[iv] Information and Control Systems for Railway Industry

Railway Traffic Management Systems by Machine Learning

Recovery from Traffic Timetable Disruption by Hybrid AI

Hitachi has developed and deployed a hybrid railway traffic management AI to support and automate the increasingly complex task of replanning train timetables. Machine learning and other forms of AI have made rapid progress over recent years. While machine learning techniques have been deployed in a wide range of applications, they have yet to see much use at the core of important social infrastructure systems such as in railways where safety is a top priority. While the convenience of railways has been enhanced by a rise in the number of direct train services, a downside is the complexity this adds to the task of replanning train timetables in the event of service disruptions. Such disruptions can be caused by abnormal weather events or incidents such as human injury accidents. Another major challenge for railway operating companies is the passing on of expertise in how to recover from these timetable disruptions, an issue exacerbated by the labor shortages associated with trends like low birthrates and aging populations. This article describes methods developed to overcome these challenges.

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1. Introduction

Hitachi has supplied numerous traffic management systems for railways. These social infrastructure systems play a central role in ensuring the safety, security, and comfort of railway transportation by performing automatic control of signaling equipment to ensure that trains operate in accordance with their timetables (train operation schedules, also known as "train graphs").

While computer control of railway networks is now taken for granted, Hitachi's history as a developer of railway traffic management systems dates back to the computer aided traffic control system (COMTRAC) for Tokaido Shinkansen that entered commercial operation in 1972. COMTRAC was supplied to Japanese National Railways (JNR) as the national railway company was then known. Over the five decades since then, Hitachi has continued to take advantage of improvements in computer functionality and performance and the latest available technologies in its ongoing pursuit of innovation, taking pride in its track record of delivering safe, reliable, and comfortable railway systems.

Machine learning has made rapid advances over recent years. This article describes how it is being put to use in social infrastructure systems for railway traffic management. While it has been common over recent times to equate artificial intelligence (AI) with machine learning, in the context of the railway industry and its long history of technological evolution, this article will define AI as being the science and practice of building intelligent computer programs[(1)].

2. History of Railway Traffic Management Systems and AI

(1) Generation 0: Technology for enhanced reliability

The main consideration during the era of COMTRAC referred to above was how to make use of computers in railway systems in a way that did not compromise reliability. This was a time when the key system considerations were things like the use of redundancy to prevent computer faults from bringing train services to a halt, guarantees of real-time performance, and controlling train movements in a way that ensured they arrived and departed on the correct tracks, as specified in the timetable[(2)].

(2) Generation 1: Control AI for trains

The increasing performance and falling cost of computers together with efficiency improvements from the breaking up and privatization of the national railway network in 1987 led to an acceleration in the computerization of traffic management on conventional railway lines. In contrast to the high-speed Shinkansen, conventional railway lines are shared by a wide range of services, including freight, express, and local trains, with more frequent instances of train routes intersecting at railway stations.

Meanwhile, the high density of railway traffic in the vicinity of major cities also prompted the development of control AI to optimize in real time the sequencing of train movements based on the ever-changing actual state of operations. This provided the ability to determine the optimal sequence of train movements and to control their operation accordingly[(3)].

(3) Generation 2: Swarm control AI for trains

With the ongoing computerization of systems for conventional railway lines in the major cities, a requirement arose for controlling operations in a way that achieved balance across entire lengths of track rather than just optimizing individual train sequencing.

As a steady stream of new commuters arrive at platforms during times such as the morning rush hour in large cities, any delay in a train's arrival will result in a larger than normal number of people wanting to board. This tends to delay the train even longer. As the gap to the preceding train grows larger and larger, this ends up throwing the interval between trains out of balance along the entire length of the line.

Leveraging the higher performance of computers in this second generation, this led to the development of swarm control AI that monitors the interval between trains along the entire line and optimizes control to keep them as evenly spaced as possible[(4)].

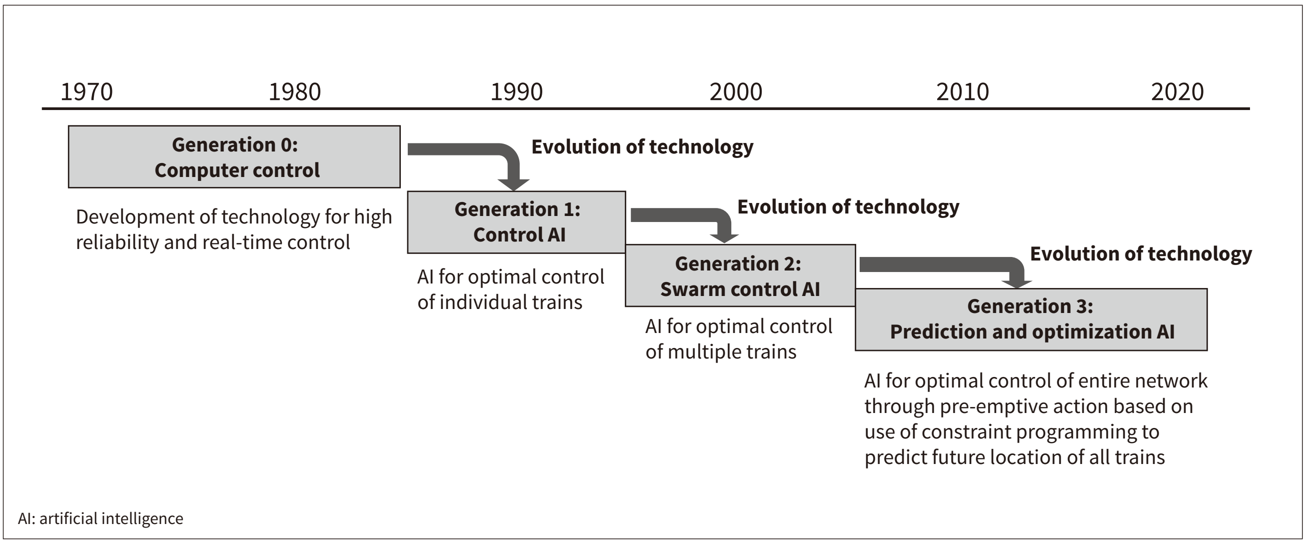
(4) Generation 3: Prediction AI for all trains

As improvement efforts by railway operating companies in areas like signaling systems and track design led to higher traffic densities, this raised the issue of how to respond to disruptions in train operations caused by abnormal weather or other incidents such as accidents involving human injury. Higher traffic densities and more diverse operating practices increase the amount of effort required to recover from timetable disruptions, increasing the number of trains involved.

Accordingly, by having the traffic management system generate continually updated predictions of what the different trains on the network will be doing, and presenting this timeline in visual form, network control staff are able to take pre-emptive action based on this forward-looking

Figure 1 — Advances in Traffic Management AI and Evolution of Technology

Traffic management AI has advanced over time to meet the evolving needs for railway transportation.



view of train movements. In terms of techniques for predicting the future, what Hitachi refers to as third-generation AI is the use of constraint programming to present a view of upcoming events that can serve as a basis for network-wide optimization. Analyses conducted using an operations simulator play an important role in predicting the future. This provides a way to visualize how the plan devised by this third-generation AI will play out over time on an operations simulator that models the actual network and incorporates the various traffic management rules[5].

Figure 1 shows these three generations of AI. These AI techniques remain in use, complementing the operation of railway traffic management systems and running alongside them, not only providing optimal control at railway stations and along the length of railway lines, but also predicting the train movements that will result from this optimal control.

3. Upcoming Challenges for Railway Industry

Recent years have seen a rise in the number of direct train services that run on different sections of track or on track operated by different railway companies. While such services, when operating normally, are a great convenience for passengers, allowing them to reach various different destinations without having to change trains, they also increase the complexity of railway operations. Similarly, they bring new challenges in terms of how to cope with major changes to timetables brought about by factors such as abnormal weather or COVID-19. Another management challenge that presents itself over a longer timeframe is that of how to pass on the expertise of network control staff against a background that includes an aging population and falling birthrate.

The need to overcome these challenges has brought rising demand for the application of AI to the task of recovering from timetable disruptions, something that has fallen outside the scope of automation provided by past railway traffic management systems. To facilitate the use of computers to recover from timetable disruptions, methods are available for documenting the expertise of network control staff in how to deal with the disruption of train services, and for then translating this expertise into explicit logic in a computer program. These methods are technically viable and can be relied on over the short term.

The problem, however, with explicitly specifying the logic of how to recover from timetable disruption in a computer program is that it lacks general applicability. This is due to the need for the program to be rewritten if it is to be used on a different railway line where different practices are used for operation and for dealing with disruptions. This led Hitachi to look at new methods with more general applicability that are based on machine learning.

4. Challenges and Solutions for Application of Machine Learning to Social Infrastructure Systems

Machine learning has made dramatic advances over recent years. With the emergence of deep learning, in particular, it has even reached the point where it can outperform humans in certain tasks. This has increased public expectations for machine learning and significantly expanded the range of problems that it is able to solve in practice. The systems used for railway traffic management can be thought of as lying at the heart of the social infrastructure. If machine learning is to be deployed in such systems, there is a need to consider the constraints that apply in the real world as well as the risk that bad decisions by machine learning might destabilize services that underpin public life. The following sections go into detail about the challenges of preventing bad decisions, the impact on people and on real-world systems, durability for long-term use, and the ability to keep up with an ever-changing world, also describing how these challenges can be overcome.

(1) Hybrid configuration to suit traffic management rules

The output of invalid plans for recovering from timetable disruptions has the potential not just to prevent recovery from the delay but even to bring train services to a complete halt. Moreover, even if the AI model does produce a good recovery plan, if the result turns out to be logically incompatible with the train movement control functions of the traffic management system, it may attempt to run the trains in a sequence that conflicts with the intentions of the network control staff.

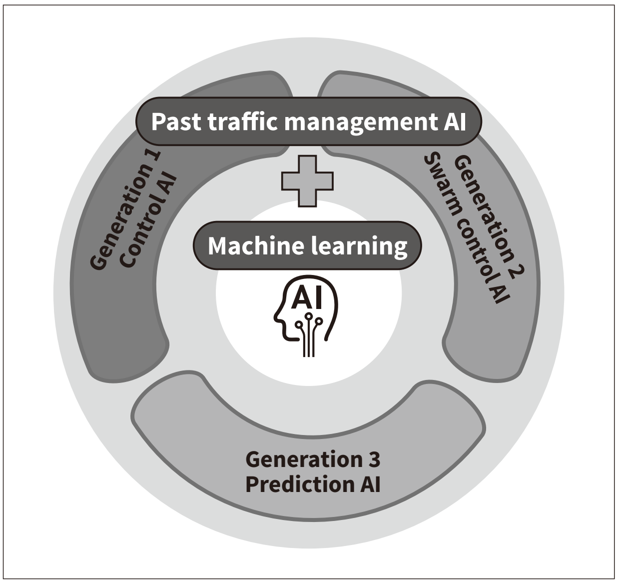
Accordingly, Hitachi has adopted a hybrid configuration for machine learning that combines it with the first, second, and third generations of AI described above. This automatically checks AI model results against the traffic management rule logic developed for these previous AI generations and triggers recalculation if a rule violation is found. This provides a mechanism for preventing the calculation of results that violate traffic management rules (see **Figure 2**).

(2) AI systemization including human

When something happens to disrupt train timetables, it happens in an environment where many trains are in service carrying large numbers of passengers. Likewise, drivers, conductors, or other staff are already onboard. When a need for recovery from disruption arises, these staff need to be reassigned and passengers advised of the updated timetable. If the changes also affect trains for which the sale of designated seating is a factor, the need to handle the seating allocation changes means that the response must also encompass the people-related side of railway operations. It also means that the changes calculated by machine learning for recovering from timetable disruptions need to

Figure 2 — Diagram of AI with Hybrid Configuration

Hitachi has developed a new traffic management AI suitable for use on social infrastructure systems that demand high reliability by combining machine learning with approaches to AI used for this application in the past.



be implemented (including these people-related aspects) and that it must be possible to explain why these changes were needed. The problem with this, however, is that the AI models generated by deep learning and other forms of machine learning are black boxes, the operation of which not even their developers can explain.

To resolve this problem, Hitachi provides a visualization of the timetable changes calculated by machine learning that translates them into the same form used to present changes produced by conventional traffic management systems.

(3) Ensuring sustainability of long-term use

A feature of railway traffic management systems is that the associated products and projects tend to have comparatively long life cycles, a consequence of the very public nature of such systems and their need to maintain very high levels of reliability and safety assurance. There are traffic management systems where Unix*-based computers installed more than 25 years ago are still in service.

If machine learning that evolves on a timeframe of days and months is to be utilized in these long-lived railway traffic management systems, some way of reconciling these different timelines is needed.

To overcome these challenges, Hitachi has adopted a configuration whereby machine learning components are treated as swappable plug-ins. While the hybrid traffic management AI described below was developed using a directed machine learning technique called gradient boosting, research and development of an AI that uses reinforcement learning to recover from timetable disruptions is also ongoing. By facilitating simultaneous use or the swapping in and out of the latest techniques, Hitachi is building systems that can continue using AI over long periods of time (see **Figure 3**).

(4) Learning from real-world data

The ongoing use of large amounts of data on the actions of network control staff for learning is important for improving AI accuracy and keeping up with changing realities. To facilitate this, Hitachi has established interfaces with the devices these staff use for their work to enable the continuous collection of such information. That is, machine learning can be performed by providing devices that are the same as those that network control staff use in practice when issuing instructions to recover from timetable disruptions, and entering instructions into these in the same way that staff would do.

When performing machine learning to adapt to differences between different railway lines, for example, this configuration makes it possible to have network control

* Unix is a registered trademark of the Open Group in the USA and other countries.

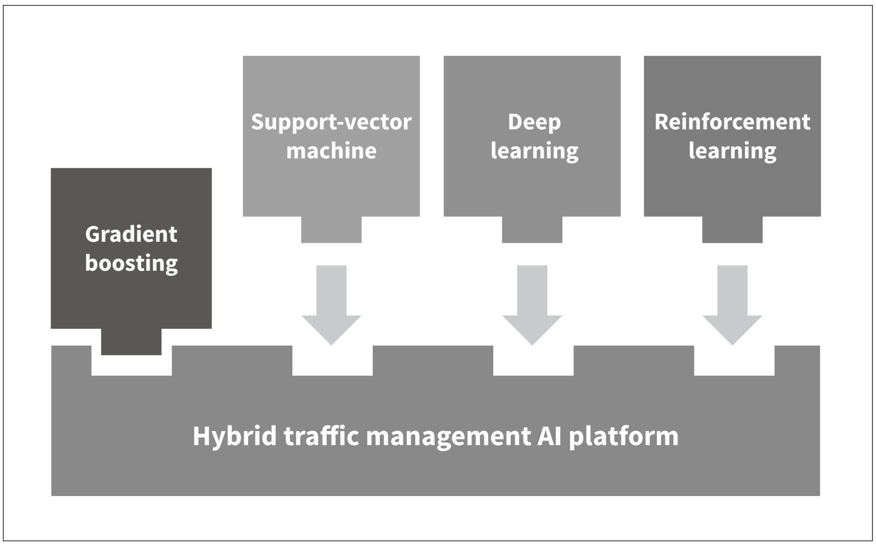


Figure 3 — Block Diagram of Plug-in Hybrid Traffic Management AI

A swappable plug-in configuration has been adopted to enable the ongoing use of rapidly evolving machine learning in railway traffic management systems characterized by long life cycles.

Figure 4 — Machine Learning by Use of Screens by Staff

The work of generating data for machine learning is made easier by having staff make timetable changes using the same screens they would use on their existing equipment.

staff enter the same instructions as they would normally use to manage operations. If the line has an existing traffic management system, it also facilitates the use of past operations data (see **Figure 4**).

5. Features of Hybrid Traffic Management AI

To provide ways of addressing the challenges described above that have broad applicability, Hitachi has developed a platform for hybrid traffic management AI. This AI is trained on past data recording the actions of network control staff when recovering from disruptions and then used to calculate such actions on its own, with constraint programming being used to check the practical viability of the plans it generates. This approach takes advantage of the capabilities of machine learning to acquire and then replicate the sort of recovery expertise held by network control staff that is difficult to document. With its use of machine learning, this platform configuration facilitates application of the AI to different railways or on other lines because it learns from past operational data that records how network control staff handled timetable recovery (see **Figure 5**).

6. Trial Using Hybrid Traffic Management AI to Plan Timetable Recovery

A trial to verify the operation of the hybrid traffic management AI described above was conducted using data on the Sydney railway network made available by the State of New South Wales in Australia(6). This involved track and timetable data on the T4 line.

Figure 6 shows an example operational recovery plan generated using the AI following a disruption to services. The graph at the top uses the train graph format to represent the initial planned timetable for all the trains on the line, with the horizontal axis representing time and the vertical axis listing the stations.

The middle screen shows the disruption caused by the delay, with the rectangle at the bottom left indicating where service was interrupted. The lines that appear shifted to the right relative to where they are drawn on the top screen represent the predicted delays resulting from the disruption. Similarly, the numerous horizontal lines represent the long periods of time these trains would spend halted between stations.

The bottommost screen shows the recovery timetable generated by the hybrid traffic management AI. This new timetable significantly reduces the number of passengers stuck in trains for long periods of time, with services able

Figure 5 — Difference between Computer Programs and Machine Learning

Whereas past practice was to replicate the timetable recovery methods as explained by the network control staff, machine learning can acquire their timetable recovery expertise from past operational data that records how they responded to such events.

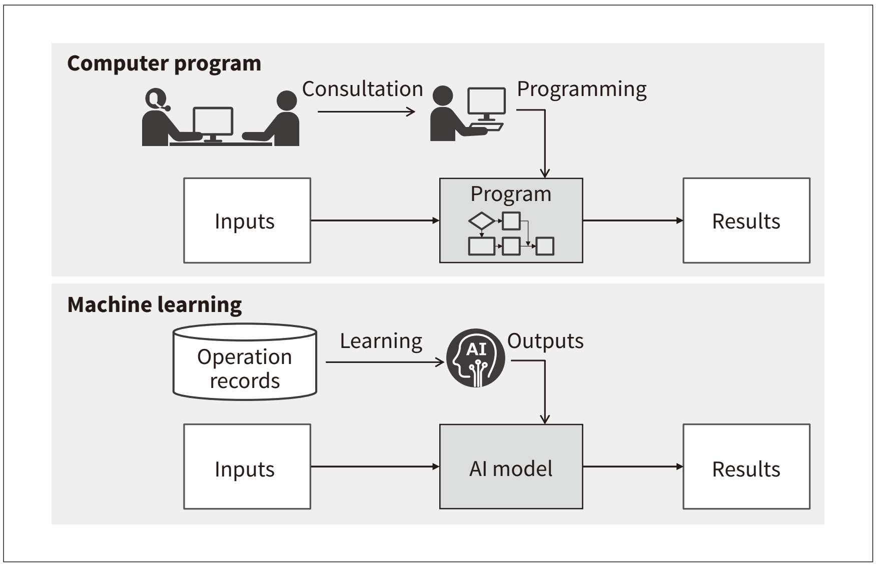
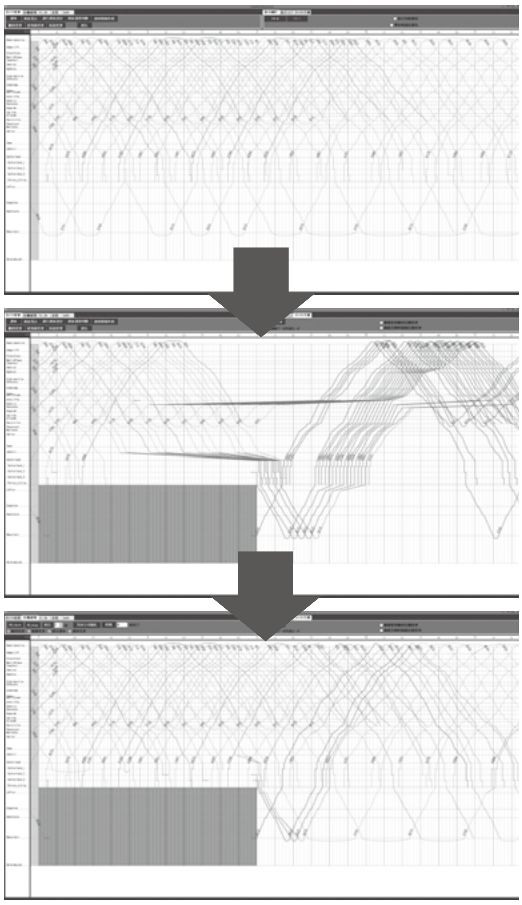


Figure 6 — Calculation Result for Two-hour Delay

The screens show, respectively, the initial planned timetable (top), the timetable predicted to result from a two-hour interruption to railway services (middle), and the recovery timetable generated by the hybrid traffic management AI (bottom).



to continue to those locations where this is possible. The new timetable should also speed up the time taken to get full services back up and running. Although performed for a simple system configuration devised for trial purposes, the planning and calculation took only about 10 s, indicating that response time should not pose a problem for real-time operation in actual deployment.

7. Conclusions

While this article presented results from a trial conducted on a railway overseas, it demonstrates the viability of using the AI on operational systems. As different railway companies and lines have different practices they follow when timetable disruptions occur, the intention is to proceed with actual deployment through the use of learning to accommodate these line-specific differences.

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