Featured Articles

Utilization of AI in the Railway Sector

Case Study of Energy Efficiency in Railway Operations

Ryo Furutani
Fumiya Kudo
Norihiko Moriwaki, Ph.D.

OVERVIEW: Leveraging its past track record in rolling stock maintenance of high-speed Class 395 rolling stock for the UK's High Speed 1 project, for which it received orders in 2005, Hitachi is advancing the expansion of its services business in the railway sector, for example, through the UK's Intercity Express Programme (IEP) and by providing rolling stock maintenance for Abellio, a railway operator. Condition monitoring systems that remotely monitor the condition of rolling stock will be the key to expanding and developing the services business. Hitachi is working on utilizing AI technology that it has developed to provide further added value using rolling stock information that is collected on a daily basis. This article covers power consumption while operating railway rolling stock, and presents an analytical case study of where feature values for reducing power consumption are identified using AI.

INTRODUCTION

INCREASED energy efficiency of railway systems, both inside and outside Japan, is being sought for the purpose of reducing CO_2 emissions as a measure against global warming[1]. Sixty to eighty percent of the energy consumed by railway systems is the energy used when operating rolling stock, and increasing the energy efficiency is effective in reducing CO_2 emissions. For this reason, Hitachi developed the A-train concept featuring a lightweight aluminum structure and main converters that apply silicon carbide (SiC) hybrid modules to achieve increased energy efficiency in the overall traction power supply system[2].

The utilization of data obtained by measuring operating rolling stock is pointed out as one means of verifying the energy savings from applying these technologies. With information and communication technology (ICT) progressing rapidly in recent years, there has been accelerated movement toward utilizing the diverse sensor information that is collected by railway systems in operation and maintenance (O&M) services. Hitachi, too, is expanding its rolling stock maintenance services through remote condition monitoring.

The use and application of artificial intelligence (AI) such as deep learning is being vigorously promoted as a technique for high speed and efficient processing of the vast amounts of information collected by these technologies.

This article describes a case study of the application of Hitachi AI Technology/H (hereafter referred to as H) to the analysis of energy saving performance in terms of rolling stock energy, and the future outlook for railway systems where AI is put to use.

UTILIZATION OF AI IN THE ANALYSIS OF ENERGY SAVING PERFORMANCE IN TRACTION POWER CONSUMPTION

Applications

In this case, some rolling stock operating data collected by remotely monitoring the condition of rolling stock was used to automatically extract the most effective feature values for reducing traction power consumption (i.e. the energy consumed by the traction power supply system when driving rolling stock motors) with H (see Fig. 1).

The technology on which H is based is a statistical technique in which the objective variables and explanatory variables must be assigned in advance. For this reason, the traction power consumption of the entire train per travel between stations at which the train stops as the objective variable for one sample, and the time-history data from the rolling stock operating

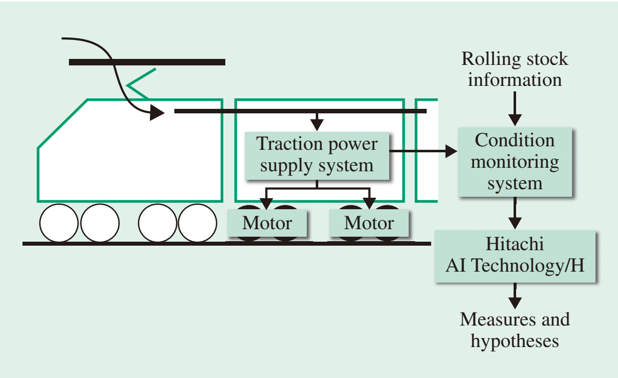

Fig. 1—Example of Utilizing H for Rolling Stock Operating Information.
Diverse sensor information during rolling stock operation is input into H, and parameters for reducing traction power consumption are automatically extracted.

TABLE 1. List of Data Input into H
Traction power consumption was provided as the objective variable, and rolling stock operating information and track infrastructure information were provided as explanatory variables.

No	Item	Item		Type	Unit
1	Objective variable	Traction power consumption		Number	kWh
2	Explanatory variables	Rolling stock operating information	Rolling stock travel speed	Number	km/h
3			Train mass	Number	kg
4			Individual carriage mass	Number	kg
5			External air temperature	Number	°C
6			Acceleration/deceleration	Number	m/s^2
7			Coupling information	Character	-
8			Operating information (notch)	Character	-
9			Up/down	Character	-
10			Operating date/time	Character	-
11		Track infrastructure information	Gradient	Character	-
12			Line feature value	Character	-
13			Curve information	Character	-

data at that time was directly assigned as explanatory variables (see Table 1).

Then, a distinctive technology of H, leap learning, was used to automatically and comprehensively generate the objective variables, correlations, and feature values having a large influence based on explanatory variables, including nine parameters of rolling stock operating data, such as the rolling stock travel speed (carriage speed), and three parameters of track infrastructure data, such as the track gradient information.

Furthermore, one year's (2013) worth of data that was collected when a specific train passes through four stations was used as the input data for H.

Application Results

Approximately 4,000 feature values were automatically generated by H based on the input data of the objective variable and explanatory variables shown in Table 1 (see Fig. 2).

The following shows one example of the feature values that were automatically generated:
(1) Carriage speed is 0 to 57 km/h
(2) Gradient is down gradient
(3) Operating time is 18:00 to 24:00 and Mass of carriage A is 45,000 to 48,000 kg

These features can be broadly divided into three categories: "feature values (1)" that are directly generated from numerical data, "feature values (2)" that are directly generated from character codes, and "feature values (3)" that are combinations of individual

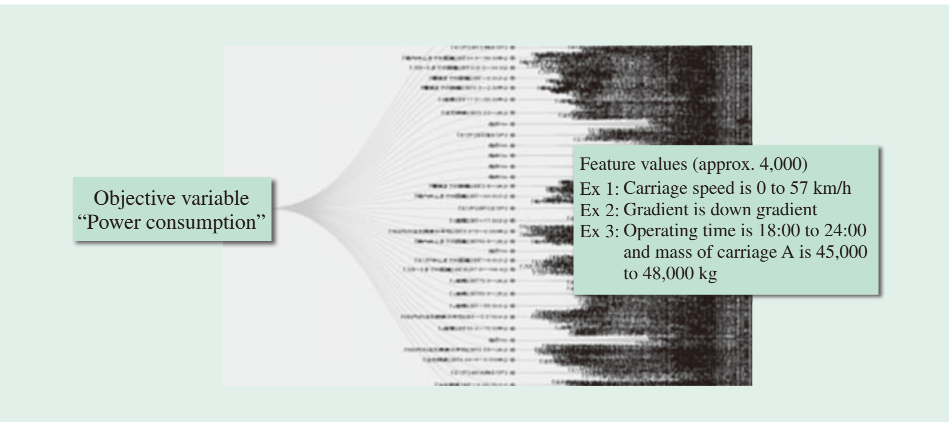

Fig. 2—Feature Values Generated by H.
For H, approximately 4,000 feature values were automatically generated from the 12 explanatory variables.

feature values. By analyzing the correlations between the objective variables and these automatically and comprehensively generated feature values, it is possible to gain knowledge and hypotheses that humans cannot process and that humans are not capable of noticing.

The following explains the effective feature values that were extracted from the approximately 4,000 automatically generated feature values. The following feature value, which has the highest negative correlation (correlation coefficient: –0.81) with traction power consumption, was extracted in August 2013:

Feature value: Operating information (notch) is Notch-off

The operating information feature value, notch, expresses a step in acceleration force for accelerating/decelerating rolling stock. For the railway rolling stock discussed in this article, among the notch positions, when the notch-off operating time is longer, traction power consumption shows a downward trend (see Fig. 3).

On the other hand, the extracted feature value with the most positive correlation with traction power consumption was the notch called “maximum notch (correlation coefficient: 0.73).” This means the maximum notch operating time should be lengthened. The fact that these feature values, notch-off and maximum notch, were extracted as effective feature values indicates that both are largely affected by driver operation. Also, in each of the other months of 2013, it was confirmed that there was a high correlation between each of the respective feature values and the objective variable.

Moreover, the traction power consumption on the vertical axis and feature value on the horizontal axis in Fig. 3 have been normalized by the travel distance of each of the four representative sections and by the travel time of each sample, respectively.

Next, Fig. 4 shows the carriage speed information and notch information for each of the following operations, Operation 1 and Operation 2, in the sample for representative Section A in Fig. 3.

Operation 1: Traction power consumption is large, and notch-off operating time is short (August 26, 2013).

Operation 2: Traction power consumption is small, and notch-off operating time is long (August 6, 2013).

According to Fig. 4, for the travel in Operation 1, travel under notch-off operation was conducted frequently for short distances, and there were long sections of travel under maximum notch operation.

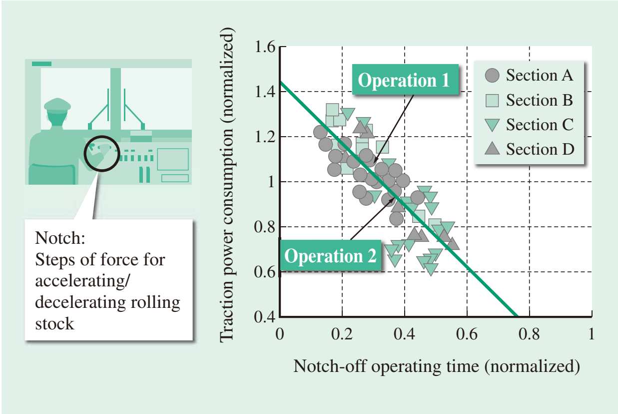

Fig. 3—Relationship between Traction Power Consumption and Notch-off Operating Time.
There is an extremely high negative correlation (correlation coefficient: −0.81) between the notch-off operating time and traction power consumption of the four representative sections on August, 2013.

Whereas, for the travel in Operation 2, travel under notch-off operation was conducted infrequently and over relatively long distances, and, in the latter half of this section, it can be confirmed that the rolling stock traveled in such a way that the section travelled under notch-off operation was longer. From this fact, it can be confirmed based on the data obtained by measuring actual rolling stock operation, that there are differences in driving skills even in the same section of travel.

Estimating the Effect of Energy Consumption Reduction

Fig. 5 shows the correlation between traction power consumption and notch operating times (notch-off, maximum notch) in Section B for the period of one year, 2013. According to the figure, the longer the maximum notch operating time is, and the shorter the notch-off operating time is, traction power consumption increases. Alternatively, it can be seen that a relationship exists where traction power consumption decreases when the maximum notch operating time is shorter and the notch-off operating time is longer. Furthermore, it can be seen that there is large variation in each of the samples and there is room for improving traction power consumption.

In this respect, if we assume that operation has improved in the 20% superset that has small traction power consumption along the regression line in Fig. 5, then a yearly decrease in traction power consumption of approximately 20% can be anticipated. Furthermore, the relationship between traction power consumption

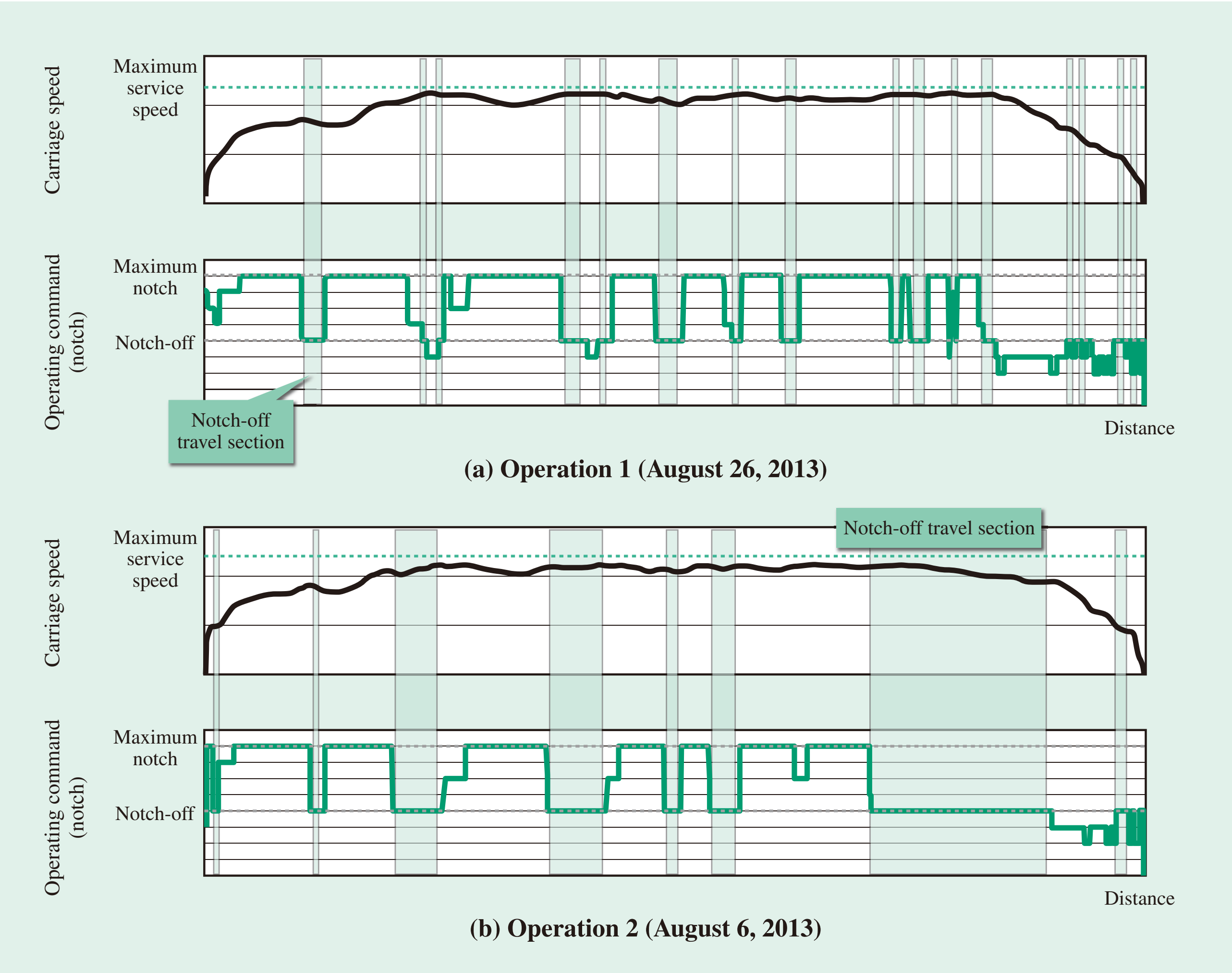

Fig. 4—Comparison of Carriage Speed Information and Operating Command Information in Section A.
With travel under Operation 2 where the traction power consumption is small, travel was conducted under relatively long notch-off operations.

and notch operating time shown in Fig. 5 shows the same tendency in the other three representative sections. And, when the four representative sections are taken as a whole, it can be confirmed that a yearly power consumption reducing effect of approximately 14% can be anticipated. Rolling stock operation information in which rolling stock ran punctually according to operating travel times was used for this analysis.

This case study introduced a study where H was applied with data limited to a representative train and four representative sections, however, Hitachi is currently proceeding with analysis of expanded travel distances using multiple trains. It is also proceeding with analysis using an expanded amount of information for explanatory variables such as the operation status of the traction power supply system which was not targeted as an explanatory variable in this article.

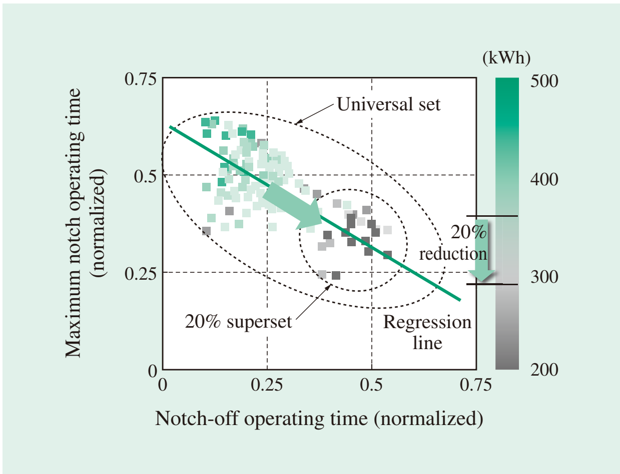

Fig. 5—Visualization of Relationship between Notch Operating Time and Traction Power Consumption.
For the year 2013, the variation in notch operating times was large, and when operation improvements were assumed, it was found that a power consumption reduction effect of about 20% could be anticipated for the year in representative Section B.

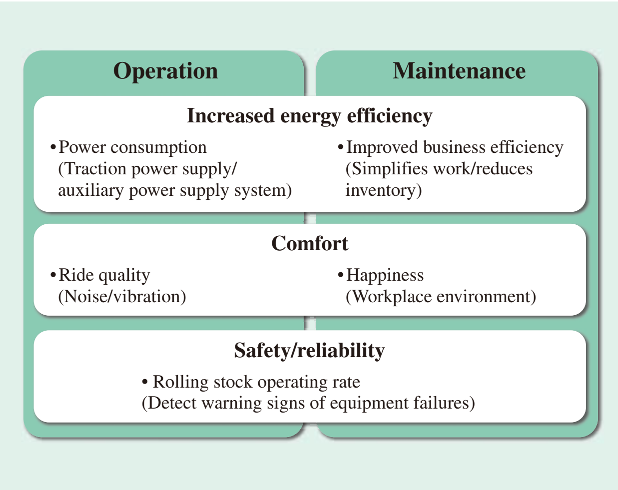

Fig. 6—Example of Applicable Targets on Railway O&M Services. This figure shows some applicable targets for H with respect to increased energy efficiency, comfort, and safety/reliability.

FUTURE OUTLOOK OF RAILWAY SYSTEMS THAT UTILIZE AI

In the future, it is anticipated that H will be applied in various situations on diverse big data that is collected by railway systems. In particular, the applied deployment of H in railway O&M services that is being promoted by Hitachi is described below (see Fig. 6).

In railway operations, comfort, etc. is one representative key performance indicator (KPI) in addition to the increased energy efficiency introduced in the applied case study mentioned above. For increased energy efficiency, it is conceivable that the power consumption of the auxiliary power supply system used, for example, for operating air conditioning or opening/closing doors, will be targeted in addition to the power consumption of the traction power supply system. The extraction of new knowledge can be anticipated since power consumption is affected more substantially by the behavior of people in the carriages. And since there are also two ways of operating, by electric rolling stock and by rolling stock with diesel engines, depending on carriage composition, the identification of increased energy efficiency measures in operation management can also be anticipated. With regard to comfort, comfort parameters relating to ride quality, such as vibration and noise can be targeted and design guidelines for operating rolling stock comfortably and safely may conceivably be gained.

Next, indices relating to the work efficiency of maintenance workers and the rolling stock utilization rate resulting from rolling stock malfunctions can be pointed out as representative KPIs in railway maintenance. If wearable sensors are made use of in maintenance services, measures for improving and enhancing work efficiency can conceivably be identified based on maintenance workers' daily activities. Moreover, maintenance workers' level of well-being (happiness) also could be applied as a measure for improving work efficiency. By improving the rolling stock utilization rate, it is anticipated that the relationship between the time-related deterioration of rolling stock and the operating conditions of rolling stock will be discovered from H, and that this can be applied to the detection of the warning signs of equipment failure.

CONCLUSIONS

This article introduced a case study where H was applied to automatically extracting feature values to reduce the power consumed in driving rolling stock, and described the future outlook for applications of H in railway O&M services.

Hitachi intends to accelerate the full-scale application of AI to the railway sector, and to promote further initiatives for increasing energy efficiency in railway operations and for improving efficiency in rolling stock maintenance.

REFERENCES

(1) Moving Towards Sustainable Mobility—A Strategy for 2030 and beyond for the European railway sector, UIC (2012).
(2) T. Mochida et al., "Development and Maintenance of Class 395 High-speed Train for UK High Speed 1," Hitachi Review **59**, pp. 39–46 (Apr. 2010).

ABOUT THE AUTHORS

Ryo Furutani

Transportation Systems Research Department, Center for Technology Innovation – Mechanical Engineering, Research & Development Group, Hitachi, Ltd. He is currently engaged in the research and development of condition monitoring systems for railways. Mr. Furutani is a member of the The Japan Society of Mechanical Engineers (JSME).

Fumiya Kudo

Intelligent Information Research Department, Center for Technology Innovation – Systems Engineering, Research & Development Group, Hitachi, Ltd. He is currently engaged in the research and development of AI and big data analysis based on statistical approaches.

Norihiko Moriwaki, Ph.D.

Intelligent Information Research Department, Center for Technology Innovation – Systems Engineering, Research & Development Group, Hitachi, Ltd. He is currently engaged in the research and development of human information systems and AI. Dr. Moriwaki is a member of the Institute of Electronics, Information and Communication Engineers (IEICE), The Japan Society for Management Information (JASMIN), Association for Information Systems (AIS).