Innovation in Railways: Platform for Maintenance Innovation Using ICT

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1 Innovation in the 21st Century

More than 10 years have passed since we entered the 21st century. Yet the nature of innovation in recent years as seen in services that have changed the world is clearly different from the "object-centered revolution" seen in the previous century.

Railways, automobiles and other modes of transport, and means of communication such as telephones were born out of the industrial revolution, which started in the 18th century. People's lives became drastically more convenient into the 20th century due to many innovations such as home electronics, and productivity in industry also expanded.

Many companies in Japan also came out with high-quality, reasonably priced, competitive products, leading the world in their individual markets. This age can be called the age of industrialized society; in other words, it was an "age of innovation centering on objects".

The innovative services that came out of the information revolution of the late 20th century have brought about major changes to people's lives and to industry in recent years. But rather than being products centered on physical objects, those services are by intangible "structures and platforms using information and data".

For example, the logistics revolution by Amazon, SNS such as Facebook, the various services available from smartphone apps, and more have greatly changed the world. But the core to services is the structures and platforms supporting them, rather than products made up of physical objects as in the 20th century. Moreover, the structures are constantly changing in collaboration with the users who enjoy those services, and the core of technologies supporting those structures is ICT, which came into being after the industrial revolution.

The differences in the 20th century business model and that of the 21st century are shown in Fig. 1 and 2. Those are demonstrated through the "products" that are the center of services and technologies supporting those along with their relation to users who are recipients of the services.

In the 20th century model, products that are the center of services are physical objects such as automobiles, telephones, and home electronics. The technologies supporting them are mainly internal combustion engines and electric power, which came out of the industrial revolution. Those products are mainly made by large corporations, and the relationship with users is one-way (company to user). It is common for those products to undergo model changes and improvements once every few years.

In contrast, "products" at the center 21st century innovation are not objects. Rather, they are structures (platforms), and the technologies supporting those include ICT and biotechnology, which came into being after the industrial revolution. The relationship with users is interactive (two-way), and users constantly play a role in increasing the value of "products" while using them. Typical examples include Amazon's customer review and recommendation functions.

Creating innovation in this age is not improvement of physical objects by means such as making TV images clearer or improving the functionality of feature phones. It can be said to be providing new structure (platforms) for constantly raising service levels in collaboration with users.

Railways have long been called a mature industry. But by achieving 21st century innovation in terms of services for customers and technology supporting railway operations, it should be possible to accomplish things such as differentiation from other modes of transportation, improved safety, and great improvements to cost structure.

2 ICT-based Smart Maintenance Initiative

The Research and Development Center of JR East Group has proposed the Smart Maintenance Initiative as 21st century innovation in maintenance of railway equipment. The Smart Maintenance Initiative goes beyond the aspects of simply improving methods of repair work. It is a proposal for new structures and platforms in maintenance overall as mentioned in Chapter 1, and we pride ourselves in it being "21st century innovation" that continues to bring about effects while constantly evolving.
2.1 Details of the Smart Maintenance Initiative

The Smart Maintenance Initiative is composed of four key parts (Fig. 3).

First is changing the basis of maintenance from Time Based Maintenance (TBM) to Condition Based Maintenance (CBM). This entails a major change in the philosophy of maintenance. By achieving the change, much more streamlined maintenance than now will be possible. The difference is explained as follows using an example of maintenance for tracks, a typical type of railway equipment.

As shown in Fig. 4, inspections in TBM up to now are conducted at regular cycles (once every three months for conventional line track) to obtain data on track irregularity. Decisions on whether or not to conduct repairs are made based on this data, and decision-making is done based on predetermined rules where repairs are conducted when set criteria (for example, 23 mm) are exceeded.

In the example of tracks, obtaining track displacement data from trains in operation would allow such displacement data to be obtained rather than performing inspections at set intervals. The more data is accumulated, the smarter the important decision-making process in maintenance is.

Justification for decision-making in TBM is prescribed by rules (internal regulations, etc.), so there is inevitably little awareness of reviewing on a daily basis. In fact, maintenance criteria for track maintenance have not changed in about 50 years.

Conversely, CBM is based on monitoring of large volumes of data obtained 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 us to identify the speed at which track deteriorates (i.e., the condition of the equipment) in units of 1 m. Decisions can thus be made on when to conduct repairs at the optimum timing while accurately predicting track irregularity by individual location, allowing very streamlined preventive maintenance.

Changing from TBM to CBM means a fundamental change in justification for decision-making for the priority matter in maintenance of "when to conduct what sort of repairs" (Fig. 5).

The effects of repairs will also greatly improve by being able to obtain track irregularity data on a daily basis.

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**Fig. 4 TBM and CBM in Example of Track Irregularity**

Such criteria are decided on based on maximum progression of irregularity taking into consideration the track irregularity (for example, 40 mm) at which derailment could occur from past data and the three-month inspection cycle. As derailment must not occur, repair criteria needs to be set with much leeway, taking into consideration maximum progression of irregularity under the assumption that inspections are performed in a set cycle.

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Asset management and maintenance work support by AI—the other key parts of the Smart Maintenance Initiative—make decision-making in maintenance smart like with CBM.

Asset management is the making of specific plans for optimal maintenance over a long span of time. It is used mainly for bridges, tunnels, and other civil engineering structures where the deterioration is slow and the scale of repair work is large. It can be said to bring out the greatest value of equipment over its life cycle.

Maintenance work support by artificial intelligence (AI) still has high barriers to overcome, but it is an effort where taking on the challenge will be rewarding. This entails various judgment work currently done by humans (veteran engineers, etc.) being supported by computers.

For example, the cause of an accident needs to be quickly identified from the phenomena (mis detection of a train by the signal system, etc. at signal failure) when equipment failures and the like occur. This is work currently done by engineers in the field. An engineer with much experience can accurately extrapolate the cause of an accident from past accidents, the state of the equipment, various environmental conditions, and the like, quickly getting to work on recovering from the accident. But identifying the cause of an accident is a difficult job for engineers without sufficient experience.

We are therefore studying whether or not it is possible to have a computer “learn” algorithms to extrapolate the causes of accidents from the vast knowledge and experience of veteran experts as well as from various conditions. Specifically, we are using the technologies of text mining and machine learning to have a computer learn a vast amount of data such as cases of various past examples and failure patterns, and we are conducting tests to extrapolate and show causes of accidents and the certainty of those causes (Fig. 10).

While degree of accuracy is still low, we believe that eventually we will be able to build a system that can make accurate judgment. This will be done by machine learning of algorithms that replicate human judgment as judgment case examples.

In this way, CBM, asset management, and judgment work support by AI form a platform that strongly backs up the essence of maintenance—accurately perceiving deterioration and making decisions with the optimal timing and method—thus interactively proposing repair plans. It can also evaluate repair results and reflect those in plans.

**Fig. 8 Decision-making Support System**

CBM has hereto been explained for equipment where deterioration of track can be directly measured and that deterioration continuously perceived. But not all equipment with railways is like that. Deterioration itself is difficult to perceive with rolling stock equipment, electrical equipment, and the like, and deterioration does not progress continuously. With much equipment, failures seem on the surface to occur suddenly. Deterioration cannot be perceived for such equipment, so inspections were carried out periodically and defects repaired if found, or lifespan was set in advance and equipment replaced all together after a certain amount of time. The “state of deterioration” actually differs by equipment, so it is possible that very wasteful replacement of equipment is done when not yet needed or that rare cases of failure before set lifespan is reached are overlooked.

Recent advances in ICT, especially progress in data analysis technologies, allow us to perceive signs and causes of failures even in types of machinery that breaks down suddenly by continuously measuring certain physical quantities (current, resistance, etc.). This has allowed us to know what the deterioration patterns and the like are.

Fig. 9 shows analysis of train door failure. We found that deterioration by individual cause of door failure could be perceived by measuring physical quantities of a condition (for example, maximum current when doors are staring to open). By deepening analysis, it becomes possible to repair or replace at the appropriate timing (ideally just before they fail) individual devices according to their deterioration status, even for devices that had previously been replaced all together after a certain amount of time. This can eliminate waste as well as prevent sudden failures from occurring.

Such an approach can be applied to turnout point machines, electrical power transformers, and the like. That will allow effective preventive maintenance of mechanical and electrical equipment where such maintenance was thought to be impossible up to now.

**Fig. 9 Example of Data Analysis for Door Device**

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**Fig. 10 Meaning of Maintenance Work Support by Artificial Intelligence**

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We are therefore studying whether or not it is possible to have a computer “learn” algorithms to extrapolate the causes of accidents from the vast knowledge and experience of veteran experts as well as from various conditions. Specifically, we are using the technologies of text mining and machine learning to have a computer learn a vast amount of data such as cases of various past examples and failure patterns, and we are conducting tests to extrapolate and show causes of accidents and the certainty of those causes (Fig. 10).

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In this way, CBM, asset management, and judgment work support by AI form a platform that strongly backs up the essence of maintenance—accurately perceiving deterioration and making decisions with the optimal timing and method—and constantly advances it. In other words, providing the cycle concerning maintenance as a structure and platform by ICT and having frontline engineers who are its users constantly improve that platform is the basis of the Smart Maintenance Vision and the reason for it being 21st century innovation as covered in the previous section.

By this catching on at the worksite, we believe that it will bring about innovative change in maintenance for railway equipment.

**2.2 Results of the Smart Maintenance Initiative**

Here I would like to cover why the Smart Maintenance Initiative needs to be realized now and what the results of that would be. First of all, Japan’s decline in population can be said to have
greatly affected the circumstances surrounding railway operations. Fig. 11 shows the change in Japan’s demographics along with the change in maintenance expenses for railway facilities at JR East since the breakup and privatization of Japanese National Railways. 

Moreover, the predicted continued advancement of ICT will allow data analysis that currently is difficult to do. The structure of the Smart Maintenance Initiative will be refined along with amassing of data, and expectations are thus high for decision-making to continue to become smarter.

3 Systems Supporting Future Railway Facilities

JR East currently utilizes a variety of systems. Those systems were created separately, however, so there currently is no integrated database or common data strategy.

In order to realize the Smart Maintenance Vision, support the front lines of maintenance, and make accurate management decisions, a large volume of data upon which those efforts are based needs to be appropriately managed and operated. JR East as a whole thus needs to review its data strategy and create a data center and communications network to accumulate, integrate, and analyze data. We also need expert personnel who can handle that work (data scientists) and organizations with authority to do so.

Fig. 14 shows the construction of a large system (platform centering on databases) for integrating the separate internal systems, organically analyzing external data (weather information and SNS data) and the like, and allowing decision-making by the same database for everyone from front line organizations to management. This is still in the conception stage, but we feel that it will be effective for improving service to customers and achieving environmental management in addition to realizing the Smart System Initiative.

4 Conclusion

I believe that it is our duty to recognize the changes in the environment surrounding railways into the 21st century, such as the decline in population, progress of globalization, and rapid advancements in ICT. Moreover, we must further advance railways as a representative infrastructure supporting Japan.

For that reason, it is important to go beyond the boundaries of railway technologies and go steadily forward in R&D with open innovation as the key to that.

In conclusion, I would like to thank all those involved for their support and cooperation.

Fig. 12 Regional Demographics

The maintenance expense reduction effects of the Smart Maintenance Initiative are difficult to accurately estimate, but decision-making becomes "smarter" as more data is accumulated. Due to that nature of the vision, the effects will continue into the future (become permanent) as shown in Fig. 13.

Moreover, the relationship between the level of maintenance for equipment and costs can be clearly visualized through the Smart Maintenance Initiative. This enables the major benefit of being able to make more precise management decisions such as what to do about expenses.