Innovation in Railway Maintenance utilizing Information and Communication Technology (Smart Maintenance Initiative)

Mitsunobu Takikawa

Introduction

Information and communication technology (ICT) is advancing at a tremendous pace in recent years, and is set to change the social environment and composition of industry. The 'Industry 4.0' national project started in Germany in April 2013 is attempting to create a fourth industrial revolution to change the composition of Germany's manufacturing industry using the Internet of Things (IoT) and 'big-data' technology. In March 2014, the Industrial Internet Consortium was launched by the private sector in the USA with participation of big companies, such as GE, IBM, Intel, Cisco, and AT&T. This plan also uses IoT and big data-related technologies to make industry as a whole smarter, and maintenance more efficient.

With major changes to global society using ICT, Japan's railways too must change proactively to become the transportation mode chosen by society in this new environment. The Research and Development Center of the JR East Group has proposed a 'Smart Maintenance Vision' so as not to fall behind in these changes, and is working on R&D for innovation of railway maintenance. This article introduces trends in ICT and the Smart Maintenance Vision along with case examples of R&D currently under way.

Recent Social Conditions in Japan

Japan's population is already declining. Its industry experienced many past successes in high-quality *monozukuri* (manufacturing) by mass-production amidst the post-war population increase and high-economic-growth era. But changes to the economic structure with falling population, diversifying values, and globalization, mean conventional ways of doing business no longer apply, and not even large corporations can rest easy.

Companies that are growing recently are creating new business models using the latest ICT. For example, a manufacturer of photocopiers successfully switched from manufacturing and selling photocopiers to a new business leasing model, making large profits (Figure 1). This new business model was successful because advances in ICT allow the company to identify the operational status of individual photocopiers at low cost, enabling maintenance before failures.

This can be said to be the

Figure 1 Change of Business Model

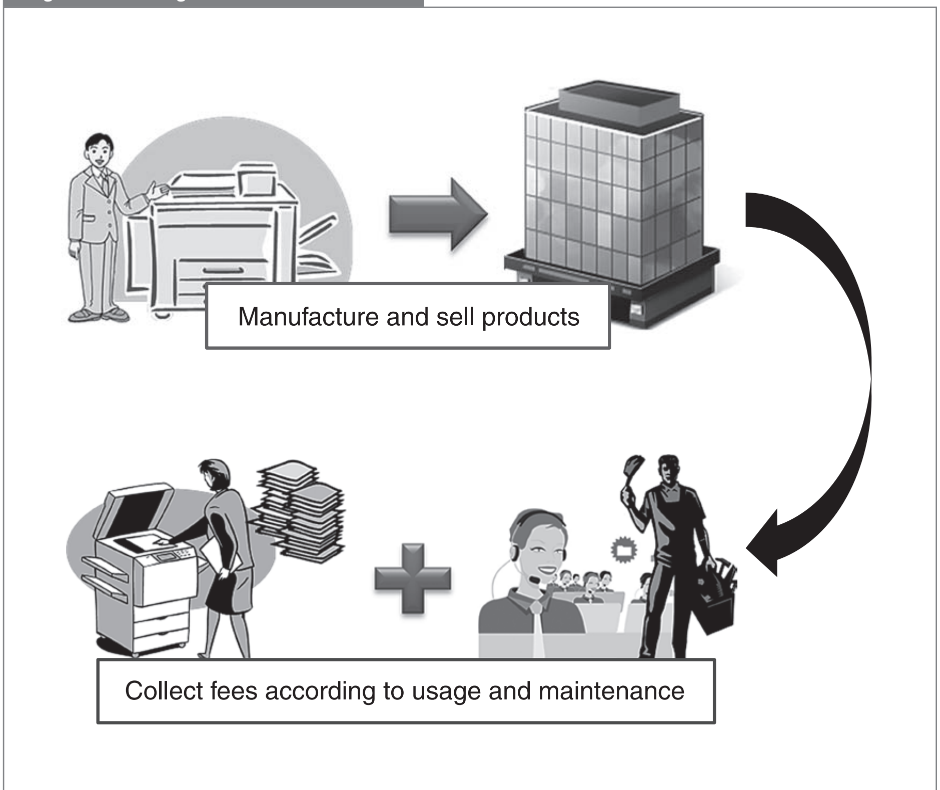
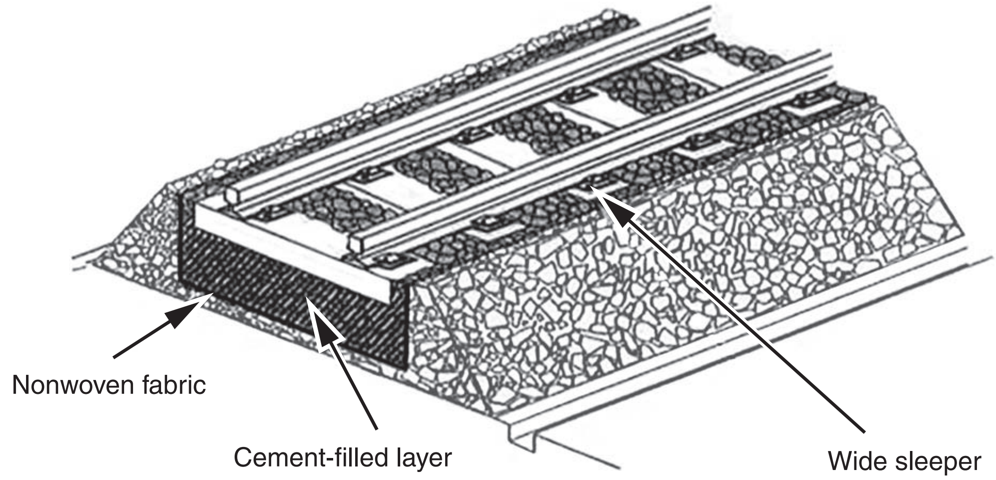


Figure 2 Low-maintenance Track



result of changing from tangible manufacturing to intangible services, utilizing ICT at the core.

Looking at railway maintenance from the same perspective, the function of conventional R&D has been to break from 3D (dangerous, difficult, dirty) work and reduce equipment maintenance costs. For example, in the area of tracks, low-maintenance tracks (Figure 2) and the like have been developed to mechanize inspection and repair so as to reduce the need for maintenance. This has reduced failures and human errors using a tangible approach. However, railways face a major change in the social environment, so maintenance must change too. Looking at case examples in other industries, intangible approaches will be needed.

Latest Trends in ICT

This section covers trends in ICT and discusses ideas for future railway maintenance.

Internet of Things (IoT)

IoT is a method for enabling 'things' to exchange information via the Internet. In the future, we may exchange information based on data gathered via sensors while being unaware that the other side is a machine; Machine to Machine (M2M) is another term with similar meaning but the IoT concept includes people as 'things'. The main purpose of M2M is to increase efficiency by automatic control of machines, aiming for a 'smart' society. IoT has come to the focus of attention due to the increase in devices and sensors that can be carried by people and the creation of a ubiquitous communications environment. For example, smartphones have many sensors, such as GPS (Global Positioning System) receivers and accelerometers, in addition to telephone and email functions. It is no exaggeration to say they are full-fledged all-purpose sensors with communications functions, and it is amazing that such devices can be purchased for less than ¥100,000 (approximately US$850).

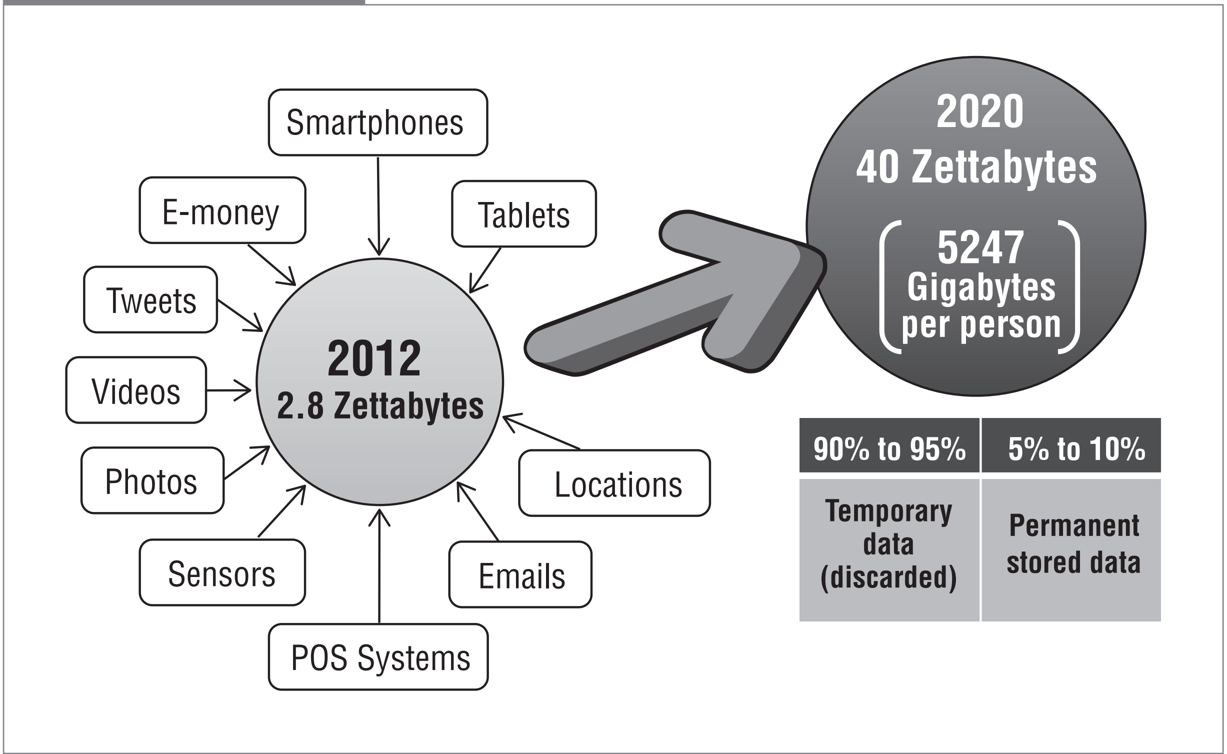
IoT is already being used for purposes such as monitoring aircraft flights and automobile status. For example, in the aviation industry, sensors throughout the aircraft monitor the status during flight. The large volumes of data are analyzed and used to identify signs of failures in advance. In railways, embedding sensors in rolling stock and mechanical equipment would enable similar maintenance.

Big Data Analytics

Big-data analytics has been used in recent years in areas such as online shopping recommendation functions and social network analysis. In IT companies and among experts, 'big data' means more than just lots of data, and is interpreted as data leading to knowledge that is helpful in corporate management and business and in people's lives. Big data includes diverse types as shown in Figure 3, including text information typified by 'tweets' and similar social networking services (SNS), photos and videos, logs generated when accessing websites and the like, and information from various sensors. The data volume amounted to 2.8 Zettabytes (ZB) (2.8×10^{21} bytes) in 2012, and is expected to grow 14-fold to 40 ZB in 2020.

In addition to services, there are expectations for big data technologies in the maintenance field. The problem of aging infrastructure built during Japan's high economic growth era has come into focus, and the Ministry of

Figure 3 Future Data Volumes



Internal Affairs and Communications (MIC) estimates that the economic impact of preventive maintenance on road bridges will be ¥270 billion. Bridges, tunnels, and other structures are maintained for railways as well because they are part of the social infrastructure. Like roads, applying big-data analytics technologies to maintenance work should bring about new industries and help make maintenance more efficient.

Artificial Intelligence (AI)

Research on AI started in the 1950s, and rule-based expert systems were in the spotlight in the 1980s. These expert systems were an attempt to express the complexity of the real world by rules alone, but they ended in failure. Reflecting the lessons learned, current AI has become closer to the thought patterns of humans by ignoring rules for data input and speculating on results by statistical processing. Recent examples of AI are Watson, which beat the champion of a famous American TV quiz programme in 2011, and Ponanza, which beat a professional *shogi* (Japanese chess) player in an official match in 2013.

Current AI systems are based on machine learning where humans teach answers. That machine learning evolved further with Deep Learning developed by Stanford University and Google in the USA in 2012. Deep Learning successfully obtained the concept of a ‘cat’ from images on a network without being taught by humans. In other words, AI became able to learn on its own without relying on humans to build knowledge. This Deep Learning technology is used not only in image recognition, but also as voice recognition technology in smartphones and tablets.

The knowledge of AI including Watson and Ponanza is a database where past knowledge is accumulated. In railway maintenance, past data gained from periodic inspections and reports of incidents is stored on many systems. If this data could be utilized effectively, there is a high possibility that we could build AI with abilities greater than veteran engineers.

Environment Surrounding Railway Business

This section describes issues related to future maintenance in terms of the environment surrounding JR East’s railway business. First, we organize issues from the standpoint of maintenance costs, and second, from the makeup of personnel.

Railway Maintenance Expenses

Figure 4 shows the changes over time in railway equipment maintenance costs and Figure 5 shows the changes in capital investment. Maintenance costs have not changed much since 1988 after the privatization of Japanese National

Figure 4 Maintenance Costs

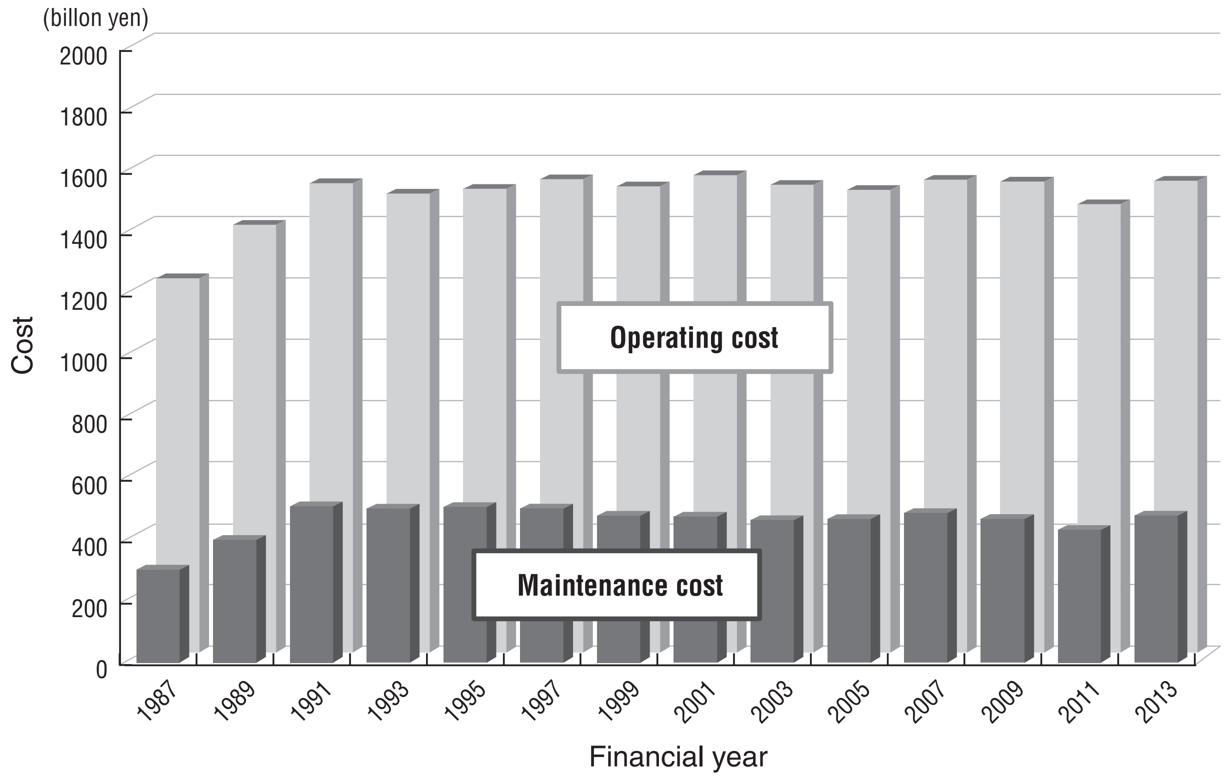
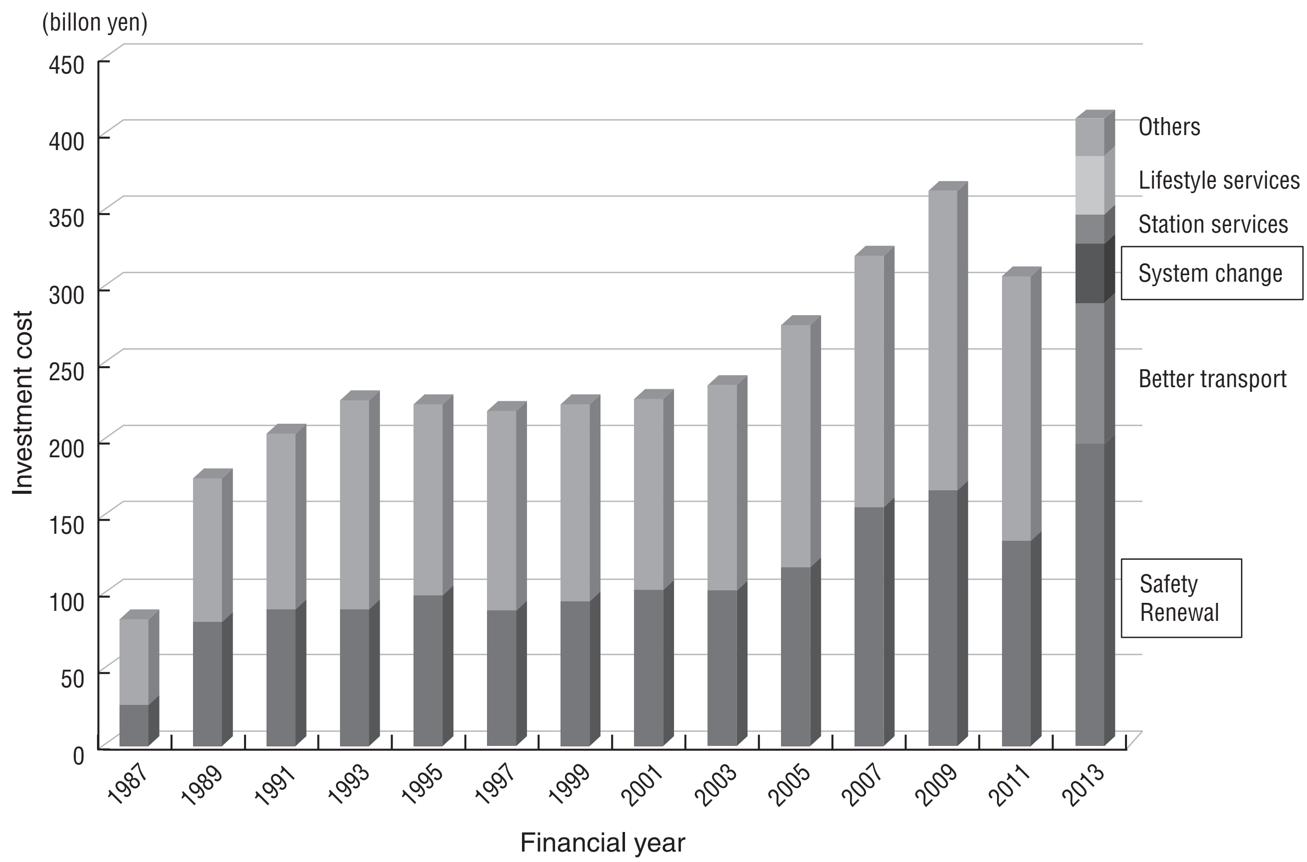


Figure 5 Investment Costs



Railways (JNR), making up between 25% and 33% of overall railway operating costs. Overall railway capital investment has been around ¥200 billion since privatization, but has been increasing in recent years. Capital investment declined in 2011 as a result of the Great East Japan Earthquake and tsunami. The amount for replacement of dilapidated infrastructure-related equipment is included in the item for safety and renewal. However, new maintenance-free equipment in the future is being introduced at equipment updates, so those expenses are included in the system change item. The low-maintenance track shown in Figure 2 is an example.

However, in current society with a decreasing population, there is no guarantee that today's expense structure and capital investment amounts can be maintained. With the anticipated fall in the number of passengers (and resultant decrease in railway revenues) coupled with increases in personnel costs as a result of a workforce shortage, the time to develop a new maintenance structure is coming.

Age Composition of Personnel

JR East had a total of 59,240 employees at 1 April 2014. Of these people, approximately 20% (11,530) are involved directly in maintenance of rolling stock and wayside equipment. Figure 6 shows the age composition for all personnel. Veteran experts age 50 or older who bear a central role in railway operation make up 43% of all employees, and they will be retiring within 10 years. Almost the same trend can be seen in maintenance, with few people in the mid-level segment in their 40s, making passing-on skills to new hires a pressing issue.

Smart Maintenance Initiative

The Research and Development Center of JR East Group has proposed the Smart Maintenance Initiative to create innovation in future railway maintenance from the perspectives of major changes in Japan's social environment with falling population, rapid progress in ICT, and the management environment. The Smart Maintenance Initiative is not a tangible approach to mechanizing maintenance work and enhancing equipment. Instead, it is an intangible approach of proposing a new structure for maintenance. The Smart Maintenance Initiative is made up of the four challenges shown in Figure 7: achieving condition based maintenance (CBM), introduction of asset management, work support by AI, and database integration. The following explains these four challenges.

Figure 6 Age Composition of Personnel

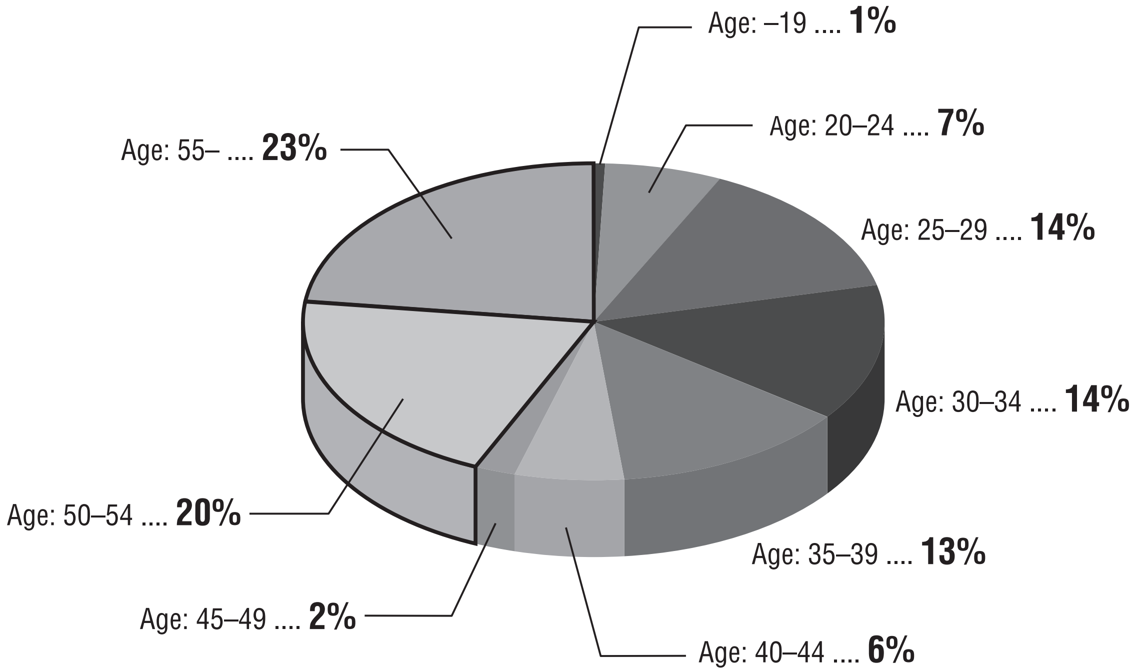


Figure 7 Four Pillars of 'Smart Maintenance Initiative'

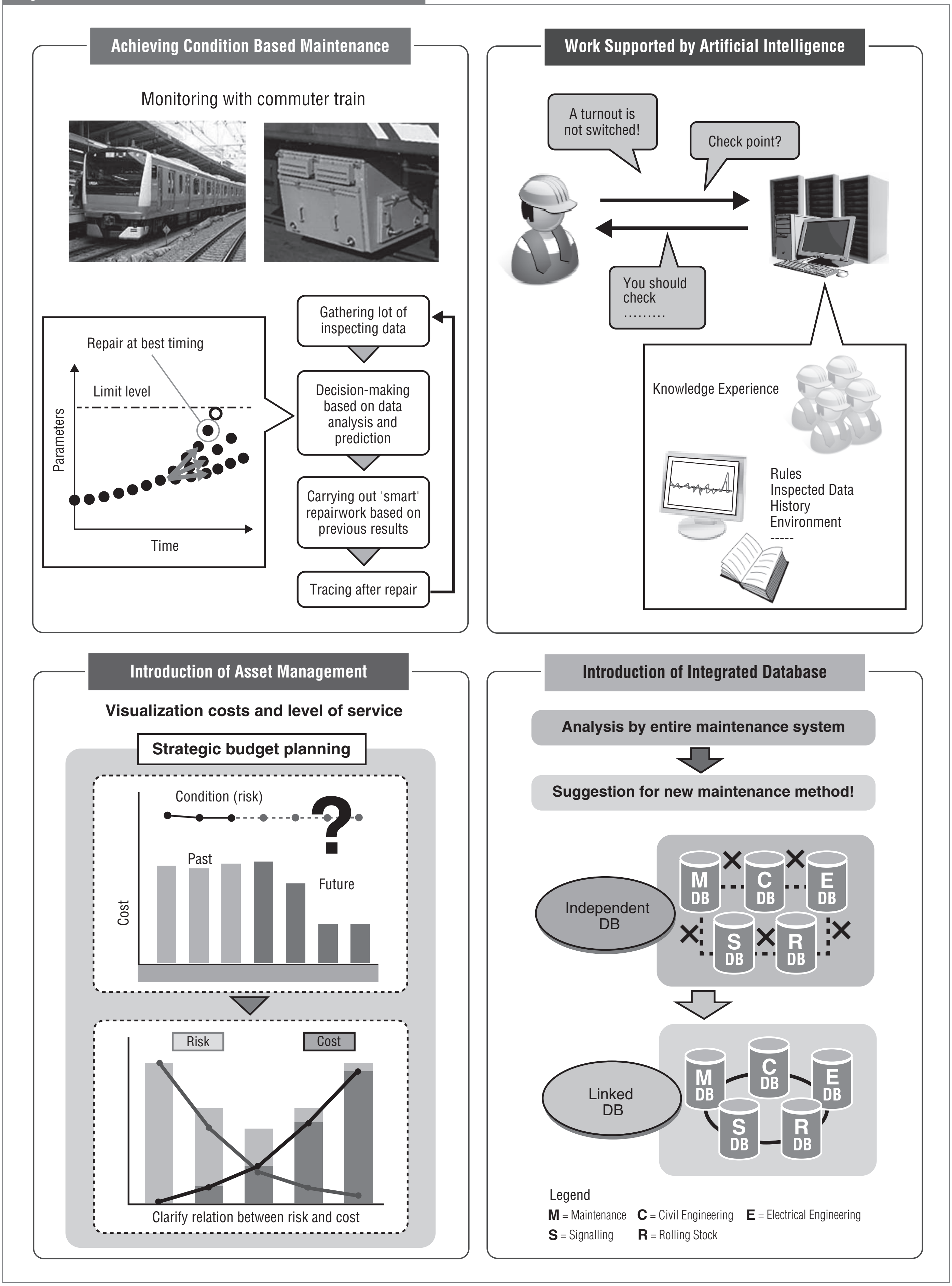
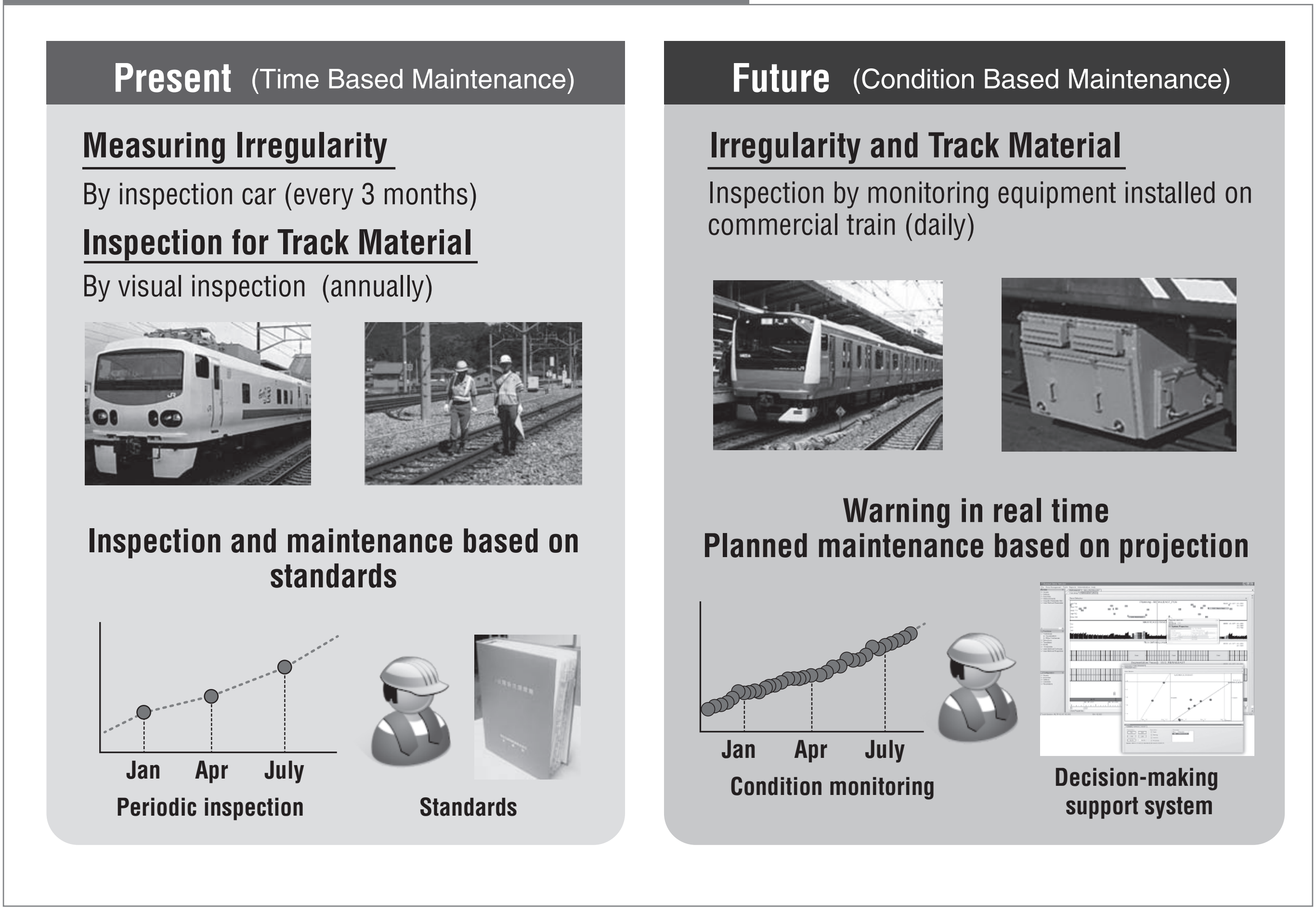


Figure 8 Time Based Maintenance and Condition Based Maintenance



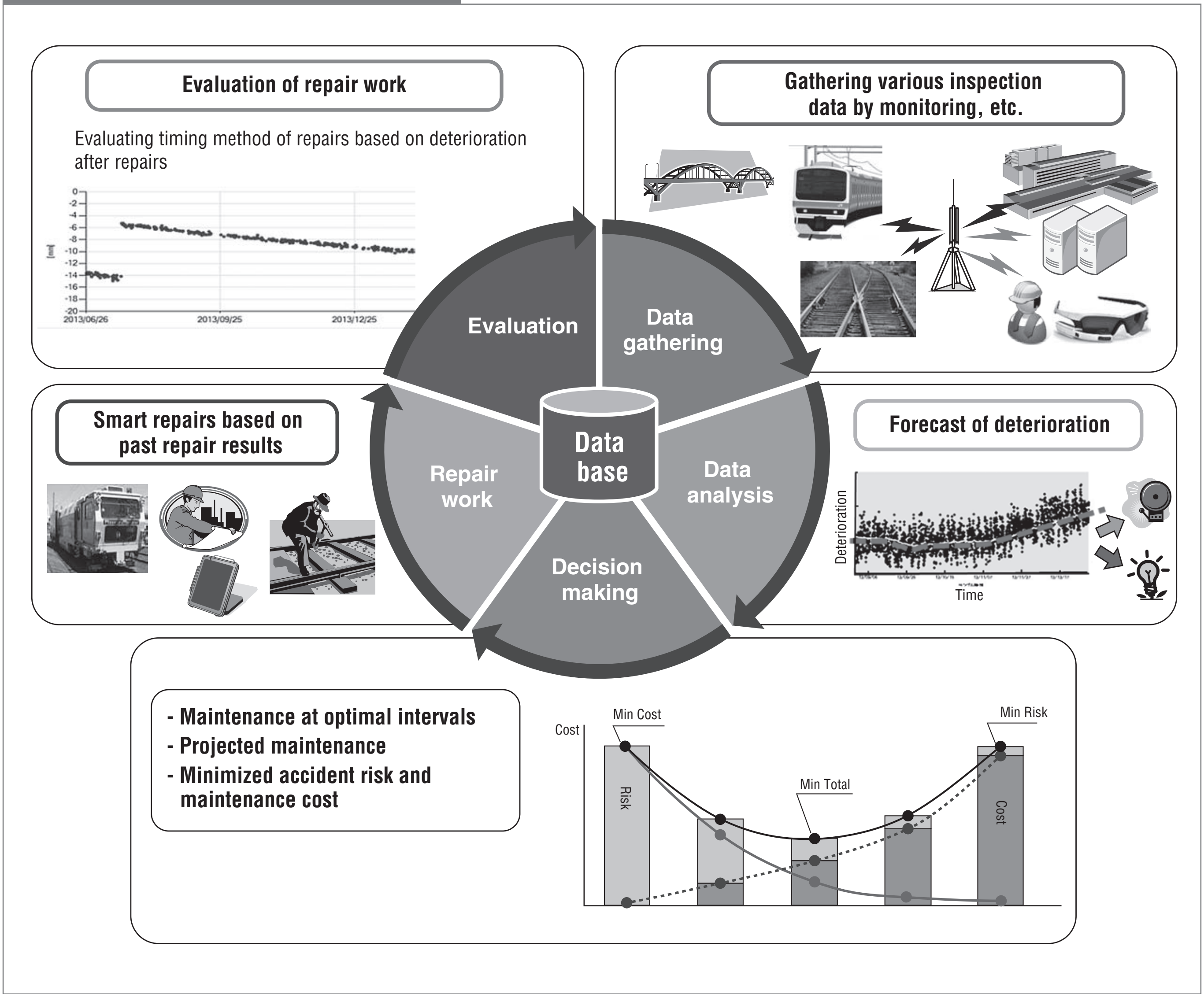
Achieving Condition Based Maintenance (CBM)

Achieving Condition Based Maintenance means changing the basis of maintenance from Time Based Maintenance (TBM) to Condition Based Maintenance (CBM). This entails a major change in the maintenance philosophy. The difference between the two is explained as follows using an example of maintenance for tracks, a typical type of railway equipment (Figure 8). Conventionally, in TBM, inspections are conducted at regular cycles (once every 3 months for narrow-gauge track) to obtain data on deformations (track irregularity). Track repairs are conducted when a threshold decided based on experience (for example, 23 mm) is exceeded. That threshold is decided based on maximum deterioration taking into consideration track irregularity (for example, 40 mm) at which derailment could occur based on past data and the 3-month inspection cycle. Inspections are assumed to be performed at a set cycle, so the threshold is uniform regardless of the track environment and a sufficient leeway must be set.

Conversely, CBM is based on monitoring the status of facilities and equipment rather than performing inspections at set intervals. In the example of tracks, obtaining track displacement data from trains in operation would allow such displacement data to be obtained every day. Analyzing that data would allow detailed identification of the speed at which track deteriorates per 1 m (per track environment). As a result, track deterioration could be predicted, allowing repairs at the optimum timing. Decision-making based on predictions would be a fundamental change in railway maintenance.

Moreover, if displacement data could be obtained every day, the effects of repairs would be instantly evident. In other words, with CBM, the cycle shown in Figure 9 could be followed on a daily basis. That cycle entails obtaining data, analyzing data, making decisions, conducting repairs, and evaluating the results (obtaining data). The more data is accumulated, the smarter the important decision-making process becomes. Conversely, in TBM, justification for decision-making is prescribed by rules (internal regulations, etc.), so there is inevitably little awareness about responding flexibly according to budget status, etc. In fact, maintenance criteria for track repair have not changed in about 50 years.

Figure 9 Condition Based Maintenance Cycle



Introduction of Asset Management

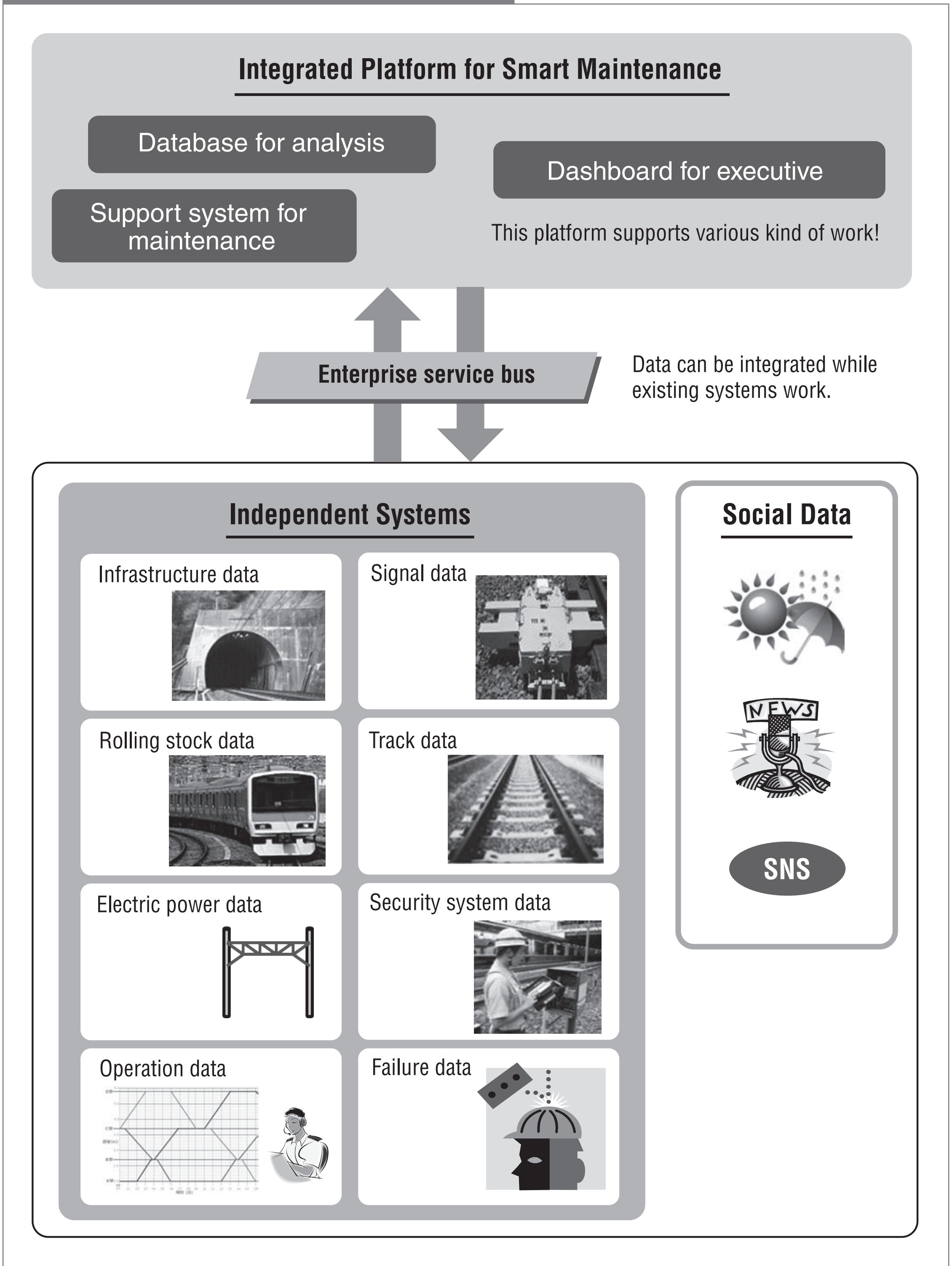
Asset management is the concept of considering equipment as assets and efficiently managing them from a long-term view. There are many case studies on this for bridges, tunnels, and other civil-engineering structures where deterioration is slow and the scale of repair work is large. However, there are currently few examples as an actual business practice. A possible reason is because identifying equipment and evaluating deterioration over the long term are difficult. If these issues could be overcome by smart maintenance, maintenance engineers could compare various repair methods and periods based on the deterioration status of equipment. This would enable optimum repair plans to be proposed over a long-term span. Like CBM, this concept is thought to be a method of supporting decision-making by maintenance engineers.

Work Support by AI

The purpose of work support by AI is to back-up evaluation work currently done by maintenance engineers. Here, AI is more than a support system using unstructured data, such as text and images; it can be applied to discovering new relationships beyond human experience by big-data analysis using structured data.

The following introduces a support method for when equipment failure occurs as a past case example using text data. When equipment failure occurs, maintenance engineers need to quickly identify the cause of the failure. Experienced engineers can accurately infer the failure cause based on past experience, the status of equipment, and various environmental conditions to quickly recover from the failure. However, it is difficult for engineers with little experience to identify the cause of a failure. If we create a

Figure 10 Integrated Platform for Smart Maintenance



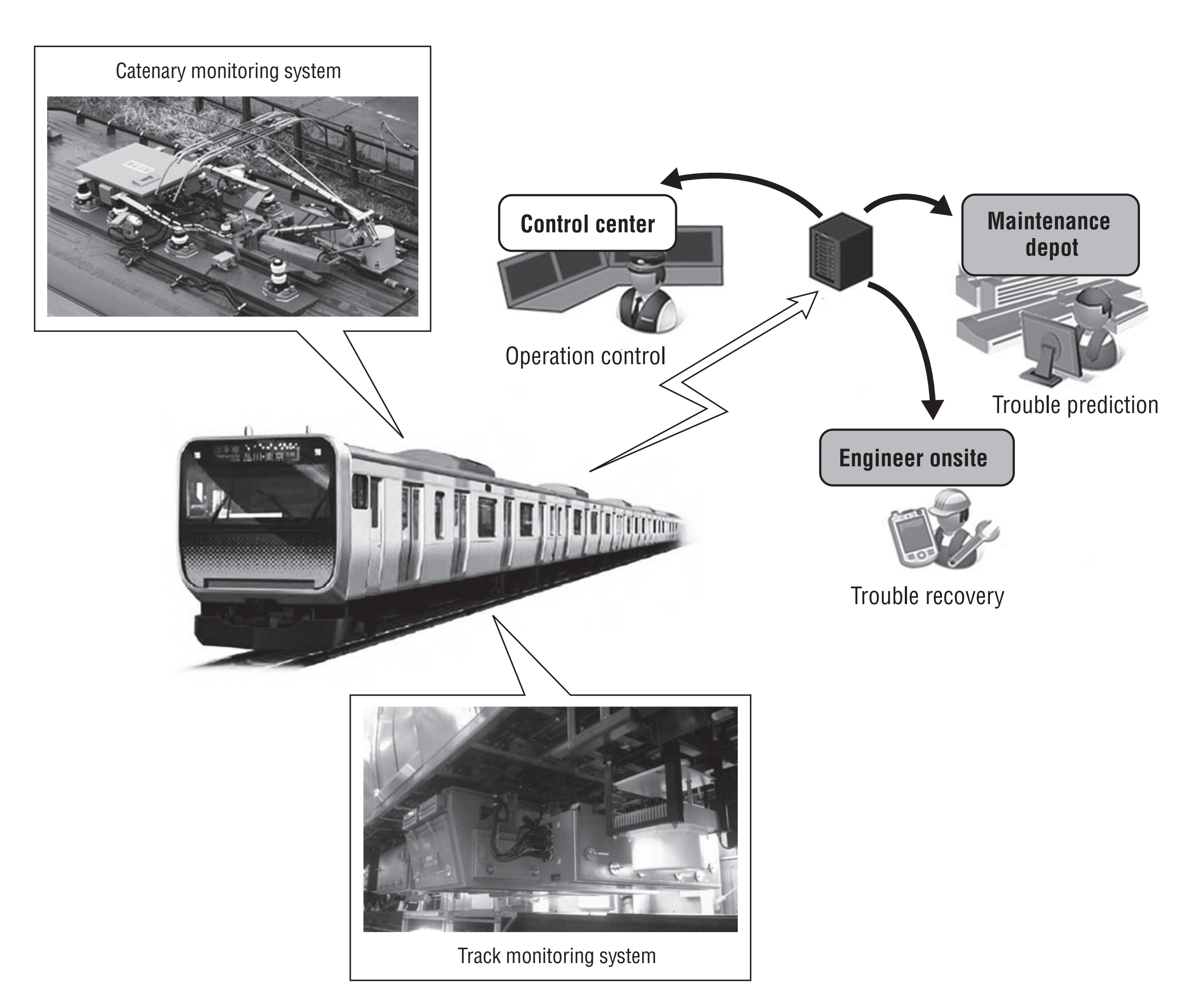
database of the tacit knowledge and experiences of veteran engineers and utilize AI-related technologies, we should be able to infer the cause of failures.

Database Integration

To make CBM a reality, introduce asset management, and achieve work support by AI, we need an environment where data is handled freely. JR East currently has various systems for individual divisions. These were established to optimize divisional work, so each has a completely independent system structure; the individual systems are not linked, and there is no common data strategy.

To make quick management decisions and provide better support to front-line divisions, it is important to

Figure 11 Monitoring Train: Series E235



manage the vast amount of data held by the company in a centralized manner. In other words, we need to integrate the separate internal systems and construct a large system (common platform based on individual databases) that can also link with external data (weather information and SNS data). Figure 10 shows this concept. Using this platform everyone from front-line organizations to management will be able to use the same data, allowing quick and accurate decision-making in the company.

Efforts in R&D

We are conducting various R&D to achieve smart maintenance. Three case studies are introduced here.

Monitoring Train: Series E235

Figure 11 shows Series E235 commuter rolling stock manufactured in 2015 for Tokyo's Yamanote Line. This is the world's first rolling stock to monitor its own onboard devices as well as wayside equipment (track equipment and power equipment) while operating. Monitoring data captured onboard is sent to the wayside by wireless communications and distributed to dispatch and maintenance worksites. Data received by an individual worksite is analyzed and can be used to plan later maintenance.

One example of monitoring data analysis is track irregularities captured by a track monitoring system on other rolling stock. Data for the same location is captured up to five times. Figure 12 shows the change in track irregularities after repairs. We can see that track subsidence after

Figure 12 Analyzed Monitoring Data (Track Irregularity)

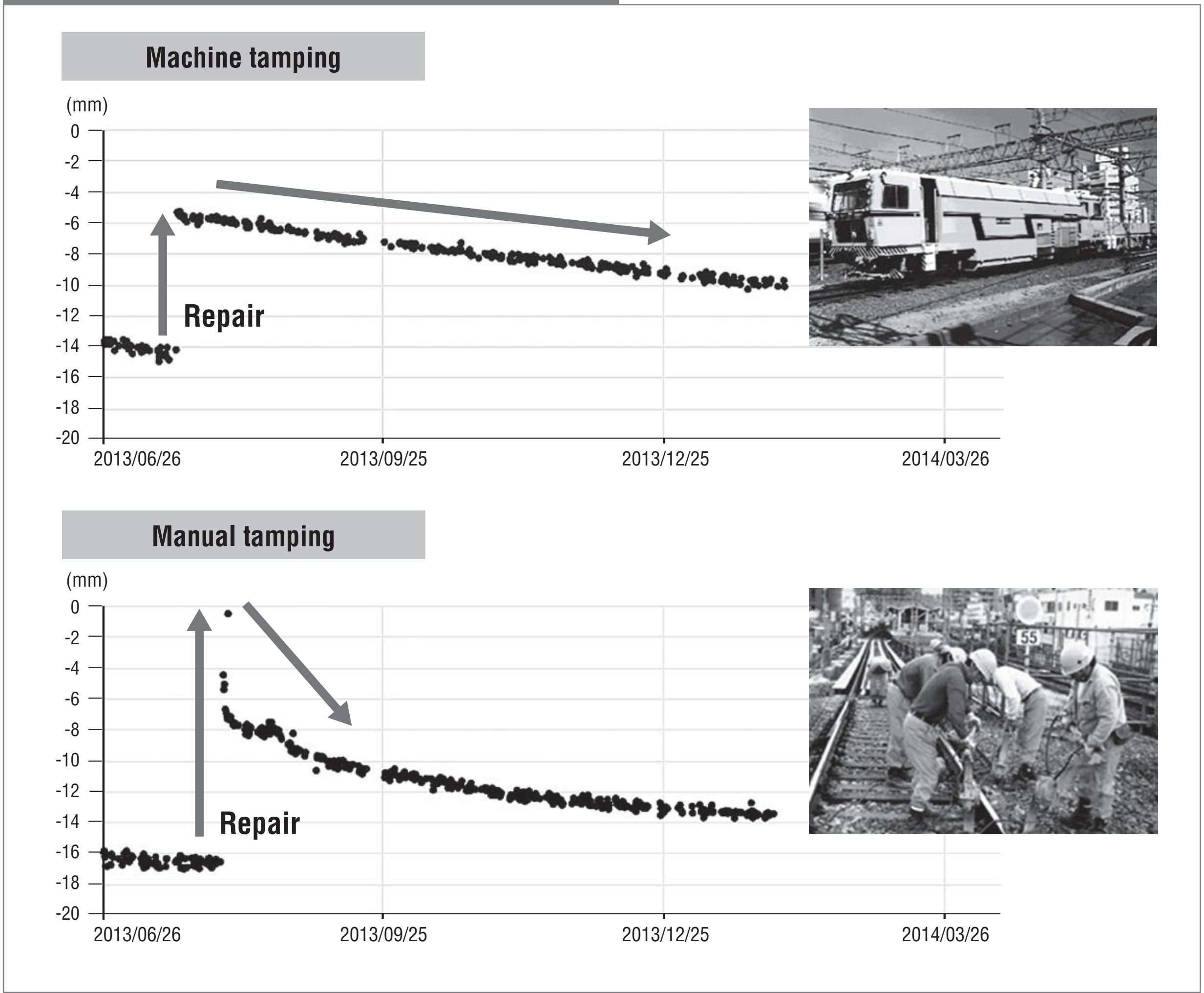


Figure 13 Example of Maintenance Support System

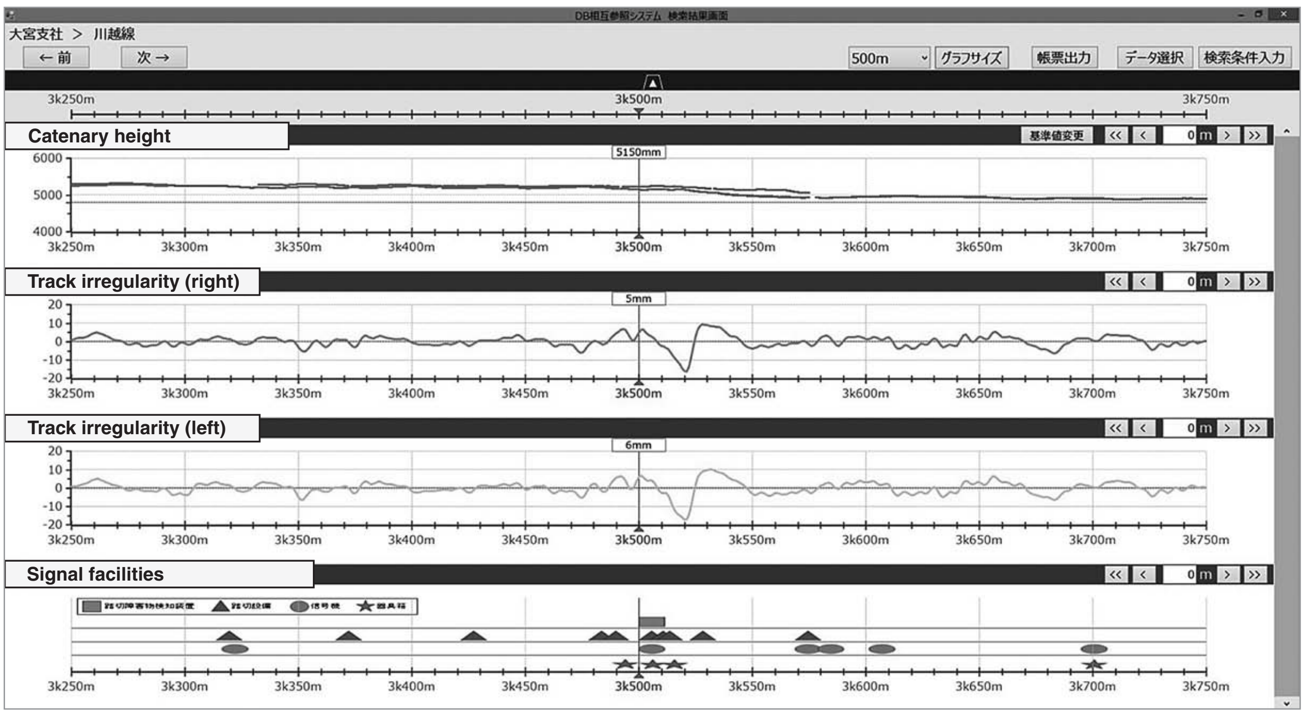


Figure 14 Point Cloud Data with Mobile Mapping System

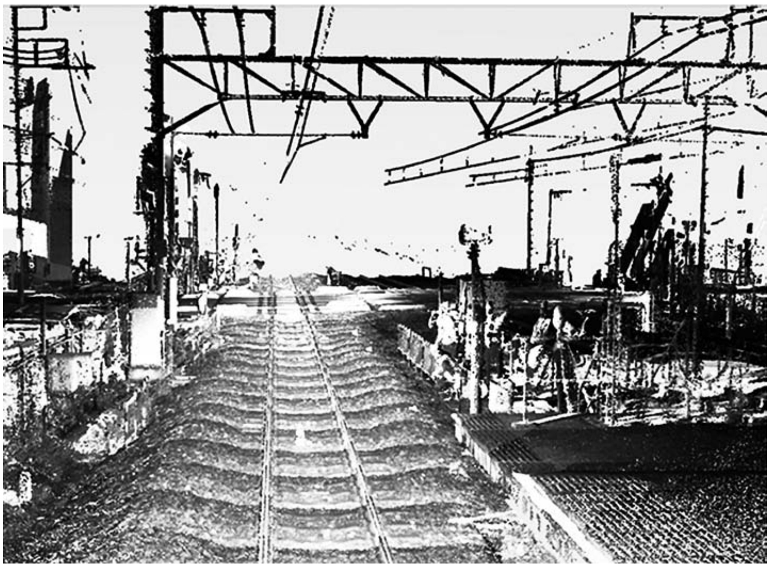
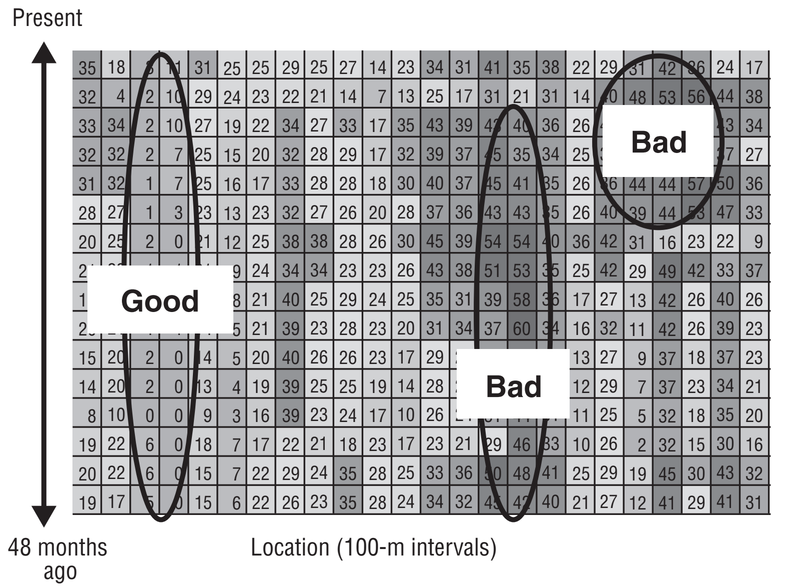


Figure 15 Heat Map Showing Track Condition History



department. We first built a prototype virtual environment and support tool where equipment and inspection information separated by system are displayed on a single screen to extract issues to solve. Figure 13 is a case study of a chart where power and track maintenance equipment is inspected and the location status of communications equipment is displayed as a list. This study showed that location information and time information are important in coordinating railway maintenance. Some equipment does not have location information, and we confirmed the necessity of providing it efficiently.

We are considering use of Geographic Information Systems (GIS) already introduced by railways in other countries as a method for efficiently managing equipment location information. Coordinates (longitude and latitude) are necessary to use GIS. For this reason, we need to build a database of coordinate information for equipment without location information. A possible solution is to use Mobile Mapping Systems (MMS). With MMS, the surrounding trackside equipment can be acquired as 3D data while running a maintenance vehicle. Figure 14 shows an example of an image obtained by measurements. Although the figure looks like a photograph, it is actually a collection of points, and each point has coordinate information. Using this data, we can efficiently obtain coordinate information about equipment.

manual repairs occurs earlier than after mechanical repairs. By constantly conducting such analysis, we can discover deterioration details by location according to differences in repair method and environment, supporting efficient maintenance.

Platform for Big-Data Analytics

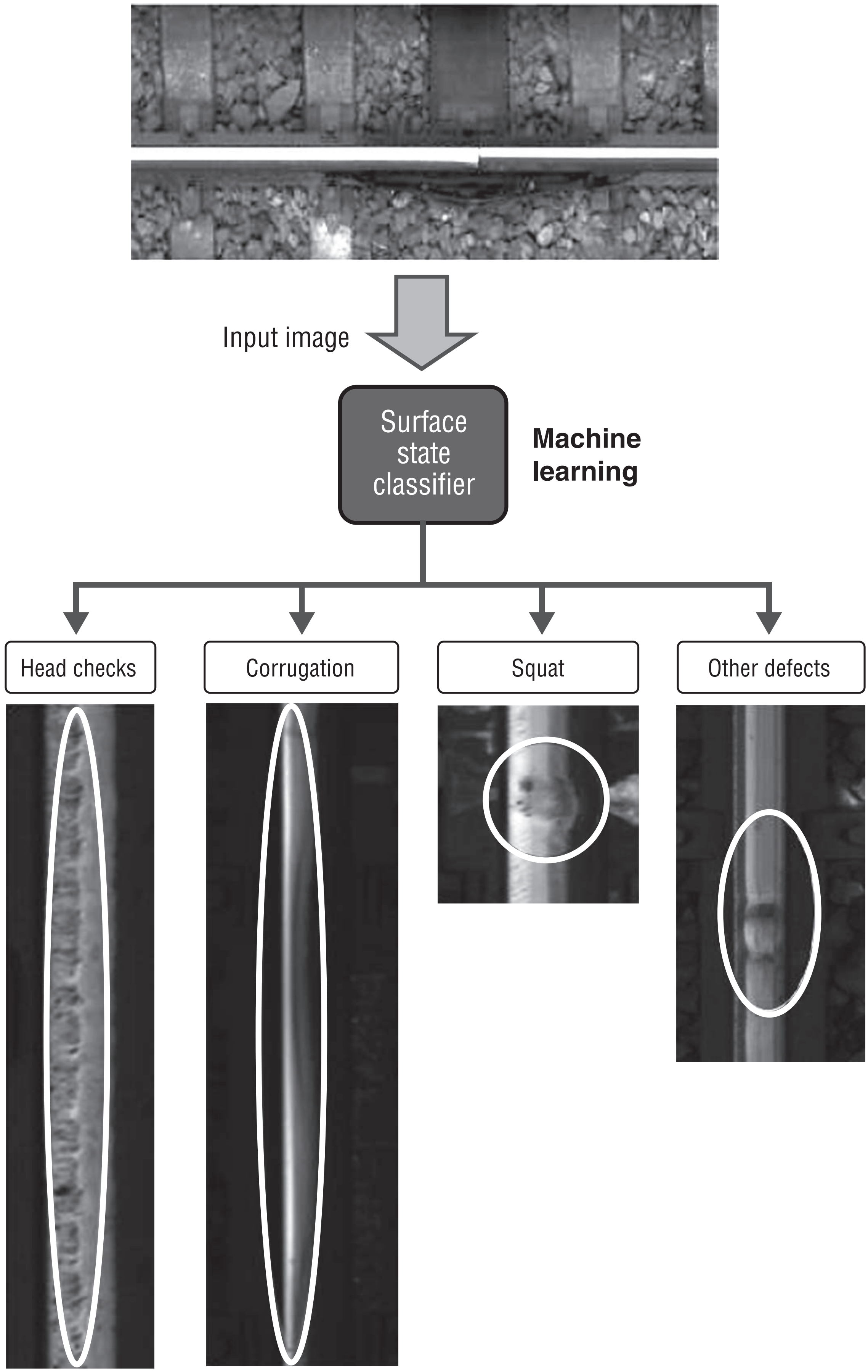
As much data as possible must be collected for big-data analytics and analysis by AI. We are studying a method to integrate inspection and specification data for wayside equipment managed by independent systems in each

Passing-on Skills

The know-how of veteran engineers is very important when conducting maintenance. However, these veterans in their 50s or older, who make up about 40% of all employees, are approaching retirement and their know-how must be passed-on to younger engineers. We have started studying the possibility of using amassed maintenance data for smoothly passing-on skills.

The first case study is a method of expressing past information so that it can be used in decision-making work (Figure 15). This expresses the status of track irregularities

Figure 16 Image Recognition using Machine Learning



every 3 months for 4 years as a heat map. The horizontal axis is the location on the line (per 100 m) and the vertical axis shows the track status history. The darker locations show where the deterioration status is good (the actual colour is green) or poor (the actual colour is red). By viewing this figure, the engineer can see the track deterioration status and changes at a glance, so it can be used as a reference in repair planning.

The second case study is image analysis using machine learning, a form of AI technology (Figure 16). This is an attempt to use images showing the rail head obtained by track monitoring devices to discover faults based on the experience of veteran engineers. This image processing implements machine learning and can reflect the know-how of veteran engineers. Even using only part of the data, rail head defects could be discovered with a success rate of about 98%.

Conclusion

The essence of maintenance—accurately perceiving deterioration and deciding the optimal timing and method for repairs—can be strongly supported by the Smart Maintenance Initiative, making CBM a reality, introducing asset management, and supporting work using AI. Furthermore, integration of databases offers a new mechanism for making the most of data that is now 'buried' in the system and is not being used effectively.

I strongly believe that achieving smart maintenance will lead to major reforms in railway maintenance. ■

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Mitsunobu Takikawa

Dr Takikawa is a chief researcher at Technical Center, Research and Development Center of JR East. He joined JR East in 1990. He earned his doctorate in mechanical engineering from Tokyo University of Science in 2013.