical Detection Data of Ultra-high Mean Value

Detection time	Superelevation mean value (mm)
2016.1	-4.31
2016.1	-2.62
2016.2	2.37
2016.2	-2.03
2016.3	-2.22
2016.3	-2.51
2016.4	-4.55
2016.4	-4.95
2016.5	-0.73
2016.5	0.28
2016.6	1.34
2016.6	1.50

A. Verification Process

This article first selects the first detection data from January 2016 to the first detection data in April as training data, and the latter two data as test data. The original data and the data after gray prediction are shown in Fig 3. The output result of the neural network is shown in Fig 4.

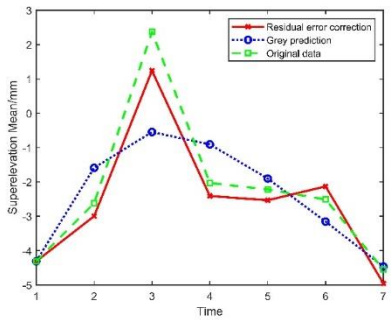

Fig. 3. The results of the residual error correction and grey prediction.

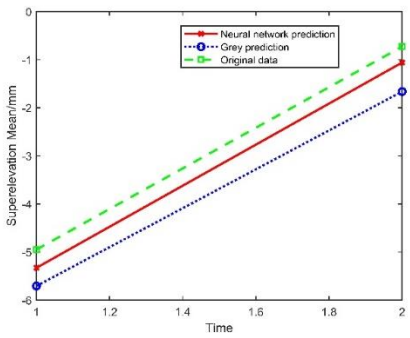

Fig. 4. The results of the neural network prediction and grey prediction.

Part of the repeated verification results are shown in Fig. 5 through 8 below.

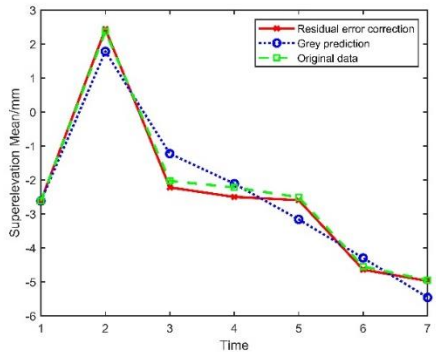

Fig. 5. The results of the residual error correction and grey prediction.

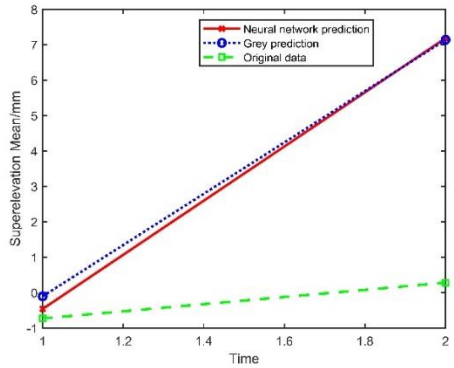

Fig. 6. The results of the neural network prediction and grey prediction.

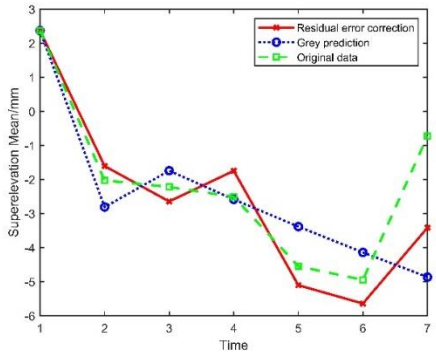

Fig. 7. The results of the residual error correction and grey prediction.

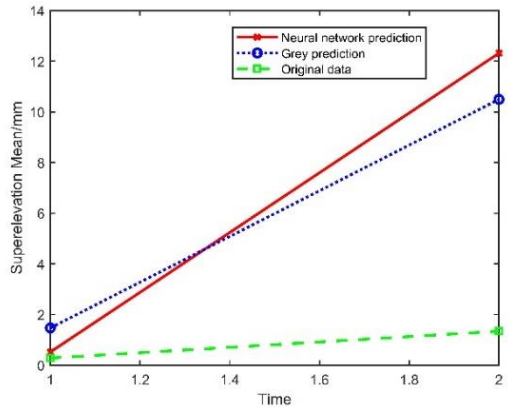

Fig. 8. The results of the neural network prediction and grey prediction.

B. Prediction Result Analysis

It can be seen from the figure that the test result of the first test point is close to the true value, and the error of the second test point is larger. Therefore, the following focuses on the analysis of the predicted result of the first test point. The true value, predicted value and errors are shown in Table II:

TABLE II: HISTORICAL DETECTION DATA OF ULTRA-HIGH MEAN VALUE

Original data (mm)	Prediction Result (mm)	Error (mm)	Relative error
-4.95	-5.3298	-0.3798	7.67%
-0.73	-0.4623	0.2677	-32.38%
0.28	0.5164	0.2364	84.43%
1.34	1.4561	0.1161	8.66%

According to the table, the predicted result is close to the true value, and the change trend of the predicted data is basically in line with the change trend of the original data. However, due to the relatively large changes in the data, the prediction method has a large prediction error for the data in the (-1,1) interval. The prediction error of the remaining data is relatively small. In summary, this method is feasible to a certain extent.

V. CONCLUSION AND FUTURE WORK

The following conclusions are drawn from the verification experiment of the prediction method using the ultra-high mean data of a certain interval of 200m in this paper.

1) The predicted result of this method is consistent with the change trend of the original data, and the predicted deviation is kept within a small range, so this method has a good predictive ability for ultra-high change trends

2) Antlion algorithm can be applied to Elman neural network like genetic algorithm. The dynamic feedback characteristic of Elman neural network can make prediction better than BP neural network.

Compared with the Elman neural network, the dynamic feedback characteristics of the Elman neural network can make predictions better than the BP neural network.

The method proposed in this article has the following shortcomings to be improved:

3) Although the method proposed in this paper can predict the change trend of the superelevation well, it cannot screen out the part of the track that does not meet the requirements of safe operation. Therefore, it is necessary to propose a scientific and reasonable superelevation sequence processing method

4) The ultra-high mean data used in this paper are equidistant data. In practical applications, the mean data of horizontal irregularities is non-equidistant data. Therefore, the further improvement goal of this method is to be able to realize the prediction of non-equidly spaced random oscillation sequences, improve the prediction accuracy, and the prediction results can better fit the future change trend.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Hongru Fan and Zhichao He conducted the research; Chen Li and Yi Yin analyzed the data; Jiabin Huang and Yongjun Xie wrote the paper.All authors had approved the final version.

REFERENCES

[1] Z. J. Ma T. Tao, H. L. Liu, P. Qiang, and J. Tan, "Track quality prediction based on non-equidistant grey model and Elman neural network," *Journal of Harbin Institute of Technology*, 2018, vol. 50, no. 5, pp. 137-144.

[2] Z. Jun, L. C. Li, Z. H. Zuo, and Y. Yong, "Research on track irregularity of high-speed railway based on wavelet transform and ARIMA model," *Railway Construction*, 2020, vol. 60, no. 10, pp. 126-129.

[3] C. Hui, Z. Q. Rao, and Y. I. Zhao, "Research progress on the prediction of orbit geometric irregularities," in *Proc. 2019 23rd Annual Conference on New Network Technology and Application*, 2019, no. 5.

[4] S. Y. Li, S. K. Liu, and F. T. Wang, "Track irregularity index structure prediction based on gray component data model," *Journal of Railway Science and Engineering*, 2018, vol. 15, no. 8, pp. 1937-1942.

[5] W. Y. Bao, F. T. Wang, S. Y. Li, and N. Zhang, "Research on prediction of track irregularities of heavy haul railway," *Railway Standard Design*, 2019, vol. 63, no. 1, pp. 29-34.

[6] L. Z. Cui and S. F. Liu, "The properties and application of GM(1,1) model based on stochastic oscillation sequence," *Mathematics in Practice and Knowledge*, 2012, vol. 42, no. 11, pp. 160-165.

[7] S. Mirjalili, "Electronic publication: Digital object identifiers (DOIs): The ant lion optimizer," *Advances in Engineering Software*, 2015, vol. 83.

Jiabin Huang is currently studying at the International Energy College of Jinan University, Zhuhai Campus. He is a junior in electrical engineering and automation. Now he is involved in the research on the direction of track parameters in the Rail Transit Research Institute.

Zhichao He is currently studying at the International Energy College of Jinan University, Zhuhai Campus. His major is automation. Now he is involved in the research on the direction of track parameters in the Rail Transit Research Institute.

Chen Li is currently studying at the International Energy College of Jinan University, Zhuhai Campus. He is a junior in electrical engineering and automation. Now he is involved in the research on the direction of track parameters in the Rail Transit Research Institute.

Hongru Fan is with Shaoguan, Guangdong, was born in May 2000. He is currently studying at the International Energy College of Jinan University, Zhuhai Campus. He is a junior in electrical engineering and automation. Now he is involved in the research on the direction of track parameters in the Rail Transit Research Institute.

Yi Yin is currently studying at the International Energy College of Jinan University, Zhuhai Campus. She is a junior in automation. Now she is involved in the research on the direction of track parameters in the Rail Transit Research Institute.

Yongjun Xie received a bachelor's degree and a master's degree in engineering from Guangxi University in 1999 and 2002, and a doctorate degree in engineering from the Microsystem Research Center of the School of Mechanical Engineering, Huazhong University of Science and Technology in 2006. Now she is the electrical engineering of Zhuhai College of Jinan University Lecturer at the Institute of Automation, postdoctoral fellow at Wuhan National Laboratory of Optoelectronics Technology (in preparation). Mainly engaged in the teaching and research of rail traction power supply technology, power system automation, precision measurement and control technology, computer science and technology, micro system and micro manufacturing.