Predictive Maintenance for station equipment and Applications for the Space field

Ryoma Yokoyama[1], Ryosuke Kono[2], Atsushi Matsuda[3], and Yohei Shiomi[4]

[1, 2, 3] *West Japan Railway Company, Osaka, 530-8341, Japan*

ryouma-yokoyama@westjr.co.jp
ryousuke-kouno@westjr.co.jp
atsushi-matsuda02@westjr.co.jp
youhei-shiomi@westjr.co.jp

ABSTRACT

Our company have a lot of stations fare equipment such as ticket gate machine. Maintenance and inspection of these require a lot of labor and cost. In this paper, we aimed to solve this problem by applying failure detection a form of machine learning. Currently, the system has been installed in all of our station equipment, and has reduced the number of failures by 20% and inspections by 30%, helping to optimize our operations. In the future, we plan to apply this method and our knowledge of maintenance and operation to evaluate the health and management of satellites in the space field.

1. INTRODUCTION

West Japan Railway Company manages about 20,000 ticket gate facilities. West Japan Railway Techsia (hereinafter called "Techsia") is responsible for the maintenance of these equipment. The maintenance of these equipment is labor-intensive and costly, and has become an issue. A variety of efforts have been made in the past to solve this problem.

In 2007, we developed a system that automatically collects the logs of anomaly data and operational data of ticket gate machine installed at each station to a server. In 2012, we developed a system called TEMS (Techsia Maintenance System) that collects and analyzes equipment status in real time. This system enables automatic calculation of inspection cycles and automatic detection and setting of inspections for equipment in poor condition according to operating conditions

On the other hand, the measures taken so far only establish a mechanism to inspect equipment in poor condition, and do not provide preventive maintenance to predict failures before they occur.

Therefore, we have developed and introduced a system that predicts equipment with a high probability of failure in the future by using machine learning. We named the system AI-TEMS (AI Techsia Maintenance System).

2. EXPERIMENTAL AND RESULT

2.1. Target Equipment

We selected equipment model to test the effectiveness of AI-TEMS. The selection of the model was based on the following factors: 1. It has the ability to collect operational data. 2. The number of periodic inspections and on-call calls is high. The following points are important. From the above two points of view, we selected three models: an automatic ticket gate machine (AG50), an automatic fare adjustment machine (FA50), and an automatic ticket vending machine (HT50). These three models are installed in 3,150 units in our service area, and together they perform approximately 20,000 periodic inspections and 9,000 on-call inspections per year.

2.2. AI-TEMS

The development of AI-TEMS was based on the existing TEMS. TEMS applied its own calculation algorithm to the log data collected from the system to extract units to be specially inspected. Instead of this algorithm, AI-TEMS uses a newly constructed machine learning model to predict failures. The system is designed so that the probability of failure of a unit that exceeds a predetermined threshold as a result of failure prediction is extracted as a target for inspection. However, for fare adjustment machine and ticket vending machines since there are a large number of blocks installed, we decided to predict the failure probability for each block of coins, bills, etc.

On the other hand, simply outputting the units and blocks with high failure probability did not reveal the causes of the increased failure probability, making it difficult for maintenance staff to know where to inspect. Therefore, we visualized the factors that increased the probability of failure by outputting them in a ranking format.

2.3. Building Machine Learning Model

The machine learning model used in this study is a binary classification model that calculates the probability of station equipment failures within N days and classifies as failures those that exceed a threshold.

2.3.1. Training Data

We used the as the explanatory variable for machine learning. As an objective variable, we need data on which part of the station equipment failed and when. For this purpose, on-call data, which is data obtained by responding to failures in the past, is used. This on-call data includes station name, model name, machine number, date and time, fault description, fault block, and so on. The machine number is the unique identification number of the station equipment.

The explanatory variables were subjected to feature processing such as aggregation to improve the accuracy of the model.

2.3.2. Output Data

The model was built to output units likely to be on-call "within 3 days" and "within 7 days". The factors that increased the probability of failure and their confidence level are also output (see Fig. 1).

Analysis Details	Within 7 days (by 09/27/2020)	
TOP	Fault Part	Reliability
1	21_days_sum_Ticket_jam_Train_pass	10.07%
2	21_days_sum_Ticket_jam_Ticket_collection	3.06%
3	21_days_sum_SOL5_Number_of_operations	2.33%
4	14_days_sum_Ticket_jam_Train_pass	2.19%
⋮	⋮	⋮

Figure 1. Example of output screen

2.4. Experimental

2.4.1. Conditions

The equipment for the experiment was selected from our Kobe area (600 units in total), and trial operation of an automatic ticket gate machine (AG50) and an automatic ticket vending machine (HT50) began in June 2020, and trial operation of an automatic fare adjustment machine (FA50) began in July 2020. The following two evaluation indicators were used.

1. number of on-calls [cases/unit/month].

2. total number of inspections [times/unit/month].

Although it is desirable to use the comparison with the previous year in the same area, we judged that it would be difficult to make an appropriate evaluation in FY2020 because the number of users decreased due to the impact of COVID-19. Therefore, the comparison was made with equipment in our Osaka and Kyoto areas in the same fiscal year. A comparison of on-call data in the past showed that the correlation coefficient between the Kobe area and the Osaka area was 0.88, and that between the Kobe area and the Kyoto area was 0.77, so we judged that a comparison with these areas would be sufficient for an appropriate evaluation.

2.4.2. Evaluation

To evaluate the model, operating data and on-call data for each model for the past year were used. To prevent overlearning, the historical data was divided into training data and evaluation data. Since the output of the machine learning model will be a failure probability between 0 and 1, whether or not the model is actually judged to fail depends on the threshold. For example, if the threshold is set to 0.8, the decision is made that the system will fail if the failure probability is 0.8 (80%) or greater. Setting this threshold higher will increase the false positive rate and setting it lower will decrease the true positive rate. Since these accuracies vary depending on the balance of thresholds, a consistent evaluation is difficult. Therefore, AUC, an index that can be evaluated independently of threshold values, was adopted for this paper. The ROC curve was drawn by plotting the false positive and true positive rates as the threshold was changed. The area under the ROC curve is the AUC. In this experiment, the model was tuned by repeatedly building and evaluating the model with the goal of achieving AUC=70% or higher.

2.5. Results-

The evaluation of the data during the trial operation in terms of the number of on-calls [cases/unit/month] and the total number of inspections [times/unit/month] showed that the number of man-hours decreased by about 20-30% for each model, and the number of failures also decreased or remained the same, so the implementation was considered effective. As an example, Table 1 and Table 2 show the evaluation results of the AG50 automatic ticket inspector for conventional lines from June to November 2020.

Table 1.
Total number of maintenances in the Kobe area

AG50		Total number of maintenances	
		Before	After (Number of CBM)
Ticket gate machine	vs. Osaka	100%	67% (37%)
	vs. Kyoto	118%	87% (48%)

Table 2. Total number of on-call in the Kobe area

AG50		Total number of On-call	
		Before	After
Ticket gate machine	vs. Osaka area	100%	82%
	vs. Kyoto area	101%	77%

3. Operation

Since the results of the trial operation conducted in FY2020 were favorable, we decided to start the full operation of AI-TEMS in FY2021. In order to start the full operation, we improved the system based on the results of the trial operation and reorganized the operations.

3.1. Points of improvement

1. Reviewing the display of factors that increase the probability of failure

During the trial period, we interviewed maintenance staff about this operation, and some of them said that some of the failure probability factors output by AI-TEMS made it difficult to determine what kind of inspection should be performed, even by looking at the item names. As a result, we have revised the features to make the ranking display easier to understand. This improvement made it easier to determine the content of inspections.

2. Review of inspection and repair specifications

In the past, inspection and repair instructions required that all parts of the equipment be inspected at regular intervals in addition to the periodic inspections scheduled by TEMS. However, since AI-TEMS has made it possible to predict and inspect equipment failures before they occur, we have decided to reduce periodic inspections to a minimum. Specifically, it was decided that only power sections, door sections, and other sections not subject to failure prediction by AI-TEMS, and some sections requiring seasonal adjustment, would be subject to periodic inspection, and all other sections would be excluded from periodic inspection items. New inspection and repair instructions reflecting this content have been prepared and will be applied in conjunction with the start of AI-TEMS operations.

3. Change the method of contacting the station for inspection

Previously, periodic inspections were performed based on a set cycle and a monthly inspection plan prepared by TEMS. Monthly inspection plans were sent to each station in advance by Techsia. However, it is difficult for AI-TEMS to notify stations of inspection schedules on a monthly basis because AI-TEMS identifies and inspects equipment with a weekly "within 3 days" or "within 7 days" probability of failure above a threshold. Therefore, in areas where AI-TEMS is in operation, it is no longer necessary to send inspection plans after prior coordination with the relevant departments, and it is possible to visit any station without prior notice during the pre-arranged inspection period.

3.2. Results

We began full-scale operation of AI-TEMS in our service area in FY2021.Table 3 shows the results of the evaluation in this operation. For the Kyoto and Osaka areas, where the new operation was launched, the evaluation was conducted using data from the first five months of operation.

Table 3. Results of this operation

	Total number of maintenances		Total number of On-call	
Compare to	FY2019	FY2020	FY2019	FY2020
Kyoto area	75%	75%	73%	97%
Osaka area	66%	87%	79%	108%
Total	69%	83%	77%	105%

In FY2020, the number of inspections was about 20% lower than in the current fiscal year due to COVID-19, although there was a trend toward less use and fewer inspections in FY2020 than in the current fiscal year, but the number of inspections was still about 20% lower. The failure rate (on-call rate) also remained at the same level. Moreover, compared to FY2019, the failure rate and the number of inspections decreased by 20% and more than 30%, respectively. Thus, it was found that failure detection based on the operating log data is effective and that, in terms of operation, sufficient results can be obtained by obtaining the opinions of the maintenance staff who actually perform the work.

4. Future

We plan to extend the application of our failure detection system and our knowledge of maintenance and operation to the space field, with the aim of evaluating the health and management of satellites. The AI-TEMS that we have developed failure detection based on the operating log data of the station fare equipment. This enables effective maintenance. The operation log data shows the status of the station equipment. The operation log data includes minor errors such as ticket jamming, etc., from which serious failures can be predicted. Similarly, the House-Keeping (HK) data represents the status of the satellites. This data includes minor errors such as one-bit errors during transmission, and similar effects can be expected. However, there are some differences. Satellites must collect data at perigee, and the period of downlink communication is limited. Also, changes in the external environment cannot be ignored. For example, radiation and magnetic fields in space vary with the satellite's position and solar activity However, we believe that these effects can be effectively managed by applying machine learning models. Currently, our company is challenging the health assessment of satellites based on the JAXA Space Innovation through Partnership and Co-creation (J-SPARC) with the Japan Aerospace Exploration Agency (JAXA).

5. CONCLUSIONS

This paper aimed to reduce the labor and cost required for maintenance and inspection of approximately 3,150 station fare equipment, such as ticket gate machines, by applying failure detection, a form of machine learning. Currently, the system has been installed in all of our station equipment and has successfully reduced the number of failures by 20% and inspections by 30%, contributing to the optimization of our operations. In the future, we plan to apply this method and our knowledge of maintenance and operation to evaluate the health and management of satellites in the space field.

This research demonstrates that the machine learning technique of failure detection can alleviate the burden of equipment maintenance and inspection and contribute to the optimization of operations. Furthermore, by applying this technique to other fields, new value can be created. Further research is needed to improve accuracy and expand the scope of application.