Special edition paper

Study on a Failure Prediction Method Using Monitoring Data from Motor Point Machines

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Motor point machines are very important equipment for a train operation system. Failure of a machine is directly linked with transport disorders. Therefore, such failures should be prevented. We examined various failure prediction methods in order to detect signs of failure and to maintain the machines before failure occurrence. With some failure prediction methods by using monitoring data from motor point machines, we studied whether or not we could find signs of operation failure. As a result, we found signs from some methods and confirmed that some methods are effective for maintenance.

●Keywords: Point machine, Monitoring, Switching failure, Identifying signs of failure, Factorial analysis

1 Introduction

1.1 Backdrop and Purpose

Point machines is are important devices that create train routes by switching turnouts. As shown in Fig. 1, they fix tongue rails to either the right or left stock rail and lock the tongue rails to prevent improper movement.

A failure where a turnout cannot be switched (hereinafter, "switching failure") directly leads to transport disorder. Thus, such failures should be prevented before occurrence by correct maintenance or, if they do occur, operation should be restored as early as possible.

Today, mainly motor point machines are used to switch turnouts. Such point machines are devices that are are controlled with electric signals and transmit motor power to tongue rails to switch a turnout. In cases where a turnout cannot be switched, we can see a tendency for the motor torque to vary from that in its normal condition. For example, when a turnout cannot be switched due to a foreign object caught in the turnout, motor torque tends to be larger.

In this study, aiming to identify signs of switching failure, we examined some methods of identifying those using monitoring data of point machines, and we verified the examination results using data of point machines on commercial lines (hereinafter, "actual machine data").

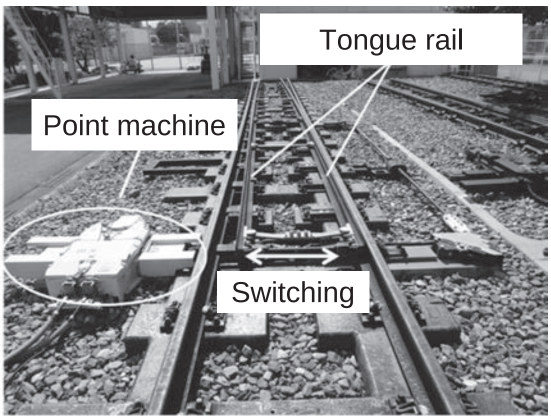

Fig. 1 Configuration of a Turnout

1.2 Overview of the ESII-Type Point Machine

The ESII-type point machine (Fig. 2) is a point machine for next-generation turnouts. Amongst other features, it adopts a servomotor to stabilize operation control as well as a gear control mechanism and status output using relay contacts, the later two being advantages of the widely used NS-type point machine.

The ESII-type point machine also has a function of monitoring switching operation where the following data is automatically recorded at switching. That data is elapsed time (seconds), torque (%), stroke (mm), rotation speed (rpm), rotation angle (°), amount of locking deviation on the normal position side (mm), amount of locking deviation on the side opposite the normal position (mm), and failure warning and other warnings.

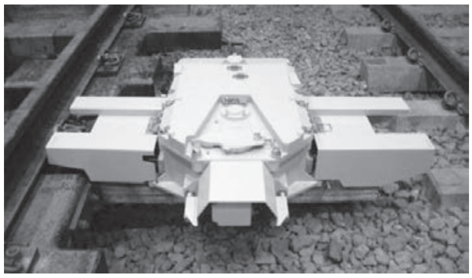

Fig. 2 ESII-Type Point Machine

2 Overview of Analysis Methods for Identifying Signs of Failure

In this study, we supposed that monitoring data of the ESII-type point machine could allow us to detect abnormality data as signs of the turnout switching failure. We thus examined analysis of torque change as an analysis method based on experiences and know-how along with wavelet analysis, estimation of density ratio, and one-class support vector machine (SVM) as statistic numerical analysis methods used in other fields. A brief explanation of each method is shown below.

2.1 Detection of Abnormalities by Analysis of Torque Change

Detection of abnormalities using analysis of torque change is a method where normality and abnormality are distinguished using a threshold specified in advance based on experience and know-how. The method combines various logics excluding

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monitoring of torque peak value and monitoring of change from average torque value explained below.

2.1.1 Monitoring of Peak Torque Value

Fig. 3 shows the relationship between switching time and torque value of the ESII-type point machine. The torque value is a value calculated from electrical current, and 100% means operation with the rated current. In monitoring of the peak torque value, the peak torque value in switching time is compared with a preset threshold, and values over that threshold are judged to indicate abnormalities.

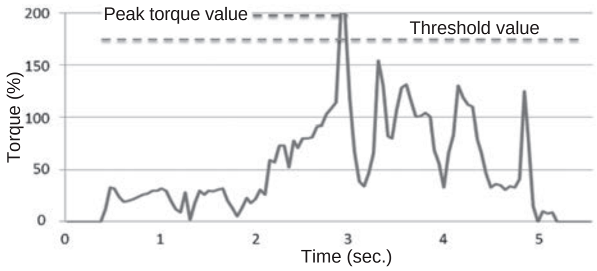

Fig. 3 Monitoring of Peak Torque Value

2.1.2 Monitoring of Change from Average Torque Value

To find the amount of change, torque data to be tested is compared with the average torque value during switching time of the latest 100 instances of switching. As in monitoring of the peak torque value, a threshold value is specified in advance. The amount of change is compared with that threshold, and values over that threshold are judged to indicate abnormalities (Fig. 4). By specifying thresholds for factors of abnormalities at the beginning, intermediate, and end stages of switching and combining monitoring using those thresholds with the monitoring of peak torque value, abnormalities such as adjustment error of the connection of the point machine and the turnout and foreign objects caught in the machine can be identified.

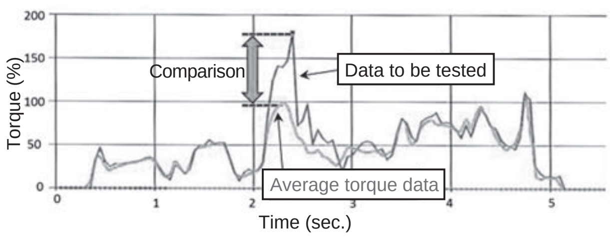

Fig. 4 Monitoring of Change from Average Torque Value

2.2 Detection of Abnormalities by Wavelet Analysis

2.2.1 Wavelet Analysis

Wavelet analysis is a method where slight difference in waveform can be detected by converting switching torque data to wavelets. By converting to wavelets past normality data as learning data and obtaining the scalogram of specified frequency components, a threshold can be calculated. That threshold is further standardized to be ±1.

The amount of deviation from that threshold of the data to be tested is calculated per frequency component, and the average value is obtained (Fig. 5).

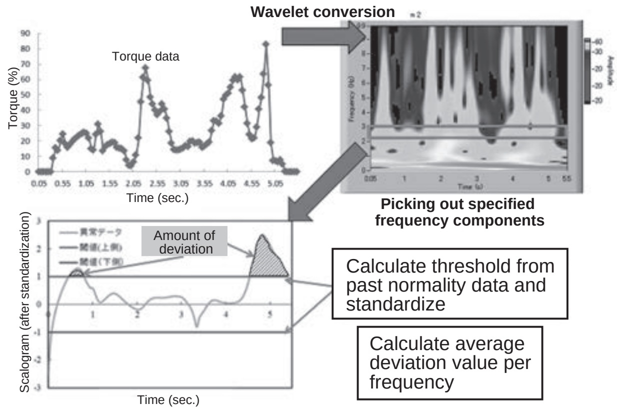

Fig. 5 Wavelet Analysis

2.2.2 Bayesian Inference

Using the amount of deviation obtained by wavelet analysis, normality and abnormality can be stochastically inferred by Bayesian inference. More specifically, probability of being normal and abnormal are calculated by Bayesian inference from the probability density distribution for deviation in past switching data, the occurrence probability from past normality and abnormality data, and the amount of deviation obtained by wavelet analysis.

By applying Bayesian updating to the calculated probability of being normal or abnormal, individual difference of point machines can be corrected, improving the accuracy of detection of abnormalities (Fig. 6).

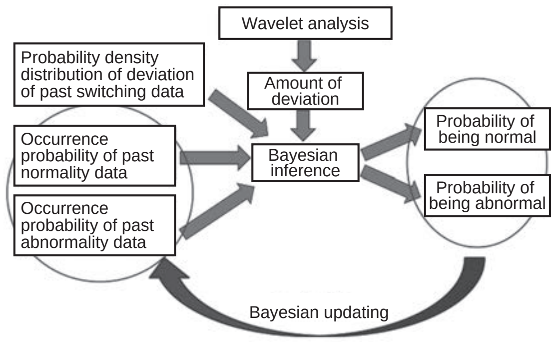

Fig. 6 Bayesian Inference

2.3 Detection of Abnormality by Density Ratio Estimation

Density ratio estimation is a method to detect abnormality by calculating the ratio of the probability density distribution of normality data to that of data to be tested that may include abnormalities. As seen in Fig. 7, by figuring out the ratio of probability density distribution of the normality data to data to be tested, the density ratio greatly deviates from 1 in the distribution range of data to be tested. This is not seen in the distribution range of the normality data, clearly proving abnormality.

It is difficult to estimate the probability density of data that shows a complex occurrence pattern. Thus, density ratio is directly calculated from the learning data prepared in advance instead of being calculated from probability densities of the two sets of data. When the calculated density ratio is over the preset threshold, the condition is judged to be normal, and when under the threshold, it is judged to be abnormal.

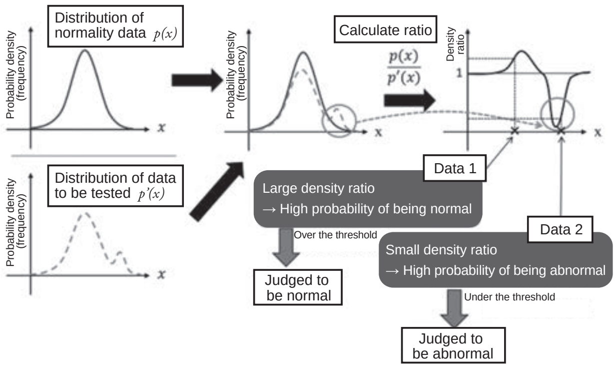

Fig. 7 Estimation of Density Ratio

2.4 Detection of Abnormality Using One-Class SVM

One-class SVM is a method where normality data in the original space is mapped in a characteristic space. In that method, data differing from other data is handled as a separate class (abnormality data), and a border is set to detect abnormality. The normal condition range is set based on learning data prepared in advance. When the data to be tested is within the normal condition range, the condition is judged to be normal, and when out of the normal condition range, it is judged to be abnormal (Fig. 8).

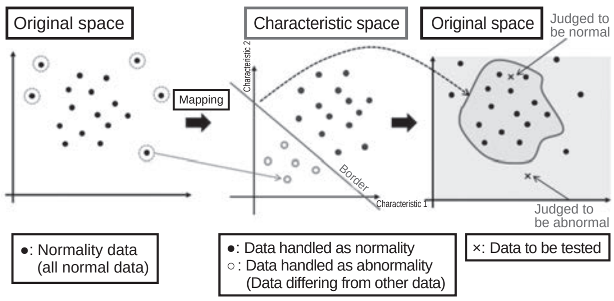

Fig. 8 One-Class SVM

3 Results and Consideration of Tests Using Actual Data

After producing a prototype analysis device that combines the logics of the aforementioned analysis methods, we carried out tests of switching data of a turnout experiencing switching failure as sample data. That turnout was put into use on October 17, 2013, and switching failure occurred on January 6, 2014. Since it had a retry function to switch again, no train operation disruption was caused.

3.1 Results of Abnormality Detection by Analysis of Torque Change

Fig. 9 shows abnormality detection by analysis of torque change. The horizontal axis is the date from start of use to the turnout switching failure. The vertical axis is the total number of instances of abnormality data such as peak torque value and amount of change from average torque value detected a day. As shown, the total number of instances of abnormality detected gradually increased from the end of November, and that number exceeded 40 a day immediately before the turnout switching failure. This proved that abnormality data as signs of a turnout switching failure can be found by analyzing torque change.

We will verify applicability by analyzing switching data of turnouts without problems.

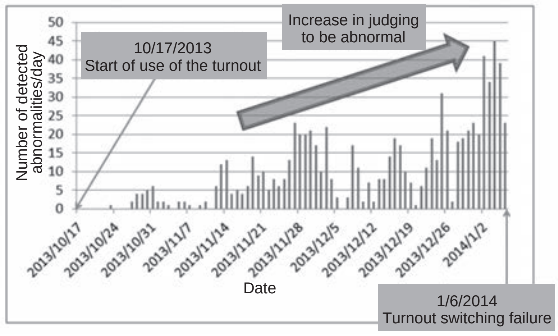

Fig. 9 Results of Abnormality Detection by Analysis of Torque Change

3.2 Results of Abnormality Detection by Wavelet Analysis

Fig. 10 shows the results of abnormality detection by wavelet analysis. The horizontal axis is the number of instances of switching from start of use. The vertical axis is the probability of being normal, with 1 as 100% normal and 0 as 100% abnormal. As the learning data, we used normality data of the period from start of use to around the 500th instance of switching. Judgment of being abnormal increased when the number of instances of switching exceeded 1,700, while the turnout experienced actually switching failure at around 2,570 instances of switching. This proved that abnormality data as a sign of turnouts experiencing switching failure can be found by wavelet analysis.

In the future, we will analyze switching data of turnouts without problems and further investigate the volume and update cycle of learning data.

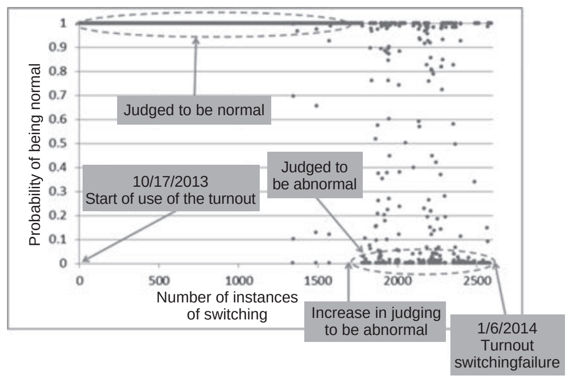

Fig. 10 Result of Abnormality Detection by the Wavelet Analysis

3.3 Results of Abnormality Detection by Density Ratio Estimation

Fig. 11 shows the results of abnormality detection by density ratio estimation. The horizontal axis is the number of instances of switching from start of use. 0 on the vertical axis means judgment of being normal and 1 means judgment of being abnormal. The white zone is judged to be normal and the colored zone is judged to be abnormal. As learning data, we used normality data of the period from start of use to around the 500th instance of switching. Judgment of being abnormal increased when the number of instances of switching exceeded 2,300, while the turnout experienced switching failure at around 2,570 instances of switching. This proved that abnormality data as a sign of turnouts switching failure can be found by estimating density ratio.

In this method, however, there were some judgment errors in the period from 0 to 2,000th instance of switching where normality data was judged to be abnormality. We will further investigate the optimal volume of learning data and setting of the threshold while increasing the number of samples of switching data.

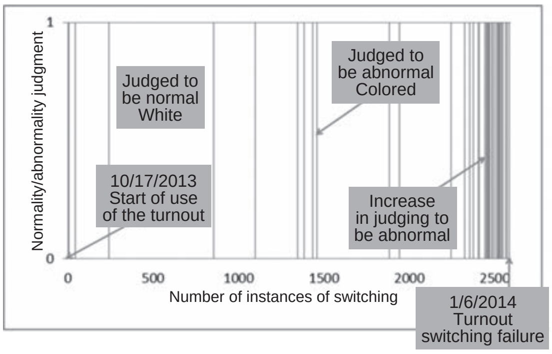

Fig. 11 Abnormality Detection Result by Estimation of Density Ratio

3.4 Results of Abnormality Detection by One-Class SVM

Fig. 12 shows the results of abnormality detection by one-class SVM. The horizontal axis is the number of instances of switching from start of use. On the vertical axis, 0 means judgment of being normal and 1 means judgment of being abnormal. The white zone is judged to be normal and the colored zone is judged to be abnormal. As learning data, we used normality data of the period from start of use to around the 500th instance of switching. Judgment of being abnormal increased when the number of instances of switching exceeded 1,000, while the turnout experiencing switching failure at around 2,570 instances of switching. This proved that abnormality data as a sign of turnouts experiencing switching failure can be found by one-class SVM.

In this method, however, there were more judgment errors than in other methods. We will further investigate applicability while increasing the number of samples.

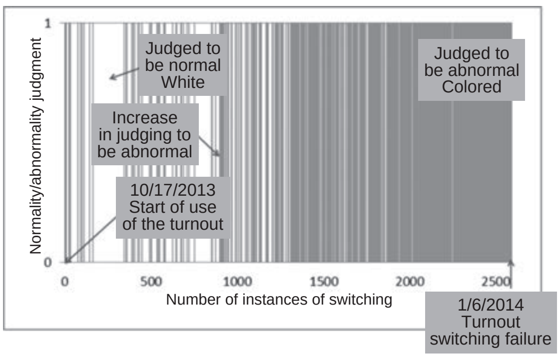

Fig. 12 Results of Abnormality Detection by One-Class SVM

4 Conclusion

In order to identify signs of turnout switching failure using the monitoring function of the ESII-type point machine, we examined various analysis methods and produced a prototype analysis device implementing the logic of individual analysis methods. We carried out tests with the prototype using actual data to investigate feasibility.

As a result, we were able to detect by all of the tested analysis methods abnormality data as a signs of turnout switching failure. There were, however, some issues such as judgment error where normality data was judged as being abnormality. We thus need to optimize the parameters and devise a warning output method for practical use while increasing data from actual point machines. We will conduct more analysis of switching data of turnouts without switching troubles for verification to put the analysis device into practical use. After improving judgment accuracy of the method of identifying signs of failure, we will study analysis of the factors behind turnout switching failure.

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