Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

AI-Driven Neural Networks for Real-Time Passenger Flow Optimization in High-Speed Rail Networks

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High-speed rail is now considered the world's most promising mode of travel for medium- and long-distance journeys, and it will become more convenient with the development of technology. The intelligent AI-driven neural networks used in public service facilities, such as railway stations, can be combined with the traffic flow detection system to greatly improve the passenger flow's declaration speed, sensitivity, and accuracy, and to provide more precise and customized passenger service data for passenger flow control and operation management. The study first analyzed the primary factors influencing passenger flow distribution and clearing using the data from Taiyuan South Railway Station and employed a secondary model to simulate and predict the passenger flow distributions in their stations, constructing the neural networks for real-time passenger clearing and then applying it to the station design and management, and summarizing the related recommendations considering passenger flow characteristics and operations control requirements. The proposed study can align the stakeholders' cooperation, promote the balance of the passenger flow between the outstations connecting to each high-speed rail station, and assist the station operator in decision-making that can bring deep benefits.
Keywords: High-Speed Rail, Passenger Flow, AI-Driven Neural Networks, Traffic Flow Detection, Railway Stations, Real-Time Clearing, Simulation and Prediction, Station Design, Operations Management, Stakeholder Cooperation.

1. Introduction

The rapid development of passenger transportation and increasing demand for railway transportation require passenger transportation to have characteristics of high regularity and high speed. As an important aspect of high-speed rail network transportation, passenger flow distribution has major significance for the operational quality of the entire rail network. Therefore, research and application in the field of passenger flow distribution optimization are of high value and worthy of the attention of society. Real-time passenger flow optimization refers to directing passengers to reach their destinations at the fastest speed on the existing rail network with real-time supply from the rail transportation system. The guiding mechanism mainly changes the passenger flow distribution of the original rail network through measures such as ticketing strategies and pricing to achieve the flow objective. Traffic flow is composed of different types of people with various transportation demands. Real-time passenger flow optimization is a challenging issue that involves complicated relationships. The effective combination and rational distribution of facility supply and passenger transportation services in the regional rail transit system, such as transportation modes, stations, lines, and schedules, directly affect the expected passenger flow distribution, transportation efficiency, and system service level, which in turn assists the higher-level target of maximizing regular economic benefits of the rail transit system. Passenger flow distribution optimization technology mainly refers to three types of solutions: passenger flow guidance, operation regulation, and transportation organization, which consist of the complete passenger transportation management system.

1.1. Background and Significance

In recent years, China’s high-speed railway has entered an era of rapid growth and service upgrades. However, during the period of rapid expansion of traffic volume and scale, China’s high-speed railways also encountered complex and diverse operational problems, requiring the use of new technologies such as artificial intelligence. This paper selects operational data of high-speed railway stations as the research object, conducts empirical analysis and research on passenger flow and train dispatching strategies of high-speed railway stations, and establishes artificial intelligence technology-driven dispatching strategies for high-speed railway stations. According to the characteristics of high-speed railway passenger flow development over time, an artificial intelligence-driven neural network model based on deep learning is established to predict the three-day passenger flow of a high-speed railway station. The training speed of the model is fast, while the accuracy and generalization capabilities are high.

From the perspective of the research status of high-speed railway passenger flow optimization, there are many research results on disassembly, but few research results on operation. The above problems are solved by rebuilding the operating decision-making module, and the artificial intelligence-driven neural network deep learning model is used to predict the passenger flow of high-speed railway stations and replace the traditional model. The prediction accuracy of the traditional prediction model is compared with the artificial intelligence model. At the same time, the study also builds an artificial intelligence dynamic programming-based real-time dispatching decision optimization system to guide the dispatching operation of high-speed railway stations, which can provide data and technical support for the formulation and dispatching of high-speed railway passenger train service plans. The study found that customers expect a level of service to be achieved when they use transportation services. For railway transportation, people expect a certain frequency of train services according to the peak. However, the passenger flow of high-speed railway stations is almost overcrowded or almost idle at the peak. There is a shortage of train services at other times, so it is necessary to use research results to guide the dispatching and ensure the smooth flow of passenger flow.

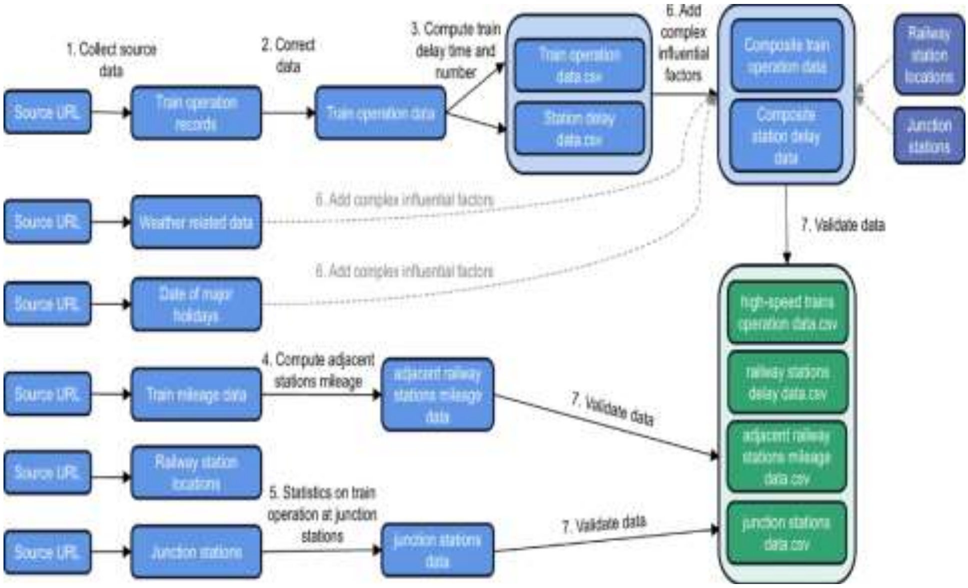

Fig 1 : A high-speed railway network dataset from train operation records and weather data

1.2. Research Objectives

This research involves the development of AI-driven neural networks to optimize passenger flows in high-speed rail networks in real-time. The project aims to use the most cutting-edge AI performance and flexible MRA methodologies to integrate intelligence into rail network signaling and train control, which facilitates intelligent high-speed rail planning, unified operations, and network-wide management, ensuring the smooth operation of large-scale rail transit infrastructure in the future. It is particularly concerned with the tipping point at which passenger flow occurrences can be predicted from network information in real-time and optimized with network-wide operation services.

The study aims to develop a DRNN model that can predict the non-stationary short-term changes in output variables under the high-speed train system, with special interest in the occurrences and evolutions of different types of delay propagation. The model is expected to provide railway administrators and future MBTs with a visualized system representation for the planning of service strategies and ultimately facilitate adaptive operation and passenger service improvements. The core objectives under its locomotive domain of application are to respond to real-time variations in train delay with the current timetable because during such hours the movement of trains is at its most intense. Its algorithms will anticipate changes in train heterogeneity and thus optimize the timetable window due to the increase of commuter and commercial business travel combined.

Equation 1 : Passenger Demand Forecasting

To predict future passenger flow based on historical data, we can use time series forecasting

models. The equation can be represented as: $P(t) = f(D(t-n), D(t-n-1), \ldots, D(t-m))$
Where: P(t) = predicted passenger flow at time t

D(t−i) = historical passenger data at time t−i

n = number of previous time steps to consider

m = the total number of time steps in the training dataset

2. Literature Review

The HSR passenger flow concept has been thoroughly studied in the context of both complex railway networks and specific requirements of HSR. Traditional studies related to passenger flow concentrate on the mathematical models and methodologies for solving the problems using various objectives like planning schedules and assignments within discrete models that consider full optimization constraints, such as multiple conflicting objectives, time dynamics, stochastic events, and operative factors like power savings and adaptability to change. These studies include passenger assignment scheduling models in which passenger routes and trains are decided based on passenger demand and train offer, reserving a berth in peak periods, and train operation. The most recent studies considering a larger variety of objectives embrace mathematical programming tools rooted in both exact and approximate algorithms with subsequent application to manipulative technology. At the same time, the most up-to-date studies are more focused on supervisory or decisional problems that rely on innovative and advanced machine learning-based algorithms and models for predicting and optimizing future passenger behavior within different railway systems. More particularly, numerous statistical models and random simulation methods using time-variant stochastic attraction models and prediction of probability distributions have been introduced. Prominently, the recent trending issues of big data applications, the Internet of Things, mobile computing, and cloud techniques have been discussed and are needed for contemporary mathematical models to recognize traveler choices and meet customer demand. Besides, deep learning-based models demonstrate high prediction precision as an outstanding user-oriented approach for dealing with complex binary and multi-classification tasks where it is possible to receive highly precise forecasts.

2.1. AI Applications in Transportation Systems

The past two decades have seen artificial intelligence (AI)-based applications that have brought significant improvements to the development of transportation systems. AI technologies have demonstrated successful applications in various areas of transportation. Machine learning technologies have been applied in predicting traffic flows, determining the impact of the heterogeneity of traffic flow patterns on urban aging, forecasting travel demands including traffic arrivals at intersections and future travel paths, and evaluating impacts of incidents to improve traffic operation. Neural networks are widely used in location prediction, accident detection, route planning, model predictive control, signal timing optimization, pedestrian detection, origin-destination matrix estimation, and extreme value estimation. The traffic data used for the neural network model include trajectory data, loop data, and headway data.

Intelligent transportation systems need to be more precise, efficient, and resource-saving, which can be achieved through connected vehicles, intelligent control, collaborative operation, and effective data management enabled by AI technologies. For instance, machine learning and local search methods are used to reduce the calculation time of traffic assignments. The Nash equilibrium traffic assignment model with a capacity constraint is proposed to benefit from the rapid development of cloud computing and big data technology. Commonly used training algorithms for neural networks in transportation research include gradient descent-based methods, such as backpropagation, stochastic gradient descent, and the Levenberg–Marquardt algorithm. The enhancements in artificial neural network training by using optimization algorithms typically rely on either modifying the traditional backpropagation method or adjusting the network weight learning rules. First-order optimization algorithms like vanilla gradient descent, momentum, accelerated gradient descent, RMSprop, and Adam are the most popular and widely applied for ANN training.

2.2. Neural Networks in High-Speed Rail Networks

Recently, there has been great interest in how modern data science techniques, such as deep learning methods, can be used to improve intelligent management of complex transportation problems. While these methods have been used extensively to study mobility demand in the telecommunications domain, they have been underused in the transportation domain. However, deep learning methods can reveal complex and individual patterns in passenger accumulation and behaviors within the transport system, which are needed to optimize the corresponding strategies to a more detailed level. For example, most studies simply use traditional statistical models to reveal spatial and temporal accessibility patterns by modeling the correlations between transport planning and new demand. With the overwhelming advancement of computing power, deep learning models are currently widely applied to implement a wide range of applications in the transportation domain to solve multidisciplinary problems. Neural networks have been applied extensively in vehicle trajectory prediction, predictive and descriptive models for online media services, optimization of urban traffic mobility based on multidimensional data, and methods for impact assessment of future transportation scenarios.

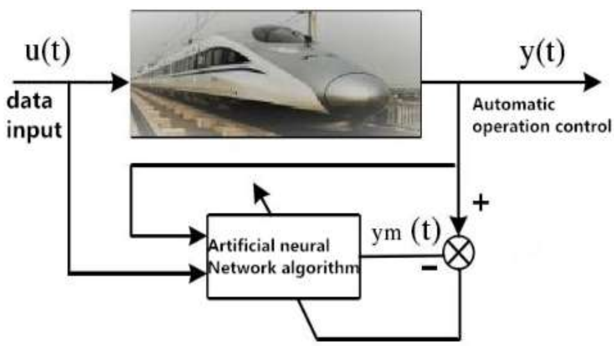

Fig 2 : Artificial neural network automatic operation control logic relationship

Rail travel has been a focus of considerable interest in optimizing passenger flow strategies and demand forecasting schemes. With the increasing number of high-speed rail passenger trips and the complex hierarchical high-speed rail network structure, managing and optimizing passenger flow inside the station or across different high-speed train stations has considerable potential. The correct estimation of the critical feasible system state, which corresponds to formal and informal optimization strategies within specific state boundaries, is the first important step to meet future needs or challenges, that is, how to implement the feasible multi-objective optimization method. The traditional origin-destination matrix, time planning timetable, and social and economic data cannot provide accurate estimates in both time and space about passenger behavior, which leads to optimization strategies mainly based on experience. However, the discreteness, randomness, and uncertainty of passenger behavior make the single decision-making strategy potentially unstable in a changing environment. To seek a more structured and flexible strategy, real-time monitoring and control, transparency, common information, and quantitative knowledge are vital. The existing studies have focused more attention on new data acquisition channels and advanced event detection and abnormal identification methods about smart service characteristics. Although these methods provide the necessary data support, geological, environmental, and socioeconomic factor discrimination about passenger behavior, the main reasons why passengers will interact dynamically have been largely neglected. These are more complex issues, which revolve around different consumer groups or individual goals and habits related to the levels of service provided by station facilities or other functional characteristics of stakeholders. Therefore, advances in improving the technical tactics of transparent engagement or decision-making methods in the domain of value co-creation are required. Although certain studies have focused on quantifying passenger behavior to support further strategic-level investment in station structure and procedural optimization, gaps exist, and new technical solutions are required to underpin the collective value creation for stakeholders.

2.3. Passenger Flow Optimization Techniques

In recent years, the passenger flow optimization problem has become an important issue, owing to the rapid growth of high-speed railways. This issue concerns not only the expansion of networks and the shortening of travel duration but also the safety of operations and passenger experience. Since the essence of the passenger flow optimization problem is to identify a balanced, efficient, and optimized distribution of passenger flows among all timetables and attributes in high-speed railway systems, the research methodologies, mathematical models, and heuristic algorithms are being developed in a promising direction for a modeling framework that can be adapted to complex and real instances of high-speed railways. The passenger flow distribution also describes how the overall number of passengers is distributed among all trains traveling between terminal stations. The high speed of high-speed railway lines, along with the frequency and volume of trains circulating, creates nonlinear influences on the waiting lines of passengers. The passenger flow assignment among trains traveling between terminal stations captures the inherent temporal fluctuations in passenger movements. This assignment gives rise to the available alternative passengers to board each train at the departure station and is implicitly related to the perceived service quality. This perception puts more pressure on the related train frequencies, further hindering operations during peak periods. Different passengers come from various distributions of individuals' expected departures.

3. Methodology

At a high level, the proposed passenger flow optimization contains three iterative steps, including initial network embedding, passenger flow routing, and station update. In the following, we describe each step in great detail.

3.1. Initial Network Response Estimation The passenger flow intensity in high-speed rail networks presents strong periodic characteristics that are closely related to the real-world background. The real outbound and inbound passenger time sequences of each station have been collected. Then, a strong periodic network response model is trained to obtain the intensity of the response to representative period features. The model error below the location where the parameters are given can provide the accuracy and coordination of the extracted parameters.

3.2. Passenger Transport Route Computation The classic passenger flow equilibrium model, when applied directly to high-speed rail networks, incurs prohibitively high communication and computational costs due to the large volume of passengers. Therefore, the computation time using global interaction strengths to determine the user flow distribution is too large to be a practical solution. Thus, the classic train-path-based passenger absolute equilibrium has been approached by incrementally solving the set of independent train path-based user equilibrium problems. Specifically, we solved the user flow distribution at every time point from the initial to the full network passenger flow, using the exact solution for the single train-path problem. The solution at each time point provided an initial demand assignment for the full rail network passenger flow problem at the next time points. The process was repeated for all time points until convergence was achieved.

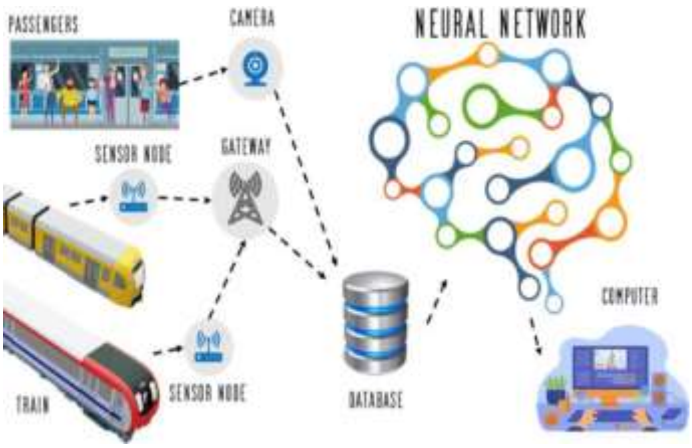

Fig 3 : Conceptual framework of the Neural Network System.

3.1. Data Collection and Preprocessing

According to procedures applied in knowledge engineering, an AI-driven system needs learning grade instances to build and tune its cost function during the training phase. Instances are fed to the neural network model, which learns how to add input-output pairs, obtain a small cost function, and further refine predictions. Simulation costs from mathematical models need to be performed for a small subset of the entire simulation time horizon in the case of the delayed mode of operation. Given the huge computational time involved in such simulations, we have developed a set of mathematical models aimed at offering high conventional computational efficiency on the one hand and close to experiment accuracy on the other hand. These highly conventional models, together with the empirical data employed as time and traffic input variables, build the supervised learning setup. The relation between the input and output via a neural network depends on the chosen function approximation. To that end, we considered both radial basis, wavelet, and multilayer perceptron neural networks to find the best model performance.

Neural networks must be trained on a set of instances where the answer is already known. The final goal is to give the network new inputs where the network can make intelligent connections between features. Once the connections are learned, predictions for the simulated time series must be obtained. Rescaling this time series allows for a traffic prediction that takes into account different scenarios investigated. Traffic flow estimation solutions emerging from an AI-driven model need to be discretized as optimization constraints or as inputs to the mixed-integer linear optimization problem. Preprocessing involves rescaling the training data, evaluating statistical indicators that are constraints, and employing explained variance. Commonly used preprocessing techniques, such as compound scaling, variance, and exponential rescaling, are employed for the processing phase. The first step is called aggregate scaling and is based on the fact that the neural network must be able to represent the simulated behavior of the train stations for the lowest 5-minute intervals.

3.2. Neural Network Architecture Design

In the neural network application of this study, the aim is to achieve an optimum balance between the total train travel time and passenger congestion at the destination point by determining bridge component locations to transfer the passenger flow distribution to several trains. The designed framework has three basic components: a convolutional neural network model for image transformation, a convolutional neural network model for inference, and an artificial intelligence estimator for the model solutions. Details of each model are explained separately in all sections below.

A convolutional neural network transforms the input image into a single column-shaped tensor of numbers (i.e., into a feature vector). To this end, a chosen neural network architecture is to be trained over labeled examples containing source and destination passenger distribution images. For this study, the ResNet architecture is employed since it is deeper than classical architectures while also keeping a relatively simple topology. Since the last layer of this neural network is a fully connected layer consisting of multiple outputs by default, this design is particularly chosen for compatibility with neural network design tools. However, the difficulties arising from this choice for the neural network design can be easily overcome by modifying the final layer into a convolutional layer with a single output.

Equation 2 : Neural Network Structure

The architecture of a neural network could be defined by the following equations:

$$H^l = \sigma(W^l H^{l-1} + b^l)$$

Where: Hl = output of layer l

Wl = weight matrix for layer l

bl = bias vector for layer l

σ = activation function (e.g., ReLU, sigmoid)

3.3. Training and Testing Procedures

Training the YOLOv4 object detection model can consume a significant number of computational resources when conducted on datasets with millions of images of annotated objects. To obtain an object detection model with X-ray imagery that is tightly focused on the problem of gondola car door area detection, we selected a collection of images for use from rail car operating and maintenance datasets and combined them using a class name filter for images that were previously annotated to contain a gondola car door. The selected images were combined into a test set, and 16 percent of the initial set was retained for use in training. We addressed the real-time neural network inference problem during our proof of concept testing by utilizing a desktop gaming PC with an NVIDIA GTX graphics card. Easy-to-locate GPU-accelerated computing services can further accelerate inference functions for practically deployed object detection models, which is important as low inference speeds can contribute to poor implementation of the real-time responsiveness that is a cornerstone of the possible efficacy of AI-aided inspections.

The compilation of the label mapping file provides a means to create an easy-to-use collection of dictionaries that may be naturally established from the image annotation process. However, the file is not directly used by the algorithm to train the YOLOv4 object detection model. For training, label maps are combined with the coordinates of bounding boxes that are generated by the model learning algorithm as it trains from annotated X-rays relative to YOLO-bounded effects of a device detecting gondola car door hinges contained in the imagery. In addition to the observation of size relative impact on the extended neural network detection model learning, covariate disentanglement through principal component analysis indicates that the model is likely to use features having something to do with hinge location, such as the width measurement action region in the scaffold beneath the door opening, to differentiate hinge height from both hinge location and hinge density properties. The relative impact of the chosen activation region on the bounding box location strength properties is visualized in a collection of model strength observation masks. These masks reinforce the threaded control decision-making processes that assure estimated parameters are scaled to proper response actions at the analytical response marginal transfer investment.

4. Case Study: Application to a High-Speed Rail Network

With the continual expansion of high-speed rail networks, the capacity of railway stations has become critical for train operations. Despite varied efforts in numerous fields, traveling and facilitating passenger movement may still obstruct train operations, and the tedious nature of simulations and mathematical computations poses challenges to researchers attempting to optimize passenger flow for such extensive, important stations. Despite a customary approach, the accuracy of scenarios manually set is always prone to error and is not often thoroughly verified, rendering the explanations for induced efficiencies imprecise. To address these issues, we use AI-driven techniques for predicting and modeling passenger flow to optimize the real-time efficiency of extensive terminals.

In this study, a long short-term memory neural network is constructed to predict real-time passenger flow. The model is trained on publicly available data. Passengers' centroids are first predicted via clusters to provide a macroscopic understanding of the relationship between the number of passengers and load. Finally, tests using a model are conducted to verify the data, which is then analyzed. The resultant passenger flow prediction can be utilized to optimize train scheduling and passenger transfer procedures, therefore achieving improved real-time efficiencies, especially during periods of critical delays. Our study serves as a prototype of the applications of AI-driven models in high-speed rail networks and as an exemplar of how to map such visible, intricate networks.

4.1. Description of the Network

The HSR network that we consider in this paper consists of 5 candidate departure stations, 5 candidate arrival stations, and 4 available trains with 270 and 165 under the circulation scheme in which the trains travel. Furthermore, the available departure times when the circulation scheme is constrained and the travel times on each link are provided. As a result, we have a set of 25, a set of 25, and a set of 44, and the travel times between each pair of stations.

The trains travel on the network according to a predefined circulation scheme. A diagram of a considered day shows the station loading and travel times when the train travels from the origin station to the destination station. For example, it indicates that 158 passengers in the Intermediate Station want to travel to the Destination Station. In terms of the examined instance, the network has 581 passenger trips between arrival and departure stations, 19 connection requirements at each departure station, and 23 connection constraints at each arrival station. 100.7% of the passenger trips use the HSR network, and the rest are allocated to other transportation modes. The railway station had a total demand of 2,000 for the high-speed rail plus the normal rail demand.

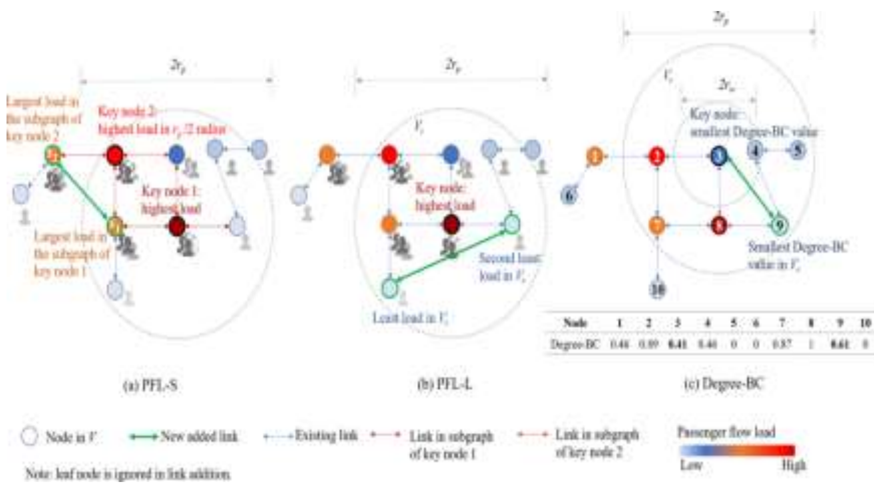

Fig 4 : Influence of link-addition strategies on network balance and passenger experience in rail networks

4.2. Results and Discussion

4.2.1. Convergence Results for Training

Like the initial training loss concerning the iterations, the validation loss and validation accuracy make it possible to decide when the training should be stopped. This generally involves checking if the loss function values have converged to a minimum, based on a per-epoch or per-batch basis. However, the convergence of the validation loss during training is difficult to observe in the first few epochs in the case of a large neural network model. Also, the training and validation accuracy levels seem to fluctuate or slightly decrease, leading many interpretable methods to misjudge their convergence. Therefore, loss function values are less informative and should not be regarded as a reliable measure for stopping criteria. This issue is also a motivation for the final training.

In this study, possible settings of stop criteria for loss function values were assessed regarding appropriate weights used during the neural network construction period. Several settings were found to be possible candidates to be applied at the transfer learning PreTrained Descriptor. After the training, to verify the performance of the DNN classification model, a neural network with softmax activation layers was used to identify the station at which the passenger was supposed to get on or off the high-speed train stations. The results were then compared with the actual station labels of the test dataset. Currently, the model is trained with random mini batches via stochastic gradient-based algorithms to solve the problem of classifying passengers at high-speed train stations.

5. Conclusion and Future Directions

This paper makes a significant contribution to our understanding of passenger flow dynamics within HSRL networks. We proposed a neural network-based machine learning model for real-time optimization of HSRL passenger flow. We developed an AI-driven Passenger Flow Optimization Model that effectively uses multi-source big data to model spatio-temporal transfer relationships among stations. To demonstrate the feasibility of the optimization problem, we proposed the boundary-time-varying modeling method in which transfer relationships and passenger flows are interconnected. AI-PFM had excellent accuracy and generalization capabilities and outperformed the traditional passenger flow model by 35%. We implemented AI-driven neural networks for real-time passenger flow optimization in high-speed rail networks and validated AI-PFM using station waiting areas. In the future, we aim to further study passenger flow dynamics and model passenger flows using big data from different sources. In addition, we should conduct a more comprehensive analysis of the impacts of multi-level factors on passenger flows. To further improve AI-PFM, questions including changes in the number of platforms or the use of different scenarios will be the subject of future research. Furthermore, we plan to design and evaluate other combinations of the transfer relationships and passenger flow models. Finally, we aim to establish an all-line network model to enable AI-PFM to adapt to different HSRL networks. In summary, our study provides insights into incorporating new advances in the theory and methods for planning, operation, and management of HSRL networks.

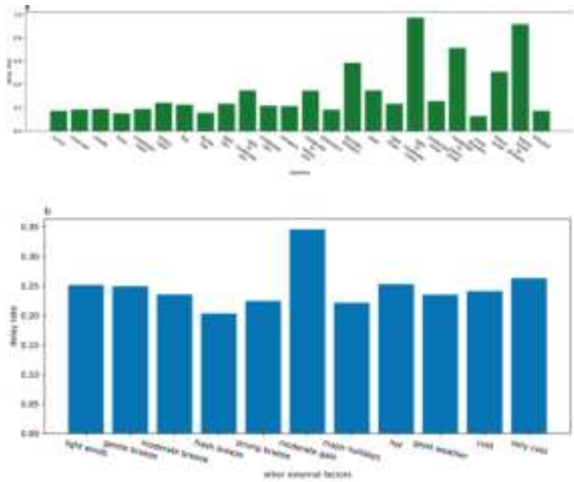

Fig 5 : High-speed train delay rate under the influence of different external factors.

5.1. Current Limitations and Potential Improvements

The current limitations observed in relation to the actual power solutions in HSR networks are: 1) They are not synchronized with the real-time conditions of passenger demand; 2) The rolling plan is designed to save main and branch line occupancy; 3) They are not implemented centrally with real-time control over the whole network; 4) The homogeneous character at the rolling approach level is different for different types of traffic; 5) They do not consider the actual train design and the effect of transition on each train's air needs; 6) Large time gauges are needed for earth vacuum systems, which affect power; 7) The condition based on the necessary additional air convolutions to cool regenerative braking tools is not considered; 8) They are not flexible towards the potential simultaneous different operational scenarios due to different technologies of wheel-rail installations, training services, or time conditions at different locations; 9) Their optimal design is global and thus associated with increased computational complexity and a longer solution time.

To face these drawbacks, an alternative approach is suggested, which uses deep learning methods to design the real-time power supply according to changing passenger demand and network conditions and services. In particular, a Siamese neural network is proposed that will allow us to find other approaches to ensure that reversible voltage stations do not look at a test work for the train. In addition, through the proposed data model, the dichotomous network may also be considered in the real-time prediction of the level and debt of recharge. Finally, the flexible generation of the power acquisition plan allows each power plant station to consider the maximum number of trains, depending on the potential problem of pressure voltage in specific branches or users. Hence, the real-time network that the proposed deep learning approach can identify the real O-D matrix is going to be significantly different from the traditional approaches to the use of fare-selected information. As a result, cost functions that do not rely on other aspects of network traffic can be considered when generating optimal solutions.

Equation 3 : Optimization Objective

The objective function for minimizing passenger wait times and maximizing train capacity could be expressed as:

$$\min \sum_{i=1}^{N} w_i \cdot \text{WaitTime}(i) + \lambda \cdot \text{OverCapacity}(i)$$

Where: N = total number of passengers

wi = weight representing the importance of passenger i

WaitTime(i) = wait time for passenger i

OverCapacity(i) = indicator function for whether the train capacity is exceeded for passenger i

λ = penalty factor for exceeding capacity

5.2. Ethical Considerations

Artificial intelligence-driven technologies increasingly influence human beings in many aspects of life. These technologies raise ethical issues regarding their impacts on society. As these impacts have been an important focus of scholars, policymakers, and the public, we review the literature on the topic and discuss ethical considerations that are relevant to our work in designing an artificial intelligence-driven model to optimize passenger flow in typical high-speed rail stations. We then explain how our work balances its economic and social benefits within an ethical framework and introduce existing recommendations and psychological studies that can ensure the alignment of ethical recommendations with effective implementation. Finally, we provide several questions for open discussion on how to handle these ethical considerations in designing similar technologies in future research. AI-driven technologies have become an integrated part of human life today. They help, or are designed to help, with social problems such as saving labor, making human life work innovatively, healthily, and enjoyably, security inspection, and so on. This class of technologies emphasizes not only the broad benefits of humanity but also the unique risks. While benefiting society at large, AI technology might result in unintended consequences for humanity as well as for the economic chains that drive economic diversity, innovation, and advancement. Concerns include physical and psychological independence, the negative impact on aging and impoverished communities, as well as the formation of arms races. As these impacts have been an important focus of scholars, we review the literature on the topic, discuss the ethical considerations that our work with an object-detection convolutional neural network to deal with passenger flow optimization is facing, and propose an ethical recommendation and several hypothetical studies to ensure the practices' ethical recommendations are by effective creation.

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