Study on Lifetime Prediction of Locking Block Based on Artificial Intelligence

Jun Cao [a,b], jianghong Gan [a,b*] and Hui Guan[c]

[a] State Key Lab of Digital Manufacturing Equipment and Technology, HUST-SANY Joint Lab of Advanced Manufacturing, School of Mechanical Science and Engineering, Huazhong University of Science and Technology, Wuhan, Hubei 430074, China.
[b] Wuhan Railway Vocation College of Technology, Wuhan, China
[c] College of Languages and Culture, Northwest A&F University, Shaanxi province of China

*Corresponding author: cao96qc@126.com

Abstract. Data analysis and data prediction based on artificial intelligence technology have a wide range of applications in daily production and life. Predicting the lifetime of the locking block enables train maintenance personnel to understand the current and future status of trains, and to develop targeted maintenance programs as well as rational train dispatching, so as to promote the realization of condition repair of the train braking system. After analysis and comparison of the mainstream prediction methods at present, the team decides to take artificial intelligence technology as the core, and mathematical models and intelligent algorithms as specific means to achieve the prediction of locking block lifetime and of maintenance timing.

Keywords: locking blocks; artificial intelligence; data processing; lifetime prediction

1 Introduction

Running gears, the core equipment of high-speed trains, plays a crucial role in ensuring the safe and stable operation of the trains [1,2]. With the rapid development of modern industrial technology, the health management of the running gear system has become a hot spot of research. Brake clamp locking block serves as a key part of the running gears, and how healthy it is will directly affect whether the train braking system can work normally or not; state assessment and health state prediction of brake clamp locking block are important contents of the health management of the running gear system [3,4]. Therefore, the lifetime prediction of the locking block will play a great role in the safe operation and health management of the train [5,6].locking block is as shown in Figures 1."

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2 Research Review

Zhan et al.[7] first numerically compute the fatigue lives, and then adopt the two commonly-used ML models including artificial neural network (ANN) and random forest (RF) to carry out fatigue life prediction. Shi et al.[8] propose an optimization algorithm based on the nonlinear Wiener process, for the prediction of the train wheels remaining useful life (RUL) and the centralized maintenance timing. Wang et al.[9] propose a tread wear prediction and optimization method based on chaotic quantum particle swarm optimization (CQPSO)-optimized derived extreme learning machine (DELM), namely CQPSO-DELM to solve this problem.

Fig. 1. the actual locking block

3 Problem Characterization Description

(1)Construction of Lifetime Prediction Models

The locking block lifetime prediction model is based on support vector machine (SVM) model. Least squares support vector machine (LS-SVM) adopts the error square term as loss function and transforms the quadratic programming problem in SVM into the problem of linear equations. The theory of LS-SVM and its main steps are briefly described as follows.

Given a set of sample data $(X_1, y_1), (X_2, y_2), \dots, (X_N, y_N)$, N represents the sample capacity, $X_i \in R^n$ denotes the input vector, and n is the number of dimensions of X, $y_i \in R$ stands for the corresponding output of each X_i. For this data set, the following relation is desired:

$$y = f(X) =< w, \varphi(X) > +b \tag{1}$$

where $\varphi(X)$ is a nonlinear mapping function, map input sample X from R^n to n_H feature space, <··> is dot product operation, w is the weight vector on n_H feature space H, while b is the offset.According to statistical theory, the issue of regression in formula (1) is transformed into the optimization of LS-SVM in formula (2):

$$\min J(w, e) = \frac{1}{2}||w||^2 + \frac{1}{2}\Upsilon \sum_{k=1}^{N} e_k^2 \tag{2}$$

$$y_k =< w, \varphi(X) > +b + e_k^2$$

where $||w||$ is used to control the complexity of the model, e_k represents the error between the predicted value and the true value obtained from regression, Υdenotes the regularization parameter (also known as the penalty function). In order to simplify calculation, introduce Lagrange multiplier α_k while transforming (2) into dyadic form:

$$L(w,b,e,\alpha) = J(w,e) - \sum_{k=1}^{N} \alpha_k \,(< w, \varphi(X) > +b + e_k^2 - y_k) \tag{3}$$

Find the partial derivatives of w, b, e, α respectively, and make their partial derivatives 0; the formula (4) is as follows:

$$\begin{cases} \frac{\partial L}{\partial w} \\ \frac{\partial L}{\partial b} \\ \frac{\partial L}{\partial e} \\ \frac{\partial L}{\alpha_k} \end{cases} = \begin{cases} w = \sum_{k=1}^{N} \alpha_k \, \varphi(X) \\ \sum_{k=1}^{N} \alpha_k = 0 \\ \alpha_k = \Upsilon e_k \\ [< w, \varphi(X) > +b] + e_k^2 - y_k = 0 \end{cases} \tag{4}$$

where, k=1,2,…,N. Define $I_N = [1,1,\dots,1]^T$, $Y = [y_1, y_2, \dots, y_N]^T$, $\alpha = [\alpha_1, \alpha_2, \dots, \alpha_N]^T$; by eliminating the variables w and e_k, (4) is transformed into the matrix shown in (5).

$$\begin{bmatrix} 0 & I_N^T \\ I_N & \Omega + \Upsilon^{-1} I_N \end{bmatrix} \begin{bmatrix} b \\ a \end{bmatrix} = \begin{bmatrix} 0 \\ Y \end{bmatrix} \tag{5}$$

In formula (5), I_N is the identity matrix of N*N, and Ω is the symmetric matrix of N*N. Each element of Ω is a kernel function satisfying the Mercer ($\Omega_{i,j} = K(\mathrm{X}_i, \mathrm{X}_j) = \varphi(X_i)^T \times \varphi(X_j), i, j = 1,2, \dots, N$).

The parameters b and α can be obtained from (5), and a regression prediction model (6) can be obtained:

$$y = \sum_{k=1}^{N} \alpha_k \times K(\mathrm{X}, \mathrm{X}_k) + b \tag{6}$$

where, $K(\cdot,\cdot)$ is the kernel function. The main kernel functions in use today include radial basis function (RBF), linear function, polynomial function and so on. In this chapter, the most widely used RBF with good global convergence performance is selected:

$$K(\mathrm{x}, \mathrm{x}_k) = \exp\left(-||\mathrm{x} - \mathrm{x}_k||^2 / 2\sigma^2\right) \tag{7}$$

where σ is the width in RBF. After choosing the RBF, further determination of the unknown regularization parameter Υ and kernel width σ in the current model is needed. The two parameters, often also referred to as hyperparameters, directly affect the fitting accuracy and generalization performance of the model.

(2)Improvement of Intelligent Algorithms

In this section, Improved Artificial Bee Colony algorithm (IABC) based on problem characterization is applied to solve the issue[10].

1)Design of the Follow-Up Mechanism

If employed bees find food sources, generate completely new solutions by performing a search operator in a variable neighborhood. For each onlooker that sets out for food sources, the tournament size is selected as four to choose better food sources, and new solutions are generated using another operator. Different from normal ABC algorithms, the proposed IABC algorithm changes the original follow time from 1 to N once onlookers set off, which makes slightly worse solutions acceptable so as to allow the algorithm to escape the local optimization trap, achieving global optimum. The acceptance criteria proposed by Lei and Guo are adopted for their simpleness and good effect.

2)The Perturbation Mechanism

If a better solution, which is a particular solution generated in the current population, has not been generated after consecutive iterations of L times, it will be replaced by a randomly generated solution in the ABC algorithm. The improvement of the algorithm in this paper is as follows when it comes to the same situation: since the solution has been iterated for many times and it carries more and better information than other solutions do in the population, its neighboring solutions are probably better as well. Therefore, the perturbation method is applied to deal with the problem. A random number [0, 1] is randomly generated, when the number is greater than 0.5, the Insert operator will be executed 3 times for the solution; if the number is less than 0.5, the Swap operator will be executed 3 times for the solution.

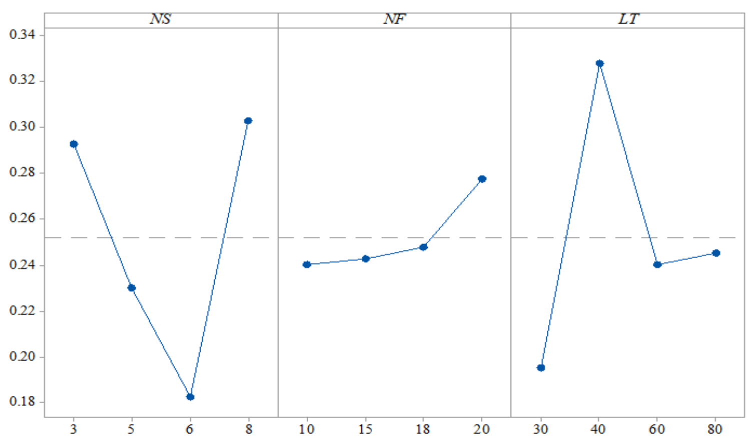

Fig. 2. Main Effects Plot

The slope of the contrast line allows for a relative comparison of the influences of various factors. Based on the mean values of three parameters (SNR), the main effects plot is shown in Figures 2. The optimal parameter combination of IABC for the current experimental conditions as follows: NS = 8, NF = 20, LT = 40.

4 Case study

The mathematical model is encoded by CPLEX. The solution method based on the IABC is programmed by Matlab. The above programs run on an Intel(R) Core TM i7 4790 processor running at 3.20GHz with 16GBytes of RAM.

Three experiments have been performed to validate the model and algorithm performance. (1) Small-scale benchmark examples for comparing the performance of the mathematical model computed by CPLEX with that of the proposed IABC algorithm; (2) Medium- and large-scale benchmark examples for illustrating the performance of the proposed IABC algorithm; (3) Compare the actual data used in practice with the data that are predicted by the algorithm. Due to space constraints, only part of the experimental content and analysis of experiment (3) is shown in this section.

The Research & Development team of Laser Intelligent Gauge randomly selected 100 from the 344 locking blocks provided by the high-power maintenance section. The parameters of the selected locking blocks were used in the lifetime prediction algorithm constructed in this study. From the algorithm, their prediction data were obtained respectively; meantime, the actual lifetime of these 100 selected locking blocks were also obtained from the maintenance section.

The points on Figure 1 are the lifetime values obtained by the high-power maintenance section and the prediction algorithm respectively, where the orange point represents the true life and the blue point stands for the predicted lifetime calculated by the algorithm. As can be seen from Fig. 3, the blue dots and the orange dots mostly overlap, with only a small number of blue ones on the periphery of the orange ones. This indicates that most of our predicted results agree with the true lifetime values, and the overlap rate is 84% after calculation, which demonstrates the correctness and reasonableness of the prediction method at the data level.

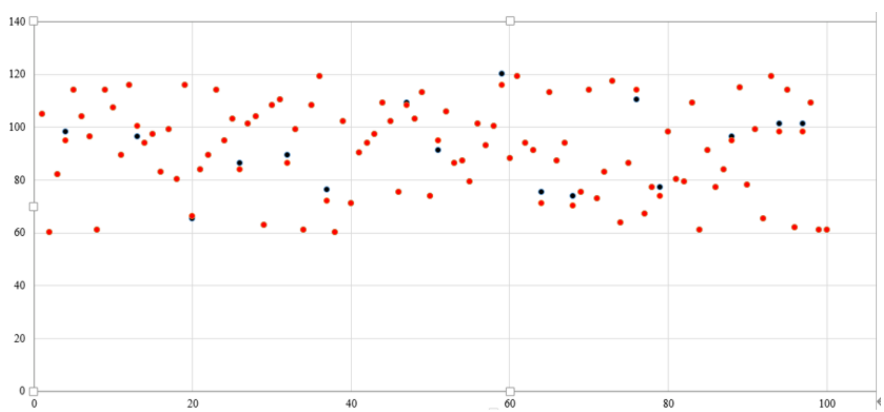

Fig. 3. Comparison chart of locking block lifetime from two methods

5 Conclusions

From the above study, it can be seen that in the field of brake clamp locking block measurement and lifetime prediction, the domestic and foreign research advances slowly. Those scholars mainly rely on manual experience and mechanical properties of trains, and seldom adopt advanced measurement technology for the analysis and research of train brake clamp locking block. According to the actual situation of train utilization and the demand of locking block lifetime prediction, this study constructs a lifetime prediction model based on artificial intelligence technology, and integrates the model into IABC intelligent algorithm. After the verification of engineering data from the high-power maintenance section, the effectiveness and reasonableness of the lifetime prediction model and the artificial intelligence algorithm have been proved.

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