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Analysis of Failure Features of High-speed Automatic Train Protection System

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ABSTRACT An automatic train protection (ATP) system is the core to ensure operation safety of high-speed railway. However, at present, failure rate change rules of the system are not well understood and the maintenance strategy is not refined. In order to improve the protection capability and maintenance level of high-speed trains, this paper proposes a decision tree machine learning model for failure feature extraction of ATP systems. First, system type, mean operation mileage, mean service time, etc. are selected as ATP failure feature parameters, and cumulative failure rate as a model output label. Second, support vector machine, AdaBoost, artificial neural networks and decision tree model are adopted to train and test practical failure data. Performance analysis shows that decision tree learning model has better generalization ability. Its accuracy of 0.9761 is significantly greater than the other machine learning models, so it is most suitable for failure features analysis. Third, interpretability analysis reveals the quantitative relationship between system failure and features. Finally, an intelligent maintenance system for ATP systems is built, which realize the refined maintenance throughout life cycle.

INDEX TERMS Automatic train protection system, intelligent maintenance, failure feature, machine learning, model interpretability, high-speed train.

I. INTRODUCTION

On August 1, 2008, the first high-speed railway at a speed of 350 km/h was put into operation in China. By the end of 2020, the operation mileage had reached 38000 km, more than two-thirds of the world's mileage. China has become the country with the longest mileage and largest scale of high-speed train networks in the world.

Automatic Train Protection (ATP) system is critical to ensure the safety and efficiency of high-speed trains. It can automatically determine speed, position and headway towards the preceding train by calculating speed profile. Two sets of ATP systems are equipped at the head and end of the train. It is composed of Vital Computer (VC), Speed & Distance Processing Unit (SDU), Balise Transmission Module (BTM), Track Circuit Reader (TCR), Train Interface Unit (TIU), GSM-Railway (GSM-R), Driver Machine Interface (DMI), Juridical Recorder Unit (JRU), etc. Each sub-equipment cooperates with each other to ensure train safety, so failure of any equipment affects normal operation of train.

The daily operation and maintenance of an ATP system shows the following characteristics.

1) The system in the high-speed vibration moving train belongs to on-board system. It directly controls the operation of high-speed train and emphasizes logic relationship and calculation accuracy.
2) The system spans five geographical time zones from east to west and six temperature zones from north to south with the running of high-speed trains all over the country. Therefore, its nature operation environment is very complicated.
3) The daily maintenance can only be carried out in a specific period, which is usually between 0:00 a.m. and 5:00 a.m. every day after the train completes the transportation task. So maintenance is not available at any time.
4) The number of ATP systems has been increasing with continuous expansion of construction scale and growing traffic density. While some systems have been used for over 10 years and a large number of ATP systems enter the high incidence period of failures over time.
5) As a repairable system with multiple failures, the determinism and non-determinism of quality change rule of an ATP system exist simultaneously, which requires higher reliability and maintainability.

At present, daily maintenance is the most important means to ensure the stability and reliability of ATP systems.

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However, the following problems still exist, and further improvement and optimization are necessary.

- Fixed single maintenance strategy. It mainly reflects in the following two aspects: fixed cycle and fixed items. An ATP system is maintained at a fixed interval according to the fixed items [1], which wastes resources to a certain extent and causes some unnecessary economic losses.
- Single maintenance strategy is adopted in the whole life cycle, regardless of failure rate. However, its failure rate is a function of time for most sub-equipment of ATP systems belongs to electronic equipment. Therefore, in the whole life cycle, there should be different maintenance strategies that can be dynamically adjusted according to failure features in different stages.
- All systems adopt same maintenance mode. Currently, there are five types of ATP systems in China, including 300T, 300S, 300H, 200H and 200C, in which there are a certain number of ATP systems. Different production processes, technical architectures and design platforms result in different system operation qualities and failure features. Therefore, refined and differentiated maintenance strategies should be formulated for each.

In order to solve the above problems, the machine learning model of decision tree for ATP failure analysis is proposed, and the intelligent maintenance system is established by model mechanism of quantitative analysis. The main contributions of this paper are as follows.

- Machine learning model suitable for failure feature of ATP systems is proposed, and its validity is verified by 10 years' practical data. The mechanism of the model is revealed through model interpretability analysis.
- Quantitative relationship between the failure rate and the failure features of China's high-speed automatic train protection system is revealed. It is shown that the change of failure rate is closely related to mean operation mileage and service time, but not to time feature.
- Intelligent maintenance for an ATP system of high-speed train is put forward. The intelligent maintenance system and technology implementation platform are built, and the refined maintenance of each set of ATP systems in the whole life cycle is realized.

The rest of this paper is organized as follows. In section II, the related work is reviewed. In section III, the failure features of ATP systems are selected and analyzed. In section IV, the learning model of failure feature is established. In section V, the interpretability of model is given. In section VI, the intelligent maintenance system is built. In section VII, the conclusion of work is drawn.

II. RELATED WORKS

To improve the safety and comfort of future high-speed railways, intelligence has become an important direction for global railways research [2], [3]. Moreover, it plays a critical role in the competition of high-speed railway around the world. Combined with the intelligent development trend, the Chinese Academy of Engineering launched a project to carry out *Intelligent High-speed Railway Strategy Research* (2035) in January 2018. It aimed to promote the leading position of China's high-speed railways. It passed the final review in January 2020, marking that China railway had made important achievements in top level planning and design of intelligent high-speed railway. At the same time, global scholars have deeply researched the intelligent fields of train control [4], [5], train dispatch [6], [7], train communication [8], [9], railway traffic conflict control [10] and other fields [11], [12].

The main embodiment of intelligence in high-speed railway was the integration of advanced technology methods represented by machine learning [13], [14] and high-speed railway networks. Intelligent failure diagnosis and prediction [5], [15], [16], condition monitoring and health management [17] were studied, such as failure intelligent diagnosis of rolling bearings [18], [19] or bogies [20], [21] of high-speed trains, switch failure prediction [22], [23], vehicle-body vibration prediction [24], as well as online condition monitoring of the pantograph slide plate [25]. It can be seen that machine learning methods have achieved remarkable results compared with the traditional methods.

As an important part of intelligent high-speed railway, intelligent maintenance of infrastructure was also actively explored and studied by scholars. Its basic idea was to take the reliability as the center, which was believed to be a cost-effective and safety-assured strategy [26]. Liu *et al.* [27] developed a dynamic maintenance strategy for a system subject to aging and degradation. Its effectiveness was demonstrated through a case study of locomotive wheel-sets. Wang *et al.* [28] proposed a bilevel feature extraction-based text mining. It resolved the unstructured verbatim and imbalance of maintenance data. Ferreira *et al.* [29] proposed a solution based on wearable components for safety of maintenance personnel on the railway. Durazo-Cardenas *et al.* [30] designed a high-level architecture automatic system for British railway extended infrastructure to realize optimum and intelligent maintenance scheduling. Su *et al.* [31] presented a multi-level decision making approach to determine an optimal long-term maintenance intervention plan for railway infrastructure, which had been applied to Eindhoven-Weert line in Dutch railway network. Considering that train operation and maintenance were mutually exclusive, Liden *et al.* [32], [33] presented a mixed integer programming model for Swedish Northern Main Line to solve the problems of integrated railway traffic and maintenance planning. The above research results showed that intelligent maintenance could reduce malfunction process time, save resources [22], and optimize the route planning of high-speed trains [34].

The application scenarios and maintenance methods for ATP systems of high-speed trains were different from those of wayside systems. Meanwhile, the existing maintenance strategies could not meet the demand of high-speed train development. Therefore, they need to be studied further, especially the cycle and items that maintenance personnel are most concerned.

This study extracted the failure features of ATP systems from 10 years' practical data, and established failure learning models of Support Vector Machine, AdaBoost, Artificial Neural Networks and Decision Tree. By performance

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measurement analysis, learning model of decision tree was most suitable and effective. The quantitative relationship between the change of failure rate and multiple failure features was obtained through interpretability analysis of the learning model, on the basis of which the intelligent maintenance system of an ATP system was established. Finally, dynamic and refined maintenance of the whole life cycle were realized.

III. ATP FAILURE FEATURE PROCESSING

Machine learning (ML) refers to the method of learning general rules from limited observation data and applying these rules to unobserved samples [13], [14]. It mainly focuses on how to learn a prediction model [35]. Firstly, factors that may affect ATP failure rate are expressed as a set of features, from which some effective features are selected. Then, feature data that will be input as models are cleaned, formatted and reorganized. In general, ATP failure feature processing includes feature selection and feature data preprocessing.

A. ATP FEATURE SELECTION

The key to develop intelligent maintenance strategy of an ATP system is to obtain the change rule of failure rate of system. Furthermore, the possible factors that may affect the failure rate will be selected as features for model training and learning. We carefully analyze the historical data of ATP failure in the past 10 years, and find that the possible factors related to the failure rate are: system type, number of systems, mean cumulative service time, mean cumulative operation mileage, and time feature. On the basis of analysis, from Aug 16, 2020 to Nov 20, 2020, we investigated and visited all 67 ATP system maintenance locations in China, and communicated with maintenance personnel deeply. According to on-site maintenance experience, the influence factors of failure rate are basically consistent with the analysis results. Therefore, the extracted failure features are the combination of historical data analysis and actual maintenance experience.

1) System type

ATP system type usually corresponds to different technology platforms, production processes and source quality, which inevitably affects the system failure rate. In addition, different types of ATP systems adopt different maintenance strategies. Therefore, system type is selected as failure feature parameter, and expressed by *x_atptype*,

$$x\_atptype = \{300T, 300S, 300H, 200H, 200C\} \tag{1}$$

2) Number of systems

A random number of ATP systems are put into use in batches. Whether the change of the number is related to failure rate is unknown. Therefore, the number of ATP systems is selected as failure feature parameter, and expressed by *x_atpnum*,

$$x\_atpnum_i = \{1,2, \ldots ,n\} \tag{2}$$

where x_atpnum_i represents the number of ATP systems of a certain type on the i-th day, x_atpnum_1 represents the initial value of a certain type. Since new products may not be put into use every day, and the number is random, so x_atpnum_i is a discontinuous natural number.

3) Mean cumulative service time

As electronic product, the quality of an ATP system can be reflected by service time. Therefore, mean cumulative service time is selected as failure feature parameter, and expressed by *x_meantime*,

$$x\_meantime_i = \frac{\sum_{j=1}^{i} x\_time_j}{x\_atpnum_i} \tag{3}$$

where $x\_meantime_i$ is mean cumulative service time of a certain type of ATP systems on the i-th day, x_time_j is service time of a certain type of total ATP systems on the j-th day, x_time_1 is its initial value.

4) Mean cumulative operation mileage

The operation of an ATP system goes along with the start and stop of the train. Therefore, cumulative operation mileage is key indicators to measure system quality. For several same type of ATP systems, the mean cumulative operation mileage is selected as failure feature parameter, and expressed by *x_meanmile*,

$$x\_meanmile_i = \frac{\sum_{j=1}^{i} x\_mile_j}{x\_atpnum_i} \tag{4}$$

where $x\_meanmile_i$ is mean cumulative operation mileage of a certain type of ATP systems on the i-th day, x_mile_j is operation mileage of a certain type of total ATP systems on the j-th day, x_mile_1 is its initial value.

5) Time feature

Time feature reflects whether the failure rate of an ATP system is closely related to time. For instance, month could indicate which period of each year failure occurs intensively or is relatively stable. It could also indirectly represent the partial information of natural environment, such as climate, temperature and humidity. Therefore, month is selected as failure feature parameter, and expressed by *x_month*,

$$x\_month = \{1,2, \ldots ,12\} \tag{5}$$

6) Cumulative failure rate

Failure rate is key factor and basis for developing maintenance strategy and realizing intelligent maintenance of systems. An ATP system works intermittently rather than continuously from power on. Therefore, although it belongs to electronic products, its failure rate is defined by operation mileage instead of service time [15], which accords with practical application of systems. Cumulative failure rate is expressed by *x_failurerate*,

$$x\_failurerate_i = \frac{\sum_{j=1}^{i} x\_faultnum_j}{\sum_{j=1}^{i} x\_mile_j} \tag{6}$$

where $x\_failurerate_i$ is the cumulative failure rate of a certain type of ATP systems on the i-th day, $x\_faultnum_j$ represents

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the total number of a certain type of failure ATP systems on the *j*-th day.

To sum up, the selection of failure feature parameters basically emphasizes cumulative effect and mean effect, and dismiss the influence of relatively large or small individual values on analysis results. Combined with practical application experience and maintenance requirements, system type, number of systems, mean cumulative service time, mean cumulative operation mileage and month are finally selected as the failure feature parameters of ATP systems. They are expressed as *X_feature*=[*x_atptype*, *x_atpnum*, *x_meantime*, *x_meanmile*, *x_month*]. The label parameter is cumulative failure rate, i.e. *Y_label*=[*x_failurerate*]. The former is the input of failure feature learning model, and the latter is the output.

B. FEATURE DATA PREPROCESSING

China's high-speed railway has begun to develop rapidly since 2010. In the same year, four types of ATP systems i.e. 300T, 300S, 200H and 200C, began to be put into operation on a large scale, and 300H-type ATP systems started from 2013. In this study, daily original data from January 1, 2010 to March 31, 2020 are taken as samples. Label parameter is regarded as failure rate and its basic information is shown in Table 1.

1) Data normalization

The distribution range of the value varies wildly due to different sources and measurement unit of each dimension feature in the original features of samples. Feature with wide range of values plays a leading role in Euclidean distance calculation among different samples. Therefore, samples are preprocessed to normalize the features of each dimension to the same value range [0,1] and eliminate correlation among different features. In this way, each feature can be treated equally when using the supervised learner. For each dimension feature *x*, the normalization criteria is,

$$f : x \to y = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{7}$$

where min(x) and max(x) are the minimum and maximum values of feature on all samples respectively.

TABLE 1. The basic information of the label parameter.

Names	Value	Descriptions
n_records	17619	The total sample size
max_failurerate	15.1369	Maximum failure rate
min_failurerate	0	Minimum failure rate
mean_failurerate	2.2537	Mean failure rate
median_failurerate	1.4326	Median failure rate
std_failurerate	2.8709	Standard deviation of failure rate

It can be seen from formula (1) that the value of system type is not a number. While in general, the expected value of learning algorithm is a number. The One-hot Encoding is adopted to create a virtual variable for each possible type of the system to convert the value into a number, as shown in Table 2.

After the transformation of formula (7) and One-hot Encoding, values of different feature parameters of ATP systems are normalized to interval [0,1], and each feature is equally treated by machine learning model.

TABLE 2. One-hot encoding value of system type.

x_atptype		*x_ atptype _300T*	*x_ atptype _300S*	*x_ atptype _300H*	*x_ atptype _200H*	*x_ atptype _200C*
300T	One-hot encoding →	1	0	0	0	0
300S		0	1	0	0	0
300H		0	0	1	0	0
200H		0	0	0	1	0
200C		0	0	0	0	1

2) Mixing and splitting data

From the perspective of Bias and Variance, Mitchell [36] pointed out that when about two thirds to four fifths of the original data samples are used for training and the remaining are used for testing, the model performance would be better. In this study, four fifths of original data samples are for training, and the remaining are for testing. The generalization ability of model in application is estimated by discrimination effect on testing set. At the same time, the training data are divided into training set and validation set. The training samples and validation samples are four fifths and one fifth respectively. Model selection and parameter tuning are based on the performance of validation set. Finally, it is obtained that the total sample size is 17619, among which the training set is 11276, validation set is 2819, and testing set is 3524.

IV. ATP FAILURE LEARNING MODEL

The common typical machine learning methods are Support Vector Machine (SVM) [37], AdaBoost [38], Artificial Neural Networks (ANN) [39], Decision Tree (DT) [40], [41]. ATP failure feature processing is the basis of machine learning model. An evaluation system and assembly line are built to evaluate the ATP failure feature analysis and learning performance of each model. The former is to measure its generalization ability, and the latter is to make predictions on validation set with different training sets.

A. MODEL PERFORMANCE MEASURE

Given a training set, machine learning aims to find an ideal model with low generalization error from the hypothesis space, so as to better predict the unknown samples, especially the samples that do not appear in training set. Therefore, machine learning can be regarded as a generalization problem to obtain more general rules from finite, high-dimensional and noisy data. Not only an effective and feasible experimental estimation method but also an evaluation standard, i.e. performance measure is required to evaluate the generalization performance of ATP failure feature learning model. Its analysis is a regression problem, and the learning model evaluation indexes are as follows [42].

1) Mean absolute error (MAE), is used to evaluate the degree to which the prediction results are close to real data set. The smaller the value is, the better the fitting ability is.

2) Mean square error (MSE), measures the change of learning performance caused by change of training set with same size, and visualizes the impact of data disturbance. The smaller the value is, the better the fitting ability is.

3) The explained variance score, i.e. square of standard deviation, indicates the degree to which the independent

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variable explains the dependent variable. The larger the value is, the better the effect is.

4) Coefficient of determination (r^2), explains the variance score of regression model. The larger the value is, the better the future samples can be predicted.

Bias-Variance Decomposition [43] shows that generalization performance of ATP failure feature learning model is determined by the ability of learning algorithm, the sufficiency of data and the difficulty of learning task itself. When MAE and MSE are small, but explained variance score and r^2 are large, a good balance will be achieved between the model ability and the complexity, learning model is neither overfitting nor underfitting, and the generalization performance is better.

B. FAILURE LEARNING MODEL

It is necessary to compare same sample data with similar analysis process in different methods to test the applicability of various machine learning methods in ATP failure feature analysis, for which the experiment flow is built. Same failure feature vector is put into regression models of SVM, AdaBoost, ANN, and DT successively. The training time and MSE etc. are adopted as performance indicators to evaluate the advantages and shortcomings of models. Then the parameters are optimized to obtain the most suitable model for ATP failure feature analysis. Finally, the generalization performance of optimal model is verified by test data.

The four regression methods are as follows.

SVM [15], [44] is an effective structural risk minimization algorithm based on statistical learning theory. The regression model of SVM is support vector regression (SVR) [45].

Ensemble learning [38] accomplishes learning tasks by constructing and combining multiple learners, and aims to integrate data fusion, data modeling and data mining into a unified framework. As an iterative integration algorithm, AdaBoost is the most prominent algorithm in ensemble learning, whose core idea is to train weak learners for the same training set, and then combine them to form a strong one [18]. In this study, AdaBoost regression is adopted for calculation.

ANN are the systems which are able to learn to use the samples by modeling the nerves of human brain, and take advantage of information they have learned to make judgement about samples they have never seen [46], [47]. Neuron is the most basic component of neural networks [39], [48]. It is helpful to adopt multi-layer functional neurons, i.e. the Multi-layer Perceptron (MLP) to solve nonlinear separability problem more generally.

Decision tree [40], [49] is a top-down recursive learning method that uses a tree structure to establish a decision model based on the attributes of data. Its basic idea [12] is to construct the fastest entropy decline tree with a measure of information entropy, where the entropy value to the leaf node is 0. The Classification and Regression Tree (CART) is adopted to learn algorithm [50], [51].

Since ATP failure feature learning is a regression problem, therefore, SVR, AdaBoostRegressor, MLPregressor and DecisionTreeRegressor toolbox are successively selected to establish learning model and tested in Anaconda software environment.

C. MODEL LEARNING RESULTS

Ten, fifty and one hundred percentage of training data are calculated to evaluate their performances in the above four methods. Time required for training and prediction could also indicate the qualities of models. The training results are shown in Figure 1. The evaluation indexes include training time, prediction time, MAE, MSE, explained variance score and r^2. The most critical quantitative values of indicators are shown in Table 3.

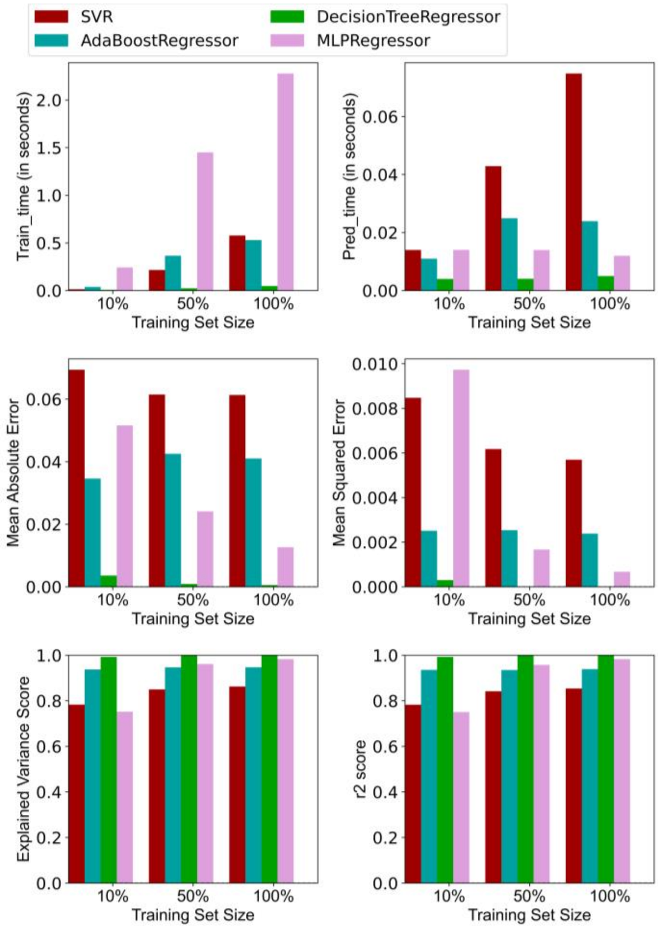

FIGURE 1. Training results of four failure learning models.

TABLE 3. ATP failure model performance of different methods.

Method	Train time/s	MSE/%	r^2
Support Vector Machine	0.6274	0.4852	0.8541
AdaBoost	0.7047	0.2452	0.9263
Artificial Neural Networks	1.7358	0.0363	0.9691
Decision Tree	**0.0401**	**0.0023**	**0.9792**

As shown in Figure 1 and Table 3,

- In terms of the time, the neural networks take the most and the decision tree takes the least in the process of training. SVM takes the most time and the decision tree takes the least in the process of prediction. Therefore, decision tree model wins from the perspective of time.

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- In terms of error, MSE and MAE of decision tree method are the lowest among the four methods, indicating that the fitting effect is the best, and the possibility of overfitting and underfitting is the lowest.
- In terms of model interpretability, the explained variance score and r^2 of decision tree method are more tended to be 1, indicating that independent variables can explain the variance changes of dependent variables better, and future samples can be better predicted and analyzed by this model.

On the basis of above performance indicators, decision tree learning model has the strongest generalization ability. Therefore, it is selected to analyze and predict the failure feature of an ATP system.

D. RESULTS DISCUSSION

The decision tree learning model represents a mapping between ATP failure rate and features. Each node in the tree represents the judgment condition of the failure feature, and its branches represent the objects that meet the node conditions. The leaf nodes of the tree represent the failure rate prediction results, and each decision question raised in the decision-making process is a test of a certain feature that affects failure rate. This is a very natural mechanism for humans to deal with decision-making problems, so the application requirements are consistent with the idea of the theoretical method.

Decision tree learning process [12] is shown in Algorithm 1, the key is how to optimally select the splits feature in row 8. With continuous learning, it is expected that the samples contained in the branch nodes belong to the same category as possible, that is, the purity of the nodes is getting higher and higher. The CART method uses the Gini index to measure the purity of data set *D*.

$$\mathrm{Gini}(D) = \sum_{k=1}^{|y|}\sum_{k'\neq k} p_k p_{k'} = 1 - \sum_{k=1}^{|y|} p_k^2 \tag{8}$$

where the proportion of the *k*-th sample in the current sample set *D* is p_k. Gini(*D*) reflects the probability that two samples are randomly selected from the set *D*, and their class labels are inconsistent. Therefore, the smaller the Gini(*D*) is, the higher the purity is.

The Gini index of feature *a* is defined as,

$$\mathrm{Gini\_index}(D,a) = \sum_{v=1}^{V} \frac{|D^v|}{|D|}\mathrm{Gini}(D^v) \tag{9}$$

In the candidate feature set *A*, select the feature with the smallest Gini index split as the optimal one, that is,

$$a_* = \underset{a\in A}{\arg\min}\ \mathrm{Gini\_index}(D,a) \tag{10}$$

Main parameter values of the decision tree learning model are shown in Table 4. The validation set is adopted to evaluate the generalization ability of the model roughly, and its performance is not so ideal. Then, GridSearch Cross Validation (CV) method [52] is adopted for parameter tuning of decision tree model. The maximum depth of decision tree is expressed as *max_ depth*, which limits its depth and avoids overfitting to a certain extent. The minimum impurity of node decrease is expressed as *min_ impurity_ decrease* to designate the threshold value of Gini impurity. When information gain is lower than this threshold, the decision tree will not split again.

Algorithm 1 decision tree learning model

Input: Training set $D=\{(x_1,y_1), (x_2,y_2),\ldots, (x_m,y_m)\}$.
Feature set $A=\{a_1,a_2,\ldots, a_d\}$.
Process: Function TreeGenerate(*D*,*A*)
1: Generate node;
2: **if** All samples in *D* belong to the same category *C*, **then**
3: Mark node as a *C*-type leaf node; **return**
4: **end if**
5: **if** $A=\Phi$ **OR** The samples in *D* have the same value on *A*, **then**
6: Mark node as a leaf node, and its category is marked as the category with the largest number of samples in *D*; **return**
7: **end if**
8: Select the optimal splits feature a_* from *A*;
9: **for** every a_*^v **do**
10: Generate a branch for the node, Let D_v denote the subset of samples in *D* whose value is a_*^v on a_*.
11: **if** D_v is null, **then**
12: Mark the branch node as a leaf node, and its category is marked with the largest number of samples in *D*; **return**
13: **else**
14: Take TreeGenerate(D_v,$A\backslash\{a_*\}$) as the branch node.
15: **end if**
16: **end for**
Output: A decision tree with node as the root node.

TABLE 4. Main parameter values of the decision tree learning model.

Notation	value	Descriptions
criterion	{"mse"}	The function to measure the quality of a split.
splitter	{"best"}	The strategy used to choose the split at each node.
max_depth	[1,2,…,50]	The maximum depth of the tree.
min_samples_ split	2	The minimum number of samples required to split an internal node.
min_samples_ leaf	1	The minimum number of samples required to be at a leaf node.
min_weight_fr action_leaf	0.0	The minimum weighted fraction of the sum of weights required to be at a leaf node.
max_features	None	The number of features to consider when looking for the best split.
max_leaf_nod es	None	Grow a tree with *max_leaf_nodes* in best-first fashion.
min_impurity_ decrease	[0,0.002,0.004,…,0.2]	A node will be split if this split induces a decrease of the impurity greater than or equal to this value.
min_impurity_ split	0	Threshold for early stopping in tree growth.

The optimization ranges of two parameters are *max_depth* = [1,2,…,50], and *min_impurity_decrease* =[0,0.002,0.004,…,0.2]. By Gridsearch CV, we enumerate all the values in the list to calculate the model score, and finally obtain the evaluation index of the specified parameter value, i.e. the best *max_ depth* = 18 and the best *min_ impurity_ decrease* = 0. The results show that MSE of 0.0021% and r^2 of 0.9833 in the optimal learning model are better than those of decision tree in Table 3.

At last, the test set is adopted to test the generalization ability of optimal model. MSE of 0.0029% and r^2 of 0.9761 are obtained, which indicates that decision tree learning model is effective and suitable for analysis of failure features of ATP systems.

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V. ATP FAILURE LEARNING MODEL INTERPRETABILITY

The best learning model for ATP failure feature analysis is determined. However, it is difficult to understand the relationship between predictors and model outcome since the four models are black box machine learning algorithms. So, we are faced with the following questions.

- What is the logic behind the model learning of ATP failure analysis? How to extract important insights from the model?
- How important is each of the features that affect ATP failure rate?
- In terms of each sample, what is the function of different characteristic variables in each prediction decision? For overall samples, how does each feature affect the prediction results of model?

All above questions involve the interpretability of model [53], [54]. Model interpretability refers to the understanding of internal mechanism of model and understanding level of its results [55]. The purpose of machine learning in this study is to develop intelligent maintenance strategy for ATP systems. How maintenance managers and personnel understand and trust the maintenance strategy depends on the interpretability of ATP failure learning model. The more interpretable the learning model is, the easier it is for people to understand why certain decisions or predictions are made.

In practical application, different types of ATP systems usually correspond to different maintenance strategies due to the difference in production processes, technical platforms, source qualities and so on. The following model interpretability analysis divides samples according to ATP types. 300T-type ATP systems accounting for 37.98% of all types, had been the most numerous and widely used type by March, 2020. Therefore, samples data of 300T-type are taken as examples to illustrate the model.

A. FEATURE IMPORTANCE ANALYSIS

Feature importance analysis is to quantitatively analyze the importance of features that affect the ATP failure rate and then put them in order on the basis of their ranking. The basic principle is to take a specific feature column, randomly disrupt the order, then adopt the optimal model to predict, calculate how much the variances of MSE and r^2 are, restore the disrupted column, move to the next feature column and repeat the previous step until all features are calculated.

The importance of each feature of 300T-type ATP systems to failure rate is shown in Figure 2. It can be seen that the mean operation mileage with 0.41 is of the highest importance, followed by the number of systems and the mean service time with 0.38 and 0.20 respectively. The importance of these three features has reached 0.99, and feature of month with 0.01 has little impact on change of failure rate.

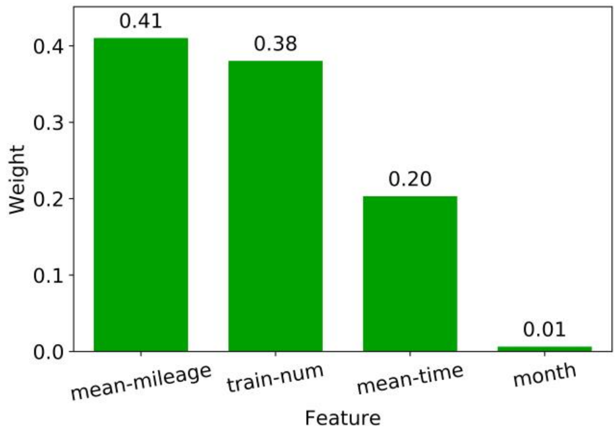

FIGURE 2. **Normalized weights for first four most predictive features.**

B. AVERAGE IMPACT ANALYSIS OF SINGLE FEATURE

How a single feature affects the change of ATP failure rate is revealed by Partial Dependence Plot (PDP). It shows the marginal effect that one or two features have on predicted outcome of a machine learning model [56], and whether the relationship between the label and a feature is linear, monotonic or more complex.

The partial dependence function for regression is defined as,

$$f_{x_s}(x_s) = E_{x_c}[f(x_s, x_c)] = \int f(x_s, x_c) dP(x_c) \qquad (11)$$

where the x_s are the features for which the partial dependence function should be plotted and x_c are the other features adopted in the machine learning model f.

Steps of PDP analysis are as follows.

Step 1: Select the best model i.e. decision tree model, and take *F1* … *Fn* as the feature and *Y* as the failure rate of target variable.

Step 2: Explore the direct relationship between *Y* and *F1*.

Step 3: Replace the *F1* column with *F1* (*1*) and find new predictive values for all observations. Calculate the average predicted value, named base value.

Step 4: Repeat *step* 3 for feature F1, from *F1* (*2*) to *F1* (*m*) to calculate the predictive values.

The impact of mean operation mileage on change of ATP failure rate expressed by PDP is shown in Figure 3.

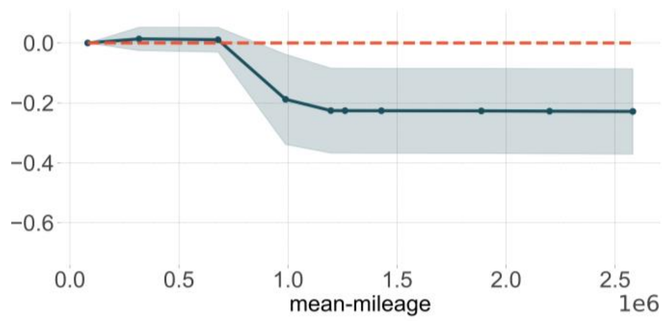

FIGURE 3. **PDP for feature mean operation mileage.**

In Figure 3, *x*-axis indicates the value of mean operation mileage, *y*-axis represents the variation value of predicted results of failure rate, and the blue shaded area is the

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confidence interval. It can be seen from the figure that when mean operation mileage is smaller than $1.2*10^6$, i.e. 1.2 million kilometers, the increase of mean operation mileage will reduce the probability of ATP failure rate. When it increases to $1.2*10^6$, the change of ATP failure rate is basically stable. In this way, the PDP of mean service time is obtained. When the mean service time reaches 550 days, the change of ATP failure rate is basically stable. It indicates that as the 300T-type ATP systems run 1.2 million kilometers or serve 550 days, the maintenance strategy could be adjusted appropriately, which can extend the maintenance cycle and refine the maintenance items.

C. INDVIDUAL IMPACT ANALYSIS OF SINGLE FEATURE

PDP adopts multiple rows of data of a feature for testing and then draws the plot according to average value. Since the average value is adopted, individual impact is ignored. How does the individual affect the results of failure rate? Individual Conditional Expectation (ICE) plot [56], [57] can answer this question. It makes the dependence of the prediction on a feature for each instance visible separately, resulting in one line per instance, instead of one line overall in partial dependence plots.

ICE plots can explore individual differences and identify subgroups and interactions among model inputs deeply. First, a feature of interest is selected to create an ICE plot. Then, predictions of each observation for that feature is made across a range of values on condition that all other features are constant. Finally, those predictions as curves on a plot are visible. By plotting these curves, the relationship between the feature of interest and the predicted target variable can be obtained. The ICE for each failure feature of 300T-type ATP systems is shown in Figure 4.

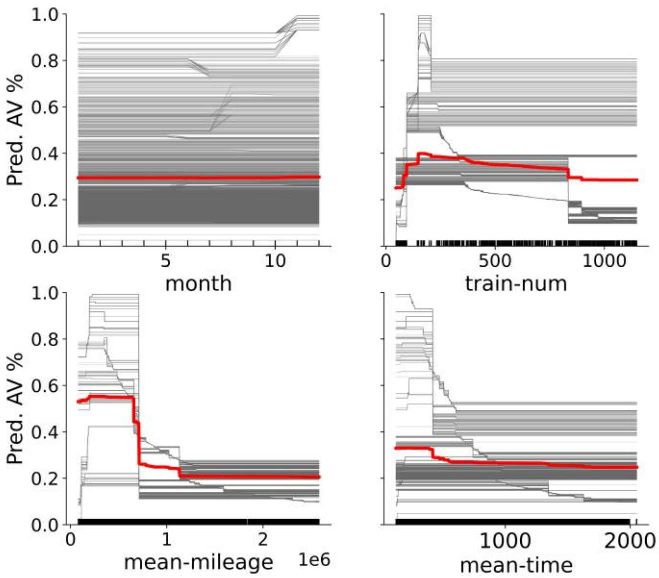

FIGURE 4. ICE for all features.

In Figure 4, x-axis represents the value of each feature, and y-axis is the predicted AV percentile of ATP failure rate. Each black solid line represents the ICE of a value of a feature, and the red solid line is PDP. The PDP is the average of all ICE curves on the plot, so the PDP above represents the average change in the predicted AV percentile over the range of a feature.

According to Figure 4, the following can be obtained.

- With the change of eigenvalue, the predicted AV percentile shows a stable linear independence, indicating that the feature of month has little impact on the change of ATP failure rate.
- There is a nonlinear independence among the number of systems, mean operation mileage, mean service time and predicted AV percentile. Firstly, failure rate rises when the number of systems is between 0 and 150, and drops slowly between 150 and 800. It is stable and no longer affects its fluctuation when the number is over 800. Secondly, the failure rate shows a downward trend as mean operation mileage is between 0 and $1.2*10^6$, and stable after $1.2*10^6$. Finally, the impact of the mean service time on failure rate shows a steady but not so direct downward trend by PDP.
- As mean operation mileage increases, the decrease in top of predicted AV percentile is larger than that of the bottom, indicating that its impact on failure rate is not independent, but related to other features.

D. IMPACT ANALYSIS OF SINGLE SAMPLE

We are interested in how each feature affects the prediction of a data point. In item prediction, the impact of each feature on results of failure rate can be reflected by values of the SHapley Additive exPlanations (SHAP). It [56], [58] was proposed by Lloyd Shapley, a professor at the University of California, Los Angeles, to solve the contribution and income distribution of cooperative game.

The SHAP value of a feature is its contribution to ATP failure rate, weighted and summed over all possible feature value combinations,

$$\phi_j = \sum_{S \subseteq \{x_1,\cdots,x_p\} \setminus \{x_j\}} \frac{|S|!(p-|S|-1)!}{p!}(val(S \cup \{x_j\}) - val(S)) \quad (12)$$

where S is a subset of the features adopted in the model, x is the vector of feature values of the instance to be explained and p is the number of features. $val_x(S)$ is the prediction for feature values in set S that are marginalized over features that are not included in set S,

$$val_x(S) = \int f(x_1,\cdots,x_p)dP_{x \notin S} - E_X(f(X)) \quad (13)$$

Assuming that the i-th sample is x_i, the j-th feature of the i-th sample is x_{ij}, the predicted value of the model for this sample is y_i, and the baseline of whole model, usually the mean value of the target variables of all samples is y_{base}, then the SHAP value accords with the following equation,

$$y_i = y_{base} + \phi(x_{i1}) + \phi(x_{i2}) + \cdots + \phi(x_{ik}) \quad (14)$$

where $\Phi(x_{ij})$ is the SHAP value of x_{ij}. Intuitively, $\Phi(x_{i,}1)$ is the contribution value of first feature in the i-th sample to final predicted value y_i. When $\Phi(x_{i,}1)$ is greater than 0, it is indicated that the feature improves the predicted value and has a positive effect. Otherwise, it reduces the predicted value and has a negative effect.

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Select the data in the 10-th item of validation set, and observe the impact of different features on final failure rate results. The SHAP value is shown in Figure 5.

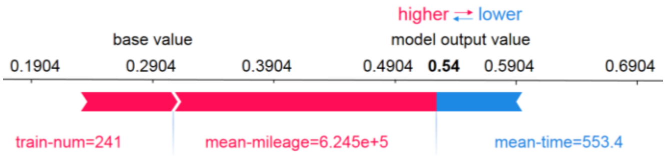

FIGURE 5. **SHAP value for one item.**

The explanation in Figure 5 shows that each feature has its own contribution, pushing the prediction results of the model from the base value to final model output. Base value of 0.2904 represents the mean output value of failure learning model on data set. Model output value of 0.54 is the output value of a single sample of the failure learning model on the 10-th item.

The strip area represents the size of value. The red and the blue indicate that $\Phi(x_{ij})$ is greater and smaller than 0 respectively. The positive effect is characterized by the number of systems, mean operation mileage. The negative effect is characterized by mean service time, which significantly reduces the predicted value.

E. IMPACT ANALYSIS OF MULTIPLE FEATURES

In the rank of feature importance, mean service time is medium, which means two possibilities. One is that it has a great impact on a small number of predictions, but little impact on overall. The other is that it has a medium impact on all predictions. This paper draws SHAP value of each feature for each sample to distinguish which possibility it is, which help understand the overall pattern better and discovery the outliers. The SHAP values of all features are shown in Figure 6.

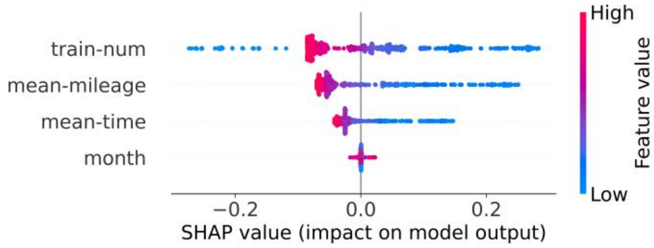

FIGURE 6. **SHAP value for all features.**

In Figure 6, *x*-axis is SHAP value representing the impact of features on predictive value and *y*-axis represents features. The color represents the value of the features, among which the color from blue to red indicates the value from low to high. It can be seen that mean operation mileage, mean service time and the number of systems contribute most to the prediction results. As the value increases, mean service time in medium permutation importance will improve the prediction result with SHAP value greater than 0, and show a positive effect, but the degree of improvement will be reduced. As the value increases to a certain extent, the prediction result decreases with SHAP value less than 0, and show a negative effect. It is indicated that mean service time has a great impact on a small number of forecasts, but limited impact on overall. So mean service time should be considered when formulating a maintenance strategy.

F. FEATURE DEPENDENCE CONTRIBUTION

According to formula (6), mean operation mileage directly affects the failure rate of ATP systems. So, how is its influence distribution? Is it a constant or a value mostly dependent on other features? Is there interaction between operation mileage and service time? In order to understand how a single feature of operation mileage affects the output of model, this paper compares its SHAP value with the feature value of all samples in the data set, and obtains the impact distribution of mean operation mileage to failure rate, as shown in Figure 7.

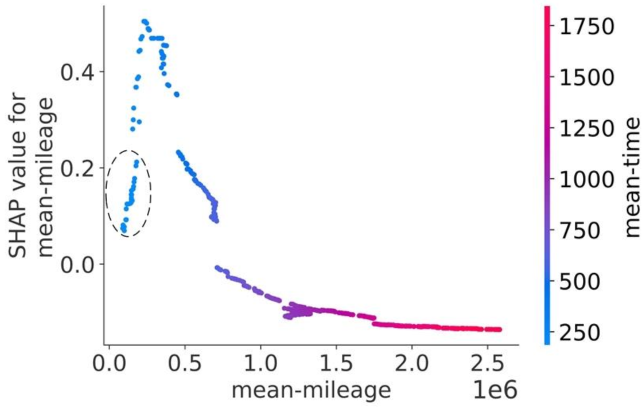

FIGURE 7. **Feature dependence contribution.**

In Figure 7, each point represents an item of data. The *x*-axis is mean operation mileage and *y*-axis shows the impact of feature value on prediction result. The dispersion in the vertical direction of operation mileage represents its interaction with service time. From the slope shape of the general plot, it can be seen that the longer the operation mileage is, the more negative impact the failure rate has. Excluding the impact of all features, the interaction between operation mileage and service time is described. As shown in the black circle of the figure, although the operation mileage and service time are short, the failure rate is still low.

To sum up, through the interpretability analysis of ATP failure decision tree learning model, the internal mechanism is visualized, and how each feature quantitatively affects the change of ATP failure rate is explained, which lays a solid and credible foundation for maintenance strategy.

VI. INTELLIGENT MAINTENANCE OF ATP SYSTEMS

The core of intelligent maintenance is to master the failure rules of ATP systems through decision tree learning model, dynamically adjust maintenance cycle and items as needed. It can fundamentally solve the problem of over-maintenance, save costs and improve the maintenance level of high-speed trains.

A. INTELLIGENT MAINTENANCE SYSTEM AND IMPLEMENTATION OF ATP SYSTEMS

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The goal of machine learning aims to output the judgment of intelligent maintenance of ATP systems, and build its architecture as shown in Figure 8. The whole system is divided into three layers: the bottom database, the middle learning and the upper application layer. The bottom database consists of production information, daily operation mileage, daily failure information and other data of an ATP system. The middle layer is decision tree learning model of ATP failure features established in section IV. The upper application is to dynamically formulate and implement intelligent maintenance strategy of ATP systems according to the results of the learning model.

According to the architecture in Figure 8, the information implementation platform of intelligent maintenance is designed to provide refined and personalized maintenance strategies for each ATP system, so as to realize the health management of whole life cycle and closed-loop control of ATP systems. The closed loop control diagram of the platform is shown in Figure 9.

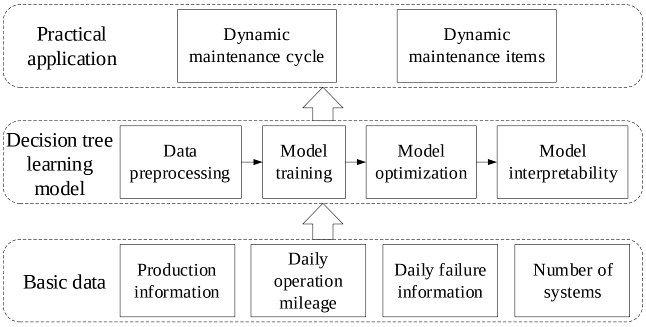

FIGURE 8. **Intelligent maintenance architecture of ATP systems.**

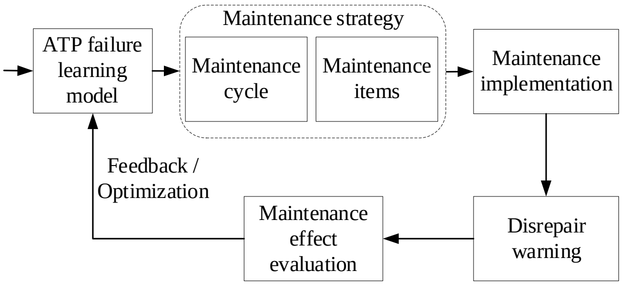

FIGURE 9. **The closed loop control diagram of the platform.**

In Figure 9, the closed-loop control process of intelligent maintenance of ATP systems is as follows.

Step 1: On the basis of historical data, the decision tree learning model of ATP failure is established.

Step 2: Refined maintenance strategy of each ATP system is developed based on the results of decision tree learning model. The maintenance cycle and items are dynamically formulated. The former specifies how often the maintenance is carried out, and the latter specifies what is to be maintained.

Step 3: The maintenance implementation is mainly realized by intelligent handheld terminal, and maintenance personnel accomplish task with under the prompt and guidance of the terminal.

Step 4: Timely alarm reminds users to pay special attention to an ATP system which is to be expired or has been overdue.

Step 5: After maintenance, the change of failure rate of ATP systems is continuously tracked and analyzed to quantitatively evaluate the maintenance effect.

Step 6: The failure learning model is optimized according to evaluation results.

So far, the intelligent maintenance information platform of an ATP system has been built, and the closed-loop control of the whole process has been formed.

B. INTELLIGENT MAINTENANCE CYCLE AND ITEMS OF ATP SYSTEMS

For maintenance personnel, intelligent maintenance is to determine the maintenance cycle and items. In practical application, maintenance strategies are differentiated and implemented according to ATP system types. Therefore, the maintenance cycle and items of each type of ATP systems are determined as follows.

According to the interpretability analysis, the number of systems has great impact on the failure change at a general view. However, intelligent maintenance targets for each ATP system, so the mean operation mileage and service time have the greatest impact on individual level. The quantitative relationship among system failure, mean operation mileage and service time is obtained according to the interpretability analysis of the decision tree learning model in section V. Within a certain range of operation mileage or service time, the maintenance cycle will be shortened along with the increase of failure rate, stabilized as it is stable, and extended with its decrease. Combined with practical maintenance experience, the cycle is set as seven, fifteen and thirty days respectively. As shown in Table 5, the maintenance cycle of each type of ATP systems can be obtained.

TABLE 5. **Maintenance cycle of each type of ATP systems.**

Type	Feature	Seven days (rising failure rate	Fifteen days (stable failure rate)	Thirty days (decreasing failure rate)
300T	Operation mileage/million kilometers	/	1.2-	0-1.2
	Service time/day	/	550-	0-550
300S	Operation mileage/million kilometers	0-0.5	0.5-	/
	Service time/day	0-600	600-850	850-
300H	Operation mileage/million kilometers	0-0.6	0.6-	/
	Service time/day	Cycle life		
200H	Operation mileage/million kilometers	0-1.1	1.1-	/
	Service time/day	0-1200	1200-	/
200C	Operation mileage/million kilometers	0-0.6	0.6-	/
	Service time/day	0-1250	1250-1500	1500-

In Table 5, the maintenance cycle of each type of ATP system is different. For example, for 300T-type, when operation mileage is less than 1.2 million kilometers or service time is less than 550 days, the failure rate shows a downward trend, and the maintenance cycle can be set to 30 days. When it is more than 1.2 million kilometers or 550 days, the failure rate is stable, and the cycle can be set to 15 days. For 200C-type, when operation mileage is less than 0.6 million kilometers or service time is less than 1250 days, the failure rate shows an upward trend, and the cycle can be set to 7 days. When it is more than 0.6 million kilometers or service time is between 1250 and 1500 days, the cycle can be set to 15 days. When it exceeds 1500 days, the cycle can be set to 30 days. So, when mean operation mileage or service time reaches a certain range, all types of ATP systems can adopt the corresponding maintenance cycle. In this way, the fixed and single maintenance interval in whole life cycle is converted to dynamic interval mode, where refined and systematical maintenance are carried out and the maintenance resources are saved at the same time.

The sub-equipment of ATP systems with high failure rate should be paid more attention in every maintenance. Table 6 has listed the top three in each. It can be seen that although the equipment with high failure rate in each type of ATP systems is not the same, the top three exceeds two thirds of total failures, indicating that most of the failures are concentrated on some pieces of sub-equipment. As long as these pieces of sub-equipment are reliably operated, the main failure sources can be contained.

In Table 6, VC-S refers to Vital Computer Software. In daily maintenance, in addition to appearance inspection, these electrical parameters and software logic should also be tested. Other sub-equipment such as GSM-R and JRU can be simply maintained.

To sum up, for each ATP system, the maintenance cycle and items are dynamically determined on a specific data service platform to realize refined maintenance in the whole life cycle.

TABLE 6 a. Failure ratio of sub-equipment of ATP systems.

No.	300T Sub-equipment	Failure ratio	300S Sub-equipment	Failure ratio	300H Sub-equipment	Failure ratio
1	BTM	0.31	DMI	0.30	BTM	0.49
2	VC-S	0.27	VC-S	0.19	DMI	0.26
3	TIU	0.19	BTM	0.17	VC-S	0.13
4	Total	0.77	Total	0.66	Total	0.88

TABLE 6 b. Failure ratio of sub-equipment of ATP systems.

No.	200H Sub-equipment	Failure ratio	200C Sub-equipment	Failure ratio
1	BTM	0.40	BTM	0.39
2	DMI	0.36	VC-S	0.20
3	TCR	0.07	DMI	0.12
4	Total	0.83	Total	0.71

VII. CONCLUSION

The decision tree learning model of failure features of automatic train protection system was proposed. It was verified by practical failure data of China's high-speed railway in the past 10 years, and its accuracy was 0.9761.

The interpretability analysis of decision tree model showed that the top three features affecting the failure rate were mean cumulative operation mileage, mean cumulative service time and the number of systems, whose importance reached 0.99. The time feature had little impact on failure rate, and the importance was only 0.01. What's more, it revealed the complex quantitative relationship among failure rate of different types of ATP systems, operation mileage, and service time. And the maintenance cycle and items of each system were adjusted dynamically, and the refined maintenance strategy in whole life cycle was obtained.

In the future, we will continue to explore more possible failure features, analyze and improve the accuracy of the model, and further improve the level of intelligent maintenance.

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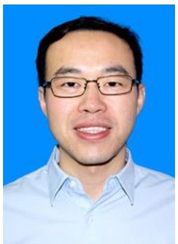

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