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Deep Learning-Based Predictive Models For Rail Signaling And Control Systems: Improving Operational Efficiency And Safety

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Abstract

The main objective of this study is to understand the current operational structure and features of Turkey's rail signaling and control systems. From this subtle information, potential deep learning techniques that improve both operational efficiency and transportation security are proposed. To this end, current signaling and control structures are detailed, while the current migration priorities and the accessibility of deep learning are emphasized. As[1] a result of this assessment, the possibilities created by deep learning algorithms in the signaling and control systems of the signaling territories are highlighted. The limitations and opportunities identified at the end of the study are based on the data set. So far, there is no deep-learning model for the prototypical data set. However, the data set that will emerge at the end of the application and pre-configuration, such as variable extraction, will make deep learning models in this field more probable.

Keywords: *Deep Learning; Railway Signaling; Transportation Security; Train Control; Unmanned Railway Systems.*

1. Introduction

The operation and management of railroads are key factors that affect worldwide competition. Countries with a high ratio of freight shifted by railroads can compete more efficiently through better-integrated transportation and logistics networks. Furthermore, the implementation of advanced software-based control systems for intelligent transportation systems, such as railroads, supports the development of urban areas. Autonomous train control and railroad infrastructure monitoring systems can improve railroad companies' operational efficiency and move them away from traditional signaling and command/control systems based on track circuits, among others. As well as developing autonomous automobiles, vehicles, or drones across urban areas, several research projects have focused on developing these systems to increase railroad transportation capacity and bring train transportation systems into the new digital era.

To ensure the safety of train communication and control, several cooperative aerial and ground-based communication data links are used, and advanced networking protocols are implemented. One of the most unsolved and traditional problems in railroad signaling and command and control systems is the detection of the train. This is overcome using several signaling solutions, such as interlocking and track circuits, to focus on track element occupancy detection. However, these solutions are expensive to develop, implement, and maintain. Furthermore, the development of these traditional systems using efficient communication

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systems based on big data and deep learning paradigms is highly complex, and the embedded system definition does not have the required performance and/or real-time execution constraints. In this way, only pioneering research projects around big data and deep learning-based signaling and command/control systems in railroad transportation have been undertaken. However, these research projects do not address the subdomains defined for the final predictive model and, in several cases, do not evaluate and analyze the implemented predictive model, which focuses on solving some critical problems in railroad transportation.

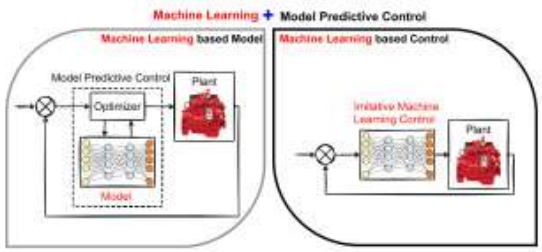


Fig 1: Deep learning based model predictive control for compression ignition engines

1.1. Background and Significance

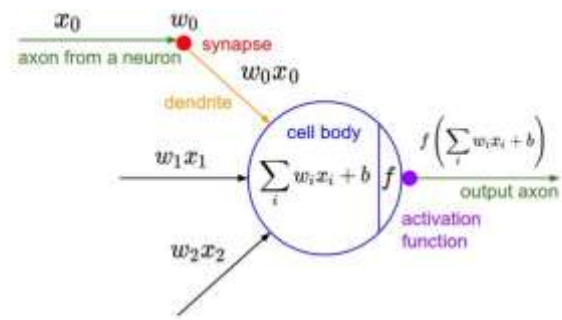
Railway systems ... eco-design and in-rail safety systems. The final design of any new railway system, in whole or part, will be governed by a combination of national regulations and reliability requirements, with particular emphasis on the operational environment and the specific corporate usage of the particular railway company or corporations concerned. In the case of a new high-speed mainline or high-density network, it is estimated that such systems could save at least 50% of construction costs. These systems would also have positive impacts on the urban underground, although the overall savings would be less. However, the design of the eco-design network and in-rail safety technologies is beyond the scope of this project.
This subject dealing with deep learning networks started as a continuation of previous work, which was mainly focused on developing deep learning models to classify and detect rail infrastructure objects in imagery data. Previous work showed that ConvNets could effectively identify and localize rail infrastructure objects such as train signal gantry frames, ground disks, and poles in rail signaling and control systems in suitable regions of interest. Then, transfer learning was utilized and experimentally evaluated in deep learning using a pre-existing ConvNet model with some different architectures to deal with a new similar recognition task that involved a relatively much smaller dataset. This helped reduce the necessity for large supervised datasets, especially for organizations that do not have enough resources to manually collect, annotate, and train a larger amount of labeled imagery data.

1.2. Research Objectives

This research aims to propose a real-time predictive model that predicts the unsecured object and asset location, as well as performs predictive maintenance of the signaling and control system based on rail infrastructure data using deep learning. We would also propose a novel DPC enclave structure for this scenario by data preprocessing, deep learning, and post-processing algorithms. The DPC enclave can provide real-time predictive methods that are essential for the seamless operation of transportation services, increasing operational safety for human lives and the efficiency of signaling and control equipment for railway infrastructure managers. The objectives of this research are as follows: First, to propose a comprehensive DPC enclave structure for real-time predictive modeling that can apply to various rail systems;

secondly, to apply and verify the proposed DPC enclave in several rail signaling and control system datasets and address the significant problem of asset management and operational dependencies; thirdly, to use the model's probability to extract the uncertainty properties of the DPC enclave; and lastly, to test the real-world application on a purpose-built railway depot with multiple existing sensors.

Equ 1: Neural networks representation



2. Rail Signaling and Control Systems

As the backbone of any dispersed long-distance passenger and freight transportation system, railroads require advanced signaling systems to mitigate potential safety risks while ensuring operational efficiency. The design of the railway signaling system has been examined for a few decades. Originally, the historically developed systems used simple manual methods and an extensive number of humans. As the systems started to advance, automatic solutions have been used to a large extent; however, many complex situations remain to be resolved with the help of operators. The first block signaling was invented only about a century ago, as systems served to control one block at a time. Only in the last two decades, the first microprocessor technology systems started to form the foundation of a complete conventional system and act as a predecessor to the modern system to resolve the majority of problems.

In recent years, new, intelligent, and sustainable changes have been discussed. Adaptation of recent intelligent technologies such as artificial intelligence, and deep learning, the utilization of new communication technologies, and the installation of distributed systems are seen as solutions when formulating control mechanisms for such industrial control applications. The main target of the system is to mitigate the probability of adverse events and human errors. However, the testing and development of such systems can be done only with a laboratory that can simulate all the critical components of the infrastructure, rolling stock, and communication of the railway system.

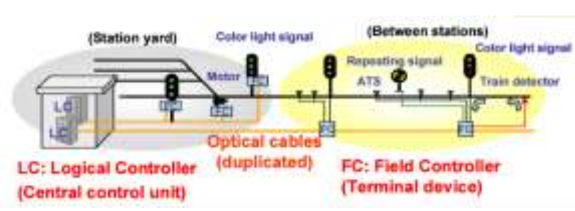


Fig 2 : Railway Signal Control System

2.1. Traditional Approaches

Railway transportation has sophisticated signaling and control systems designed to ensure the safe, efficient, and reliable operation of services. The safety and steady operation of the trains primarily depend on the correct classification and prediction of signal states by the signaling and control systems. At present, there is a wide variety of signaling and control systems in practice, such as the Automatic Warning System in the UK, the European Train Control System throughout the European Union, the Centralized Traffic Control in the United States, and the automatic train operation in China. Although the signaling and control systems are state of the art and meet the performance requirements at the time of their establishment, they can still be optimized regarding the prediction accuracy and comprehensiveness of the generated signals. Therefore, in this study, deep learning techniques are utilized to solve several sub-problems present in the international railway signaling and control systems to improve signal forecasting accuracy, train ranking prediction comprehensiveness to set the optimal train routing options, and train prioritization to address any potential capacity issues with train traffic and improve operational efficiency.

Traditional methods that are widely used in the railway industry aim to solve such forecasting and regression problems. However, these models have certain drawbacks. Non-deep learning-based models use traditional time series forecasting and regression methods such as linear regression, logistic regression, autoregressive integrated moving average models, and other simple machine learning algorithms. These models have many assumptions such as a linear relationship between input and output, homoscedasticity of residuals, correlation between residuals, and independence of residuals. Additionally, these kinds of models cannot capture representations and complex structures of data effectively. On the other hand, deep learning-based models can capture high-level abstractions due to the multiple levels of neural networks.

2.2. Challenges and Limitations

• Unexpected Conditions: Periodically, the signaling and control systems process the infrastructure equipment events or equipment or system states. The vast majority of these messages are deterministic and generated by the signaling control software, which processes the asynchrony of the operation or maintenance-related root causes of some asynchronously occurring messages. However, there is also the process of other, relatively rare, unusual but not unexpected messages commonly referred to as conditions. The recommended definition is "non-signaling event," which is unnecessary and should be a declaration for the potential signaling event unless the operation or maintenance of the abnormal message is to identify and troubleshoot. Operational safety remains a priority for the railroads, regardless of whether various levels and phases of autonomy are commercially simplified or whether there is an immediate formal transition to an autonomous railroading system fulfilling the responsibilities of the train crew.

• False Positives and Design Immunity: A challenge for any deep learning-based predictive model is to avoid false positives or false negatives because, based on the vendor's choice, the target product requirements, the prescribed product analytical method, other recognized or similar technical inputs, and any associated safety standards should have approval authority. Data science and machine learning application-oriented immutable requirements, directives, and design standards are challenging achievements for the software engineering profession as stakeholders, including the projected signals of constructability, interoperability, maintainability, reducibility, and testability.

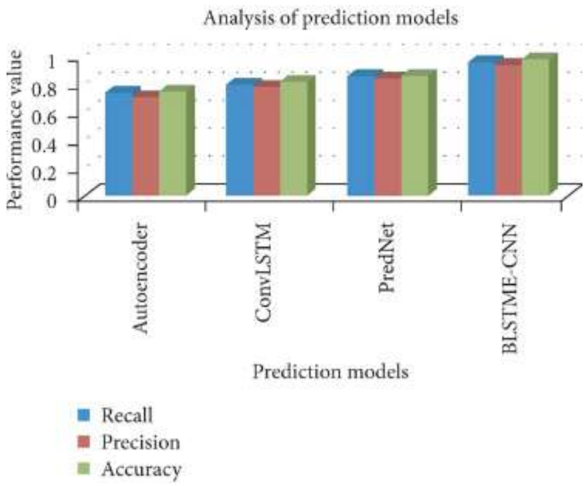


Fig : A New Hybrid Deep Learning Algorithm for Prediction of Wide Traffic Congestion in Smart Cities

3. Deep Learning in Rail Systems

Deep learning is a representation learning framework with several levels of representation, obtained by composing simple but non-linear or linear modules that transform the data in sophisticated ways. It consists of multiple processing stages to learn rich feature hierarchies, and models learn this hierarchy by optimizing an objective function, such as the probability of the input conditioned on the parameters. Concerning artificial neural networks, deep learning improves the performance of supervised tasks, particularly by enhancing generalization capabilities. Currently, this approach has obtained better performance in many fields, including computer vision, speech recognition, audio coding, and recommendation systems. Nevertheless, its use in the signaling area in rail control systems has been limited.
In the signaling and control systems, data is continuously being generated by different kinds of sensors integrated from different equipment and industrial devices in real-time. This data is employed to maintain the safety of rail transportation. Since the amount of generated data is increasing, many researchers are using this data to improve predictive, operational, and safety systems in signaling and control. However, the amount and variety of data generated in these areas cannot be exploited in all their possibilities for several applications that require the understanding of the particularities related to these functions. Data from rail signaling and control systems are challenging because of the different phenomena present in the rail operational environment and variations in the design of components. This is due to the nature of the data, the intrinsic uncertainty of the derived information, and the differences in measurement conditions. Moreover, telecommunications between trains and places of operation are specialized and not always available, and communication costs between and within controllers should be reduced.

3.1. Overview of Deep Learning

Deep learning is a field within machine learning based on learning data representations, as opposed to task-specific models such as translation or object detection. These representations can be layered, and composed of multiple levels. Deep learning has recently achieved state-of-the-art results in numerous application domains such as automatic speech recognition, image classification, and language processing, to some extent replacing handcrafted features used to learn a hypothesis. Deep learning has been rapidly advancing in the field of computer vision over the past years due to the improvement of DNN-based model architectures, increasing the possibilities of applications for computer vision. For example, convolutional neural networks can today recognize a thousand objects in the object recognition challenge dataset; most of these results today are using convolutional neural networks.

In the field of audio signal processing, recurrent neural networks have broken records in tasks such as language modeling, word error rate, machine translation, and speech synthesis. In the field of natural language processing, recurrent neural networks have achieved great success in various domains such as language modeling, word error rate, machine translation, and speech synthesis. Owing to advances in neural networks over the past years, we have developed several sets of computer vision models to address challenges in railway signal recognition, rejection of weather obstacles, and detection of object discontinuities.

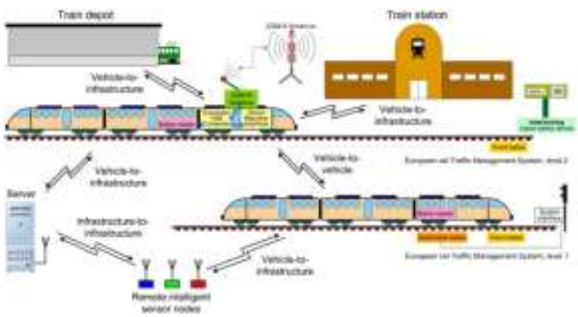


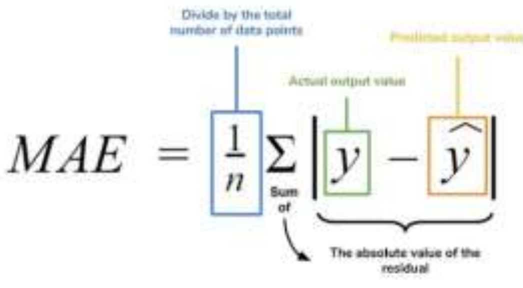
Fig 3: An Overview of Deep Learning in Rail Systems

3.2. Applications in Railways

Deep learning-based predictive models have also shown advantages in the railways. A large-scale deep learning model for the classification of the noisy railway axle counting system fault has been built. A train energy-saving method based on the deep reinforcement learning model has been proposed. The results reveal that the deep reinforcement learning model is feasible and effective for the implementation of a train driving style that saves energy. A railway wheel-slip control method based on a fuzzy sliding mode controller and deep learning algorithm has been proposed. The feedback linearization method is used to design the sliding mode of the wheel-slip control, and the supervised learning of the deep learning algorithm is adopted to adjust the fuzzy control parameter.

A mileage prediction method for diesel engine trains based on a stacked long short-term memory network has been proposed. The results indicate that the proposed stacked LSTM prediction model can effectively solve the shortcomings of the traditional model and better predict the mileage of runaway trains. A deep learning architecture-based predictive maintenance model for railway track data has been proposed. A deep learning framework to generate simulated train movements has been proposed. The results show that the proposed deep learning model can effectively capture the operational characteristics of the railway system and generate train movement records that are comparable to observed train movement records. An advanced and accurate energy forecasting system for electric trains that uses a combination of artificial intelligence models has been proposed. The results reveal that the proposed two-stage strategy has superior energy consumption trajectory forecasting capability compared to the traditional autoregressive methods with exogenous models and conditional generative models. The results indicate that the deep learning model can effectively be used to characterize train movement and improve the scheduling of critical tasks within the railway system.

Equ 2: Loss Function & It’s Types In Neural Network



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4. Case Studies

In this section, we present three case studies based on using our proposed models for solving real-world industrial problems. We developed several applications to help the signaling and control systems and their operation for our main case studies, including timetable conflict prediction, timetable modification with minimized delay propagation, delay and speed regulation prediction, safe train movement enforceable space warning overlay, speed KPI prediction, safety integrity level balance warning overlay, exception finding for the heating sleeve eccentricity checking, along with the possible following application of tuning the low and critical angle movement adaptive thresholds, and priority allocation optimization to minimize train speed restriction penalties, and outer ring realignment for an intact sensor signal. Station capacity is a significant concern as more trains are desired to be handled within the station, especially during rush hours. This problem can be further aggravated due to longer trains and train platforms operating within a limited fixed period, which can expose some safety issues. We constructed a virtual signal for the side platform controlling the low and critical angle on the railway signaling system and adjusted on an instant-by-instant basis the admission capacity into the station. It is designed for the main platform applications without the acquisition of the full domain system. The passengers present a demand for capacity on a true demand simulation level, and their physical constraints were designed.

Data for VSS are obtained from multi-modality tracking. The decision-making or classifying is done by using the signal aspect predicted by the machine learning model, uniquely identifying the signal needed on a signal stand; without any adjustment of its behavior from the control person in charge, it can handle all train movements worldwide. The difference is a low, medium, or high angle movement indication on TVPS, used for train operation authorization through the moving block signaling. The challenge of using this system is the safety of train operation concerning the low and critical angle on TVPS, as it is designed to handle all train movements, including high-speed operation. We used an RNN to model a similar light rail train structure, which also utilized a composite signal aspect to drive the movement.In our case studies, we explored advanced applications of our proposed models to address critical industrial challenges in railway signaling and control systems. One key focus was the development of a virtual signal system (VSS) designed to optimize station capacity during peak hours, particularly in the context of longer trains operating within constrained timeframes. By employing real-time adjustments to admission capacity on side platforms, we effectively managed passenger flow while enhancing safety. Our approach leveraged multi-modal tracking data and machine learning models to accurately predict signal aspects, facilitating seamless train movements without manual intervention. The VSS accounts for various angle movements, including low, medium, and high, ensuring safe operation even at high speeds. To tackle the complexities of these systems, we utilized a recurrent neural network (RNN) to simulate light rail train dynamics, reinforcing the reliability of our solutions in diverse operational scenarios.

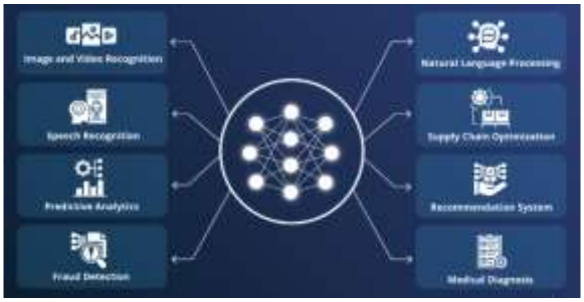

Fig 4: Cases of Deep learning

4.1. Real-World Implementations

For real industry practices, the scalability and reliability of the implemented algorithm are key issues for industry operations. Delving into the activation of deep learning models on those real difficult problems is not just a scientific issue, but also the key drive that makes a huge technological and economic impact. In the rail transportation industry, rail signaling and control systems are tasked with guiding train movements and ensuring that train movements comply with complex constraints, thus maximizing safety and network throughput. To implement deep learning algorithms in practice, we address issues including efficient computation and seamless integration with distributed control and management systems. Several deep learning models, including MLP, RNN, and CNN/DCNN, are deployed as predictive models for complex network operations problems in the rail signaling and control domain. Efficacy demonstrations and performance analyses are presented to elaborate on the proposed approaches. In general, it is not fast and sample-efficient to apply deep learning-based algorithms to solve the raw input of these complex constraint optimization problems. Modern regularization tricks and architectures allow deep learning models to be applied to previously difficult control and learning problems. The predictive ability of deep learning models is key for the application of models to industry problems. The training data need to contain the most important features of any possible combinations of input that are likely to happen online, and the responses should be the optimized levels complying with network operating standards.

4.2. Performance Evaluation

To evaluate and compare the forecasting performance of the deep learning-based predictive models, the following error measurements and associated statistics are used in this work: mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), and R-squared (R2) value. MAE is an absolute error-based measurement. RMSE is a square root-based measurement. Both MAE and RMSE quantify the forecasting performance by measuring how close the predicted values are to the actual values. MAPE is a percentage error-based measurement. It expresses the forecasting error as the average percentage deviation of the predicted results from the actual values. The R2 value measures the variation of the predicted values compared to the actual values. It quantifies how well the predicted values perform by comparing them with the actual values.

For training and comparing the models, the hourly ARI was predicted for three weeks using the previous three months' traffic counts. An 80%:20% data split in time was used for training and testing purposes. The LSTM model uses a 3D input shape consisting of the number of samples, sequence length, and number of features as required. Each fully connected hidden layer contains 100 units, and all hidden layers use the hyperbolic tangent activation. The temporal sequences and the associated predicted results are normalized back to their natural form for performance evaluation. A forecast function is applied to train the predictive model to recognize the temporal sequences of the time series and predict future values. The performance of the model is evaluated based on how accurately the predictive results align with the future real-world values for the testing dataset by using a normalized metric. Additionally, common error measurements, MAE, RMSE, MAPE, and R2, are used to evaluate the forecasting performance of the deep learning-based predictive model.

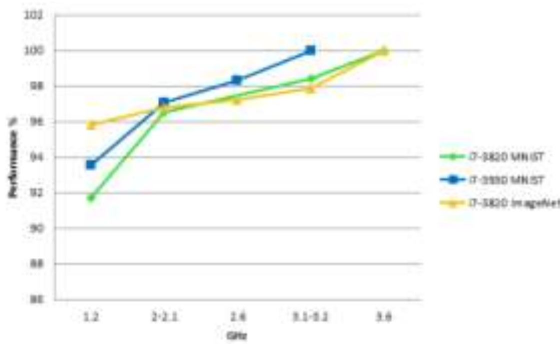

Fig : A Full Hardware Guide to Deep Learning

5. Benefits and Challenges

The benefits of deep learning-based predictive models for rail signaling and control systems are numerous. Chief among these is the ability of deep learning models to scale in accuracy as the size of training data grows, making them much more powerful than conventional train control models that depend heavily on precise rule-based algorithms. Additionally, given enough training data and computational resources, deep learning models are often better at identifying rules and performing feature learning, including discovering novel feature hierarchies that are otherwise difficult for human domain experts to handcraft. This makes deep learning predictive models an exciting frontier for data-driven model creation where the currently available rule-based conventional methods have failed to deliver.

Despite their high accuracy, one challenge of using deep learning predictive models for rail signaling and control lies in the necessity of syncing the prediction of such models with the track circuit detection system. Additionally, the predictions of the deep learning model also need to be checked against the rules of train control to avoid conflicting actions. Another difficulty lies in the deployment of deep learning predictive models. Conventional computer processors, which are used in the onboard equipment and interlocking units of rail signaling and train control systems, are typically not powerful enough for deep learning model deployment. Moreover, the running time for deep learning models is also a concern that requires addressing. The use of such powerful models also demands powerful computational resources for both training and prediction.

5.1. Operational Efficiency Improvements

Deep Learning-Based Predictive Models for Rail Signaling and Control Systems: Improving Operational Efficiency and Safety

5.1. Operational Efficiency Improvements Railway transportation is famous for its punctuality. This is due to the strict operational discipline and the static schedule nature of the railway. Any uncertainty in operating elements can result in long delays and can consequently be catastrophic. There are many reasons for uncertainties, including infrastructure degradation, natural disasters, track limitations, technical stumbles, operating emergencies, and human factors. Even though maintenance scheduling and procedures for the infrastructure, vehicle, and control systems are meticulously planned and executed, black swan events are always uncontrollable. Fortunately, advances in data collection mechanisms improve operating visibility and help identify potential threats before they become catastrophic. More importantly, data open up mathematical methods for early-warning signals using predictive modeling, strengthening operating efficiencies by: 1. early planning, acquiring resources, and implementing precautionary measures in dangerous windows; 2. statistical screening for distinguishing genuinely threatening abnormal operations from chronic operating conditions; and 3. making the train-path scheduling AI-adaptive instead of static schedule-oriented for synchronizing with unanticipated events, self-configuration, flexible control, and optimization. To achieve better operational efficiencies, the amount of real-time data collected from the entire domain during operation, whether from onboard trains, traffic control centers, trackside sensors, or IoT devices, directly affects the performance of predictive modeling. With the arrival of advanced technology, it will be feasible and cost-effective to collect such vast datasets for real applications without a bottleneck. Of course, the quality of data is fundamentally more important than the amount of data. The validity of models is determined by the data characteristics and their applicability. Most operational data include temporal dependencies and comprise repeated static field values and time-series features. It is usually costly to build general deep-learning models to encapsulate both cross-sectional and time-series features; therefore, simple models with great performance are good choices.

5.2. Safety Enhancements

Given the high potential of predictive models, which can anticipate the degradation of assets or signal anomalies indicating system flaws, there are also opportunities to improve safety by taking preemptive corrective measures, thus preventing incidents from occurring. In this context, safety implies analyzing the implications of the absence of a railroad accident. With predictive models focused on operating edge signaling system components, the potential exists to predict underlying problems and make preemptive corrections, reducing the railroad risk profile, which assumes fewer disasters. With timely information about rail car wheels that are possibly out of balance, which can lead to high-impact loads, crossing warnings can be issued until remediation has occurred, improving public and railroad personnel safety. Another example concerns the possible preemption of people other than the train crew entering the station platform within the safe zone indicated by the train proximity detection system. Traditionally, electronics, which may be affected by weather and animal intrusion, have been used to determine any issues with the safe zone indication. A predictive algorithm that can provide the safety system with timely information about something being out of balance, for example, allowing prediction of the likely impact point, can increase confidence in the hardware system, reduce false positives, and increase station system safety. Similar models can be developed for maintenance issues involving the wheel velocity sensors within the station platform. Building these monitoring applications into the increased computing power of the onboard signal system computers provides opportunities to increase safety and operational efficiency.

Equ 3: Loss Function Logistic Regression

$$h_\theta(x) = \theta_0 x_0 + \theta_1 x_1 + \ldots + \theta_j x_j \quad = \theta^T x \quad = \begin{bmatrix} \theta_0 & \theta_1 & \ldots & \theta_j \end{bmatrix} \begin{bmatrix} x_0 \\ x_1 \\ \ldots \\ x_j \end{bmatrix}$$

$$Where\ x_0 = 1$$

6. Conclusion

This chapter presented a comprehensive review of different deep learning-based predictive models and discussed their capabilities and applications in enhancing the reliability, efficiency, capacity, robustness, and safety of one of the most critical and safety-sensitive components of a modern rail system, i.e., the signaling and control systems. We reviewed several real-world applications of some of the most recent and advanced data-driven and predictive deep learning-based models such as Auto-Regressive Deep Neural Networks, Deep Neural Networks, Recurrent Neural Networks, Long-Short-Term-Memory Networks and Temporal Convolutional Networks, and Renormalized Residual Networks within different signaling and control systems including Train State Detection, Speed/Prediction Control, Over-the-Air Virtual ETCS Level/Mode and Data Populating, and discussed the significant performance improvements of these data-driven deep learning-based predictive models compared to their conventional counterparts. We also investigated two different challenges of the application of deep learning tools and discussed collaboration pathways between industry and academic researchers for overcoming these challenges.

The models can not only be utilized to enhance the operational conditions and safety of signaling and control systems either through prediction adjustments and optimization for satellite-based signaling and control systems but also provide the necessary conditions for satellite signaling and control application services. We envision that this review could provide both industry and academic researchers interested in using deep learning methodologies for more efficient exploitation of the large number of digitalization elements obtainable from the evolving fleets of modern rail vehicles with effective rail signaling data from GIS and operational systems. The current models and practical results provided within this chapter should help researchers to address relevant theoretical and empirical difficulties, as well as to investigate various driver behavior, traffic, signal, and control terrain evidence-based studies.

6.1. Future Trends

Future Trends. The future of rail signaling and control systems will undergo radical changes supported by advances in deep learning and its applications in optimization, prediction, control, decision-making, diagnostics, and prognostics. This will involve the use of complete temporal and spatial data, including additional data modalities, such as videos, Lidar, radar, and millimeter-wave measurements from front panels, sensors installed along the track, and in-vehicle measurements, such as waviness of rail surface, rail surface temperature, wheel profile, pantograph wear, and environmental data, including specific weather event data and altitude of the track. The future will also see the use of additional data from other transport entities, including dynamic timetable data, which will impose new constraints on the considered data-driven models. These models will evolve into interpretable deep learning models using mechanisms such as dropout, denoising, cost-sensitive classification, voting ensembles, and noise-resistant models, including robust and adversarial deep learning models. Additionally, hardware accelerators will be produced to speed up the computation of deep learning models on FPGA and ASIC circuits, and increasingly, the need for robust, real-time, fault-tolerant deep learning models.

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