

AI-Driven railway regulator inspection planning system: enhancing railway safety inspection prioritisation and incident management


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ABSTRACT

This paper presents an innovative approach, with an application named AI-Driven Railway Regulator Inspection Planning System (the System), to enhance the safety inspection prioritisation and incident management of railways from regulator's perspective. The conventional approach to inspection planning relies on predetermined schedules and the manual selection of inspection items, which is time consuming and not conducive to objectively identifying high-risk assets and optimising resources. The system utilises Natural Language Processing (NLP) and Convolutional Neural Network (CNN) algorithms to quickly extract the semantic meaning of incident and maintenance deferral details, analyse information from various data sources, and derive the relationship among the incidents, maintenance deferrals, and inspection items. Finally, the System assigns weights based on the severity level to generate the normalised risk score of assets. The System also collects and analyses incident data to identify patterns and facilitate trend analysis, with a user-friendly search interface for the efficient retrieval of past cases, assisting in incident analysis. The System was successfully deployed in Electrical and Mechanical Services Department (EMSD), the Government of the Hong Kong Special Administrative Region (HKSAR) of the People's Republic of China, demonstrating benefits such as an enhanced understanding of incident relationship, streamlined inspection planning, and proactive safety improvement. The System offers valuable guidance for wider application in railway systems, fostering improved safety, operational efficiency, and resource optimisation.

KEYWORDS Railways; smart planning; risk-based prioritisation; artificial intelligence; data analytics; incident analysis; natural language processing; machine learning

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1. Introduction

1.1. Background

The Railways Branch (RB) of the Electrical and Mechanical Services Department (EMSD) is the regulator for railway safety in Hong Kong through the empowerment of the Mass Transit Railway Ordinance (Chapter 556), Mass Transit Railway Regulations (Chapter 556A), and other applicable ordinances of the Law of Hong Kong, while MTR Corporation Limited (MTRCL) occupies the largest railway network in Hong Kong. The main functions of the RB include ensuring the adoption of appropriate safety practices by railway operators; investigating safety-related railway incidents and following up the operators' improvement measures; assessing and approving new railway projects and modifications to the existing major railway facilities; handling complaints and enquiries on matters related to railway safety; and promoting public railway safety, etc.

Hong Kong's railway network serves around five million passenger journeys daily. The railway system in Hong Kong is a complex collaboration of electrical, mechanical, and civil systems, including rolling stock, signalling and telecommunication, traction power supply, tunnel ventilation, viaducts, tracks, and foundations. With the extremely limited two-hour daily maintenance windows given the long operating hours to meet demand, effective

and efficient maintenance becomes more important to minimise breakdowns and upkeep customer satisfaction.

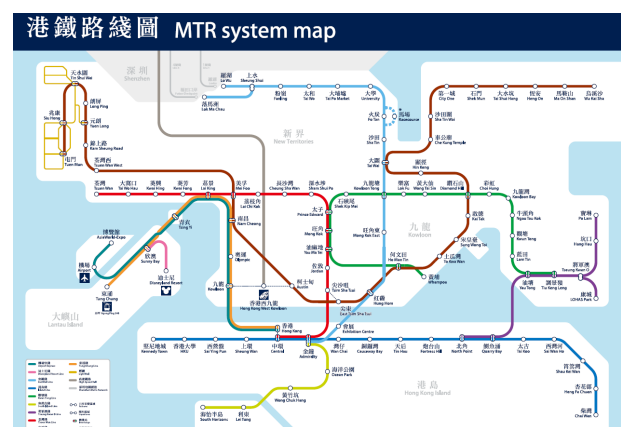


Figure 1. Hong Kong MTR system map.

1.2. Risk-based maintenance

In the railway industry, risk-based inspection approaches are becoming prevalent. These methods prioritise maintenance activities based on the potential impact of failures, enabling more effective resource allocation (Alawad et al., 2020; Alawad, 2023). Additionally, data analytics and predictive maintenance

are employed to enhance the decision-making processes in inspections, allowing for timely interventions before issues escalate (Alexis et al., 2020; Aven, 2010).

In aviation, the Safety Management Systems (SMS) provide a structured framework for managing safety risks in the International Civil Aviation Organisation. This systematic approach can inform and improve railway inspection practices by offering insights into risk management and safety oversight (Commission Directive, 2009; Ikuya et al., 2010).

Overall, there is a clear trend toward data-driven and systematic inspection planning across various sectors, which can significantly enhance railway operations by improving the safety outcomes and optimising resource utilisation.

In line with international practices, the EMSD conducts “risk-based inspections” to monitor railway safety, focusing on areas posing higher risks based on track records. Safety inspections are also arranged accordingly. In addition, the EMSD monitors MTRCL’s internal systems and practices to ensure adherence to international safety standards. By effectively managing the limited two-hour daily maintenance window and constraint of limited resources, a risk-based approach prioritises inspection resources. Understanding the asset criticality and its associated failure risk, the EMSD could prioritise inspection with the most significant impact if issues occur. Through analysing the likelihood and severity of potential failures, risk-based inspections could be planned to strategically focus on historically higher risk areas, thoughtfully schedule safety checks, and diligently monitor to ensure MTRCL’s compliance with the applicable international standards and best practices.

Safety Critical Items (SCIs) play a crucial role in maintaining the safety in the railway system, and their performance directly impacts the overall safety levels to a certain significant extent. SCIs are identified collaboratively by designers, maintainers, and operators, using specific selection criteria to determine the safety consequence of the credible failure of the engineering item being assessed during new railway project works or any design change to the existing system. To ensure their continued satisfactory performance and the fulfillment of the required safety functions, stringent maintenance controls are necessary.

Table 1. Examples of safety critical items.

Rolling stock	Coupler, wheel, axle, emergency brake, door lock device, etc.
Signalling system	Interlocking relay, track circuit, point machine, balise, etc.
Permanent way	Weld (flash-butt weld and thermit weld), crossing and check Rail, Sleeper, etc.
Power system	Overhead conductors, balance weight, bracket and anchor, section insulator, isolator, etc.

The railway network in Hong Kong comprises more than 1,100 registered SCIs that are spread across 99 stations, and 68 stops and trains serving a distance of over 270 km of network. However, effectively maintaining such a vast system presents significant challenges due to its scale and complexity, as well as constraints on personnel and time.

Given these constraints, it is crucial to conduct focused and efficient safety compliance inspections. To achieve this, the EMSD utilises risk prioritisation techniques to systematically target the most critical SCIs within the limitations of scheduling and available resources. This focused approach on the riskiest components allows the optimised verification of the areas of the greatest safety concerns. It also assists the EMSD in planning compliance inspection and ensures that the inspection efforts are directed towards the areas where the safety concerns are most pronounced.

1.3. Incident management and investigation

The EMSD oversees railway safety by requesting MTRCL to address all the safety concerns during the design, construction, operation, and maintenance stages. MTRCL is required to demonstrate that the railway system is meeting the international standards that are customised for Hong Kong, while the EMSD assures due diligence to mitigate all the safety risks to an as low as reasonably practicable level when operating the railways.

Upon the receipt of an incident notification from MTRCL, the EMSD acquires and records as much information as possible about the incident. The EMSD then takes follow-up actions to ensure that MTRCL is implementing remedial and preventive measures in response to the incident. The EMSD also monitors the progress of the identification of the root cause of the incident and the implementation of rectification measures to prevent recurrence. Each incident is treated as a valuable lesson to improve the safety and reliability of the railway system.

Furthermore, incident categorisation is conducted to organise and classify them based on their involved system, severity, impact, or other relevant factors. This helps the EMSD in prioritising incident response, allocating resources effectively, and identifying the common patterns or trends. Moreover, incident trend analysis is implemented by examining the incident data over a period to identify

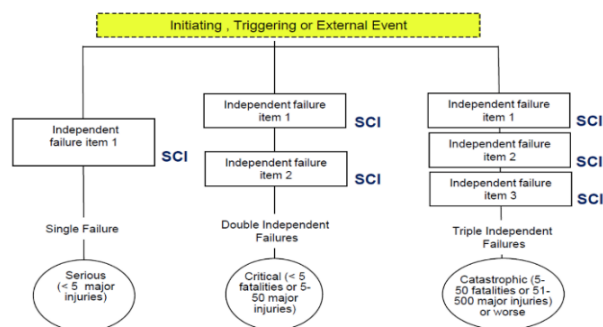


Figure 2. Selection criteria of SCIs.

patterns, tendencies, or changes in the frequency and nature of incidents. This analysis helps the EMSD to understand the emerging risks and make informed decisions to mitigate future incidents. However, generating trend analysis reports and categorising incidents manually can be a labour-intensive process, so it is worthwhile to further explore automation and digital solutions to streamline the processes.

1.4. Objective of this project

To enhance the effectiveness of SCI inspection planning and incident analysis, the EMSD initiated a pilot project to develop an AI-driven railway regulator inspection planning system in order to prioritise the inspection resources for MTRCL’s maintenance work on high-risk assets and streamline the conventional manual processes required in incident analysis. The specific objectives are as follows:

- (1) Transforming the current manual practices to an AI-driven approach to SCI inspection planning; and
- (2) Formulating incident trend reporting and an incident search engine for smart analysis.

1.5. Methodology and technology

The conventional approach to railway inspection planning has traditionally relied on predetermined schedules and the manual selection of inspection items based on the assessed safety risks (International Civil Aviation Organisation, 2013; Khan et al., 2015; Lai et al., 2016; Leitner, 2017; Liu, 2022). It heavily relies on the experience of EMSD engineers and it is time-consuming due to the large volume of data that need to be reviewed in detail manually such as incident investigation reports, maintenance deferral records, SCI register, etc. provided by MTRCL.

Table 2. Useful data source.

1. Incident investigation reports	Records the documenting of the incident sequences, root causes, and corrective actions taken
2. Maintenance deferrals records or release of concession	Records the documenting of maintenance backlogs or deviations from the maintenance standards
3. SCI register	Registers the cataloging of all assets or systems identified as safety critical

With the advancements in technology, there has been an increasing adoption of text mining or Natural Language Processing (NLP) techniques to analyse railway safety, which includes enabling the extraction of the relevant information from textual data, such as incident reports or maintenance deferral records, to identify patterns and correlations (Minjoon et al, 2017; Podofillini et al., 2006; Raffel et al., 2020; Railway Safety Directive, 2004; Syeda et al., 2017; Vladimir et al., 2016).

In addition, Convolutional Neural Network (CNN) models, which are particularly effective in analysing structured and multi-dimensional data, have been utilised for feature extraction in the context of railway safety and applied to extract meaningful features from incident data (Wang et al., 2023; Zhou, 2011). Furthermore, the adoption of management systems which incorporate incident trend analysis and smart planning could leverage the power of data analytics and AI to identify the trends in incident occurrences, visualise incident patterns, identify the common characteristics among incidents, precisely identify high-risk railway assets, prioritise inspections, and improve the operational efficiency (Zhou, 2018).

Management systems employing AI and data analytics can leverage these capabilities. By identifying the trends in the past incident occurrences and their common characteristics, they can precisely pinpoint high-risk assets and prioritise the inspection resources. This improves operational efficiency over manual methods.

Bidirectional models like Bidirectional Encoder Representations from Transformers (BERT), through their bidirectional training, offer a more comprehensive understanding of language. When integrated with big data databases, these technologies bring significant improvements to the indexing of unstructured text and dimensional data, which previously required manual efforts.

The Convolutional Neural Network (CNN) is one of the techniques used to retrieve the patterns of information. Imagine that the attributes of incidents, such as equipment details, incident location, and incident types, have been retrieved from BERT and other feature extractors. The structure of CNNs and Fully-Connected Layers can correlate patterns and calculate the cosine similarities in the multi-dimensional embedding tensors.

A CNN utilises convolution to extract features and relationships across features. Compared with Fully-Connected Networks (FCNs), a CNN provides higher efficiency in feature extraction to achieve higher prediction accuracy under the same amount of training datasets. Compared with Long-Short-Term-Memory (LSTM), a CNN has closer complexity in parameter sizing. The deep layer of LSTM networks will overfit the model, while the shallow layer of LSTM networks does not provide enough cross dimension relationship feature extraction capabilities compared with a CNN.

BERT’s structure provides natural language processing and data understanding capabilities in various textual data sources. Compared with the Recurrent Neural Network (RNN) and LSTM types of model, BERT’s structure exhibits extraordinary textual understanding power across complicated paragraph retrieval.

With the integration of the above tools and technologies, the EMSD can smartly optimise the inspection planning for SCI maintenance work by MTRCL. By utilising advanced analysis techniques on a vast volume of railway data, limited resources can be strategically allocated based on the actual risk priorities.

This significantly enhances railway safety and improves the operational effectiveness.

2. AI-Driven railway regulator inspection planning system

The core of the System solution is centred around its AI system. This system utilises NLP to extract meaningful semantic information from unstructured free-text reports and records. Advanced algorithms are employed to compare content across incident reports, maintenance deferral records, and the SCI register to identify patterns and correlations.

The AI system analyses these similarities and differences to calculate risk scores for all SCIs. By quantifying the relative safety risks, the AI system generates an accurate ranked list of SCIs. This ranked list helps inspection planning teams strategically allocate inspection resources based on the actual priority needs. Compared to the manual analysis methods, the data-driven risk scoring and prioritisation offers a more precise, efficient means of targeting the highest-risk infrastructure and equipment first. This optimised and intelligence-led approach enhances the maintenance and inspection effectiveness of both the EMSD as a regulator and MTRCL as a regulatee. The System's architecture is outlined by several components, as shown in Figure 3.

Table 3. System architecture of the system.

Component 1 Data Ingestion Module	
Ingest incident data, maintenance deferral and SCI registers from data sources in types including Excel and PDF files	
Component 2 Comprehensive AI System	
Automatic tagging using NLP	Identify key information from the free text of data
Relationship mapping using a CNN	Map the correlation between different data sources
Component 3 Incident Database	
Extract semantic meaning using Elasticsearch and an indexing engine	<ul style="list-style-type: none"> Enable high-speed searching using textual indexing Keyword tagging is stored in Elasticsearch for efficient retrieval
Storage of unstructured data using MongoDB	<ul style="list-style-type: none"> Organise key-value tagged AI results in a tree structure for relationship retrieval Store common pre-processing results and facilitates high-speed tag retrieval
Storage of structured data using MySQL	<ul style="list-style-type: none"> Store system information in a row-based table Support row-based indexing and relationship joining
Component 4 Application server (web searching portal)	
Web portal using API interfaces for the display of results	<ul style="list-style-type: none"> Allow users to search for incidents and related PDF details across different time spans using the interface Display the AI model outcomes on dashboards and knowledge graph

2.1. Transforming manual practices to an AI-driven approach on inspection planning

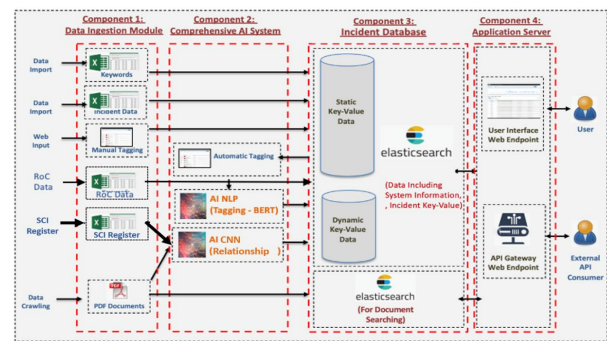


Figure 3. System architecture of the system.

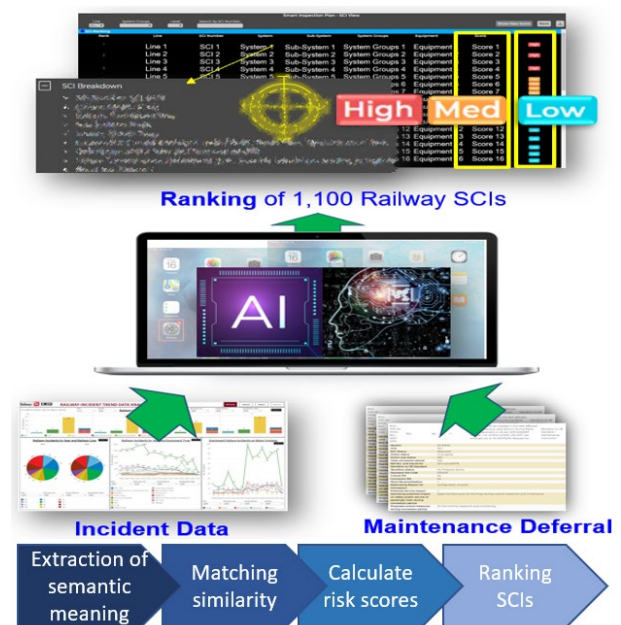


Figure 4. Design flow of the system.

Take an example: in a scenario where Train 01 experiences a Type D brake failure while approaching Station B on 1 January 2024, the AI-Driven System begins the data collection related to the incident. It gathers an incident report detailing the brake failure, a maintenance

deferral records from 31 October 2023 concerning the same braking system, and notes that the brakes are classified as a safety-critical item. Using NLP, the System extracts key details such as the incident location and equipment type. It then employs a CNN to analyse the historical data, identifying four similar brake failures in the past year, especially during high-stress operational periods. The System calculates a high-risk score based on frequency (four incidents), severity (the recent incident is critical), and recency (the incident occurred recently). As a result, it ranks the need for the inspection of the braking system on Type D trains at Station B as high and recommends that regulators prioritise this inspection to prevent potential future incidents.

2.1.1. Extraction of semantic meaning

The System utilises NLP to quickly analyse information from various data sources. The System provides valuable insights by analysing and interpreting various presentations and jargon commonly found in incident investigation reports and maintenance deferral records. It extracts important details like time, location, system, equipment, root cause, SCIs, etc. This helps individuals unfamiliar with the System or background understand and extract meaningful information.

For the semantic information retrieval, the NLP model starts with the pre-training dataset and performs fine-tuning with the historical textual dataset. It ensures an accurate retrieval of semantic feature vectors and embedding information from various data sources. The prediction model is initialised using transfer learning techniques with pre-training from similar scenarios. Data augmentation for incident feature enforcements are used to improve the prediction accuracy.

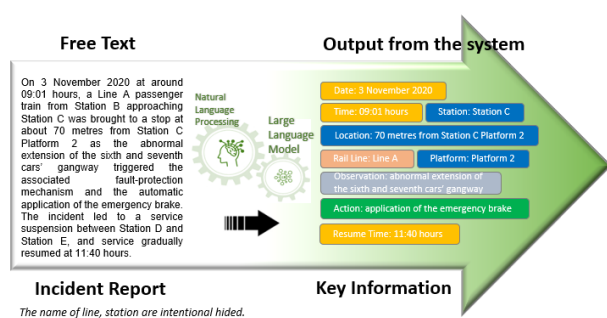


Figure 5. Semantic meaning extraction.

2.1.2. Matching the similarity

Utilising deep learning techniques, the System analyses incident investigation reports, maintenance deferral records, and SCI registers to identify connections and relationships. By considering the relationship between incidents and the contributing factors of incidents and maintenance deferral records, and the involvement of SCIs, the risk score of SCIs can be calculated.

2.1.3. Calculating the risk score

The System assigns different weights to the incidents and maintenance deferral records based on various factors such as recentness, frequency, consequence, etc. To evaluate the risk level of SCIs on the same scale, the System further applies weighted occurrences and confidence levels of matching results and normalises the final risk score on a scale of 0 to 100.

$$\text{SCI Risk Score} = \text{Weighted Incident Occurrences} + \text{Weighted Maintenance Deferral Occurrences} \quad (1)$$

In order to allow the System to understand the practical operational trade-off and make the decision tunable, the user-defined variables are set to allow users to specify the weights to adjust the trade-off under different circumstances to optimise the best-fitting scenario results for operators to use. Users can adjust their weights according to the trade-off required from time to time.

2.1.4. Ranking the SCI

The risk score ranks SCIs as high, medium, and low risk. With the System's ranking and risk assessment capabilities, it supports the EMSD to make decisions on inspection prioritisation and resource allocation.

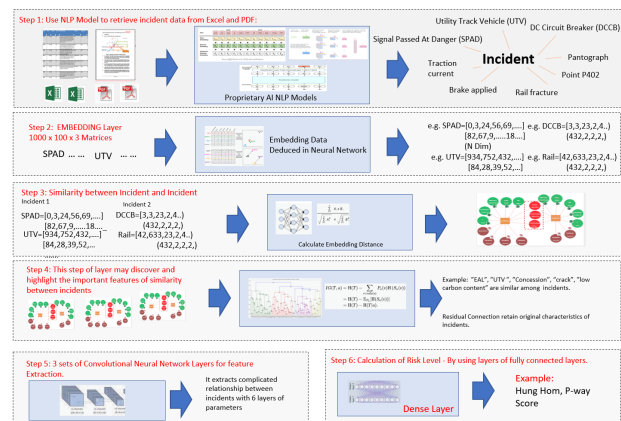


Figure 6. The AI model architecture for the calculation of SCI risk score.

2.2. Formulating incident trends and incident search engine

To determine the appropriate actions for the EMSD's work in incident investigation, it is essential to have early detection of incident trends and risks. To facilitate this, this developed system also monitors the railway safety performance and serves as a comprehensive database that records all incidents, enabling the continuous identification of incident trends and patterns for risk forecasting.

Additionally, the System functions as an incident search engine, allowing users to retrieve information from

historical records by entering specific questions or queries. This search functionality provides quick access to past incident reports and maintenance deferrals, enhancing the efficiency of information retrieval and analysis.

2.2.1 Incident trends

The System collects and analyses incident data to identify patterns based on various factors such as the time period, railway sub-systems, and operating lines. By conducting trend analysis, the System facilitates a comprehensive understanding of railway safety performance.



Figure 7. Incident trends in the System based on the railway sub-systems, operating lines, and selected period.

2.2.2. Incident search engine

In addition, the System offers a user-friendly search interface that allows users to efficiently query past cases. Users can use natural language queries or apply filtered criteria to retrieve relevant historical records. This knowledge sharing capability is instrumental in identifying incident signatures and patterns, and leveraging lessons learned from near-misses to strengthen prevention measures across the System.

3. Results

3.1. Performance evaluation of the system

The System underwent a pilot trial in a railway system with a two-year dataset of incident investigation reports and maintenance deferral records. The validation of the System commenced in January 2023, running in parallel with the traditional approach.

Data go through a pipeline of data cleansing and pre-processing, and 80% of the data are used for training while 10% of the data are used for testing and 10% of the data are used for validation. The accuracy of the System represents the capabilities of NLP to understand the textual meaning from an incident report or a maintenance deferral record and perform extraction into the correct categories via tagging. During data validation, the accuracy is calculated by comparing the tagging by the System against the tagging by users using the below formula:

$$\text{Accuracy} = [1 - (\text{Total number of missing tags of all documents} / \text{total number of tags of all documents})] \times 100\% . \quad (2)$$

Accuracy tests were conducted for the applied Albert-Ensemble NLP model via comparison with a typical T5 model and the results were 86% and 84%, respectively. After the fine-tuning of the NLP model, the accuracy results in the round 2 testing increased to 95% and 86%, respectively. In addition, it was observed that only the Albert-Ensemble model has the capability to provide “N/A” answers for unanswerable questions in the SQuAD 2.0 dataset.

Table 4. Accuracy.

BERT Models	Accuracy in round 1	Accuracy in round 2	Ability to provide “N/A” Answers
Albert-Ensemble	86%	95%	Yes
T5	84%	86%	No

Based on user feedback, the System has demonstrated several significant benefits. Firstly, it enhanced the understanding of incident connections objectively without human bias. Secondly, it streamlined the inspection planning by detecting recurring issues. Additionally, it produced a risk assessment that prioritises compliance inspection and maintenance in areas where they are most needed. The proactive safety improvement facilitated by the System, along with the optimised use of resources, contributes to better overall operations.

3.2. Limitations and the way forward

While the initial results of the System have been encouraging, it is important to note that the System’s accuracy can be continually refined by ingesting additional incident reports and maintenance deferral records, along with regular updates to statistical models and machine learning algorithms.

Further, it is suggested for the System to further develop a feedback system to collect feedback from expert users regarding matching errors and potential inaccuracies. Thus, this enables the System to continuously refine its ability to correlate data sources to a higher accuracy level. This interactive feedback loop could also enable AI algorithms to adapt future matching and risk analysis based on user validation.

In conclusion, the System has demonstrated its effectiveness and numerous benefits in SCI inspection planning. By leveraging advanced technologies and data analytics, the System has proven to improve the efficiency, reliability, and objectivity in the inspection process. Effective stakeholder collaboration is crucial to the project’s success and implementation. The System’s implementation provides valuable guidance for wider application in railway systems.

Future enhancements of the System could potentially involve the analysis of real-time sensor data like trainborne inspection data, preventive and corrective maintenance records, online weather data from the Observatory, and the latest available resources in the EMSD for inspection, using AI technology. This would support an even faster response, safer operations, and higher reliability expected by the community.

Last but not least, the ultimate aim of a safety regulator is “zero incidents”. At the same time, there is also an awareness that the community is expecting a very high level of reliability. It is essential to continue working closely with railway operators to strive for these dual goals.

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