Modeling and Comparative Analysis of Urban Rail Transit Passenger Flow Forecasting

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Abstract

With the progression of smart urbanization, passenger flow prediction has emerged as an in- 1 tegral component of urban rail transit. To comprehensively characterize the essence of passenger flow prediction in urban rail transit, this paper focuses on modeling short-term prediction issues. Firstly, mathematical definitions are given for line network and station passenger flow, Origin-Destination (OD) passenger flow, and sectional passenger flow. Based on this foundation, a comprehensive mathematical modeling of short-term passenger flow prediction is conducted. Finally, this paper 6 summarizes the advantages, disadvantages, and conducts a comparative analysis of methods for short-term passenger flow prediction. Through mathematical modeling and comparative analysis of methods, this paper presents a comprehensive modeling framework for short-term passenger flow prediction. It decomposes the problem into more specific components, facilitating a profound understanding of its complexity and offering clear directions for diverse research aspects.With the continuous expansion of subway construction and the rapid development of intercity railways in urban areas, the subway network is becoming increasingly complex and the operating entities are becoming increasingly diverse. It is becoming increasingly urgent to establish an objective, fair, and reasonable ticketing system. The core issue is the allocation of travel routes under various transfer modes. This paper propose a rail transit network model based on station, route, network topology, and line vehicle dispatch information, which includes in-station and out-station travel time, transfer travel time, waiting time, and driving time. Furthermore, the influencing factors of each part of the travel time were analyzed, and theoretical analysis and simulation experiments revealed the impact of the randomness of travel time on passenger travel time under the constraint of exact vehicle entry and exit times.

Keywords

Rail Transit; Passenger Flow Forecast; Modeling; ModelsAllocation of Passenger Flow between Routes, Travel Chain, Travel Time, Bayesian Analysis.

1. Introduction

As urban rail transit undergoes rapid expansion, the operational model has transi- tioned to a network integration featuring "multiple operators and multiple lines". Furthermore, passenger flow in urban rail transit generally displays randomness, leading to considerable fluctuations at different times. Especially during unforeseen events, there is a substantial increase in passenger flow, potentially resulting in incidents such as stam- 18 pedes and causing significant societal consequences[1]. To prevent the occurrence of such incidents, it is essential to proactively forecast passenger flow during unforeseen events, allowing operational companies

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to devise sound scheduling plans for effective passenger flow management and risk mitigation[2]. Therefore, accurate and scientifically robust pas- senger flow forecasting methods are of paramount importance for optimizing operational scheduling and ensuring safety management in urban rail transit.

Passenger flow forecasting is primarily categorized into three aspects: short-term, medium-term, and long-term[3]. Medium-term and long-term passenger flow forecasting spans several months or years, assisting urban planners, traffic managers, and relevant agencies in making long-term decisions, which include urban planning, transportation infrastructure construction, and public transportation operational strategies. Short-term passenger flow forecasting typically involves predicting the near future (hours or a few days ahead)[4, 5], allowing transportation operators to make prompt decisions to address unforeseen situations, optimize services, and improve efficiency.

In urban rail transit, passenger flow manifests a high degree of randomness and is intricately influenced by external factors, rendering short-term passenger flow prediction a challenging undertaking. In order to comprehensively comprehend and address this issue, I conducted thorough research and analysis. By conducting a comprehensive study of the static factors (line attributes, station topological structure, station attributes, and surrounding environment) and dynamic factors (peak hours, weekdays, holidays, and weather, etc.) of short-term passenger flow prediction, I established a comprehensive model for the passenger flow prediction problem. This model offers a comprehensive and systematic framework for short-term passenger flow prediction. This framework is designed to furnish operating companies with more precise and practical tools for passenger flow prediction, addressing the uncertainty and complexity inherent in the operations of urban rail transit systems.

2. Modeling Passenger Flow Prediction Problems

2.1. Defining the Urban Rail Transit Network

Assuming the urban rail transit network is comprised of stations $\mathbb{S}=\{s_1,s_2,\cdots s_n\}$ and lines $\mathbb{L}=\{L_1,L_2,\cdots L_m\}$,station and line matrices can be utilized to represent the topological relationships within the network N.

$$B = \begin{array}{c} \\ L_1 \\ L_2 \\ \vdots \\ L_m \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_n \end{array} \\ \begin{bmatrix} b_{1,1} & b_{2,1} & \cdots & b_{n,1} \\ b_{1,2} & b_{2,2} & \cdots & b_{n,2} \\ \vdots & \vdots & \ddots & \vdots \\ b_{1,m} & b_{2,m} & \cdots & b_{n,m} \end{bmatrix} \end{array} \tag{1}$$

These matrix elements are:

$$b_{k,l} = \begin{cases} 1, & \mathrm{S}_k \in L_l \\ 0, & \mathrm{S}_k \notin L_l \end{cases} \tag{2}$$

For each line $i=1,2,\cdots,m$, its attribute M_i is defined, with $M_i=0$ indicating a bidirectional linear line and $M_i=1$ indicating a bidirectional circular line.

For any station s_i, where its attribute is represented as $w_i = [Ts_i, Ss_i, Sc_i]$, Ts_i signifies the station type $Ts_i = 1$ for interchange, $Ts_i = 0$ for regular; Ss_i represents the peripheral environment, $Ss_i = 0$ for the business district, $Ss_i = 1$ for residential area, $Ss_i = 2$ for tourist attraction. Sc_i denotes the station's integration with other transportation networks, $Sc_i = 0$ indicates a connection to bus stations, $Sc_i = 1$ represents a connection to train stations, and $Sc_i = 2$ indicates a connection to airports. Therefore, the station's attributes can be effectively represented by a matrix.

$$W = \begin{array}{c} \\ Ts_i \\ Ss_i \\ Sc_i \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_n \end{array} \\ \begin{bmatrix} Ts_1 & Ts_2 & \cdots & Ts_n \\ Ss_1 & Ss_2 & \cdots & Ss_n \\ Sc_1 & Sc_2 & \cdots & Sc_n \end{bmatrix} \end{array} \tag{3}$$

When conducting modeling of the urban rail transit network N, the standard approach involves using a station-to-station adjacency matrix to depict the topological relationships among stations.

$$A = \begin{array}{c} \\ S_1 \\ S_2 \\ \vdots \\ S_n \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_n \end{array} \\ \begin{bmatrix} a_{1,1} & a_{2,1} & \cdots & a_{n,1} \\ a_{1,2} & a_{2,2} & \cdots & a_{n,2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1,n} & a_{2,n} & \cdots & a_{n,n} \end{bmatrix} \end{array} \tag{4}$$

These matrix elements are:

$$a_{i,j} = \begin{cases} 1, & \mathrm{S}_k \in L_l \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

Thus, we employ a five-element tuple to describe the entire network $\mathbb{N} = [S, L, W, M, A, B]$.

2.2. Definition of Short-Term Passenger Flow in Rail Transit

Assuming the observation intervals are $\tau = \{\tau_1, \tau_2 \cdots \tau_N\}$ .Typically, $\tau_k, k \in \{1, 2, \cdots N\}$ is used to represent continuous, non-overlapping time segments in the rail network. These segments divide the time from the start to the closure of train operations in a day, thus defining the scale of the observation time window. In addition, the passenger flow function set is defined as $P_x^D(\tau_k; y)$, where x denotes different types of passenger flows (station flows, Origin-Destination (OD) passenger flow, and sectional passenger flow); $D = \{d_1, d_2, \cdots d_Z\}$ represents the collection of date days, with d_i indicating the $i-\text{th}$ day; $y = \{s_i, s_j, L_i, r_c, \mathbb{N}\}$ is the set of observed passenger flow positions, where s_i and s_j represent the originating and destination stations, and r_c refers to a specific section. Thus, starting from the observed positions, passenger flows can be classified into station flows, OD flows, and section flows.

(1) Station passenger flow

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Station passenger flow typically encompasses entry, exit, line entry exit, and network entry-exit passenger flows. Entry passenger flow refers to the number of passengers entering a station s_i within a specific time period τ_k in the railway network and is represented as:

$$P_{in}^{D}\left(\tau_k ; s_i\right), i=1,2,\cdots,n; k=1,2,\cdots,N \tag{6}$$

The exit passenger flow at a station is analogous to the entry passenger flow and is expressed as:

$$P_{out}^{D}\left(\tau_k ; s_i\right), i=1,2,\cdots,n; k=1,2,\cdots,N \tag{7}$$

Line entry passenger flow denotes the sum of entry passenger flows at all stations on a given line L_i during a specific time period τ_k and is expressed as:

$$P_{in}^{D}\left(\tau_k ; L_i\right), i=1,2,\cdots,m; k=1,2,\cdots,N \tag{8}$$

Correspondingly, line exit passenger flow can be expressed as:

$$P_{out}^{D}\left(\tau_k ; L_i\right), i=1,2,\cdots,m; k=1,2,\cdots,N \tag{9}$$

Network entry passenger flow denotes the cumulative entry passenger flow at all stations across all lines during a specific time period τ_k and is expressed as:

$$P_{in}^{D}\left(\tau_k ; \mathbb{N}\right), k=1,2,\cdots,N \tag{10}$$

Therefore, network exit passenger flows are expressed as:

$$P_{out}^{D}\left(\tau_k ; \mathbb{N}\right), k=1,2,\cdots,N \tag{11}$$

(2) Origin-Destination (OD) passenger flow

OD passenger flow denotes the count of passengers traveling from station s_i to station s_j within a time period τ_k on the network $\mathbb{N}$. The symbol $P_{OD}^{D}\left(\tau_k ; s_i, s_j\right)$ represents the passenger flow value for a given OD pair. Assuming network $\mathbb{N}$ and line L_j, the relationship between entry and exit passenger flows and OD passenger flows are expressed as follows in the formula:

$$\sum_{k=1}^{N} P_{in}^{D}\left(\tau_k ; s_i\right)=\sum_{k=1}^{N} \sum_{j=1}^{n} P_{OD}^{D}\left(\tau_k ; s_i, s_j\right),(i \neq j) \tag{12}$$

$$\sum_{k=1}^{N} P_{out}^{D}\left(\tau_k ; s_i\right)=\sum_{k=1}^{N} \sum_{j=1}^{n} P_{OD}^{D}\left(\tau_k ; s_i, s_j\right),(i \neq j) \tag{13}$$

(3) Sectional passenger flow

Sectional passenger flow signifies the count of passengers passing through a particular cross-sectional point within a segment on the line during a specified statistical time period. Consider a particular line L_k with a starting station at s_i and an end station at s_j . making $L_k = \{s_i, s_{i+1}, \cdots, s_j\}$. Define the cross-section between adjacent stations on the line and utilize the symbol to denote cross-sectional passenger flows for both the up and down directions. Hence, cross-sectional passenger flow can be represented as:

$$P_{\sec}^{D}\left(\tau_k; r_c\right) = P_{\sec_1}^{D}\left(\tau_k; r_c\right) + P_{\sec_2}^{D}\left(\tau_k; r_c\right) \tag{14}$$

(4) Short-Term Passenger Flow Prediction

Before conducting short-term passenger flow forecasting, it is essential to ascertain historical passenger flow data. AFC data generally contains details about passenger entries and exits at stations, along with entry and exit times, from which relevant historical passenger flow data can be extracted. This data encompasses passenger flow data for all time periods in the previous Z days and for the time periods that may have occurred on the Z+1st day. Consequently, historical passenger flow data $P_x^D\left(\tau_k; y\right)$ for the previous Z days can be represented as a matrix Q, while passenger flow data for the time periods that have already occurred on the Z+1st day can be represented using a variable-length vector q.

$$Q = \begin{bmatrix} P_x^{d_1}\left(\tau_1; y\right) & P_x^{d_2}\left(\tau_1; y\right) & \cdots & P_x^{d_Z}\left(\tau_1; y\right) \\ P_x^{d_1}\left(\tau_2; y\right) & P_x^{d_1}\left(\tau_2; y\right) & \cdots & P_x^{d_Z}\left(\tau_2; y\right) \\ \vdots & \vdots & \ddots & \vdots \\ P_x^{d_1}\left(\tau_N; y\right) & P_x^{d_1}\left(\tau_N; y\right) & \cdots & P_x^{d_Z}\left(\tau_N; y\right) \end{bmatrix} \tag{15}$$

$$q = \begin{bmatrix} P_x^{d_{Z+1}}\left(\tau_1; y\right) \\ P_x^{d_{Z+1}}\left(\tau_2; y\right) \\ \vdots \\ P_x^{d_{Z+1}}\left(\tau_N; y\right) \end{bmatrix} \tag{16}$$

In this context, Q represents the historical passenger flow data matrix for the previous Z days; q is a variable-length vector representing passenger flow data for time periods that have already occurred on the $Z+1$ st day (which can be an empty vector); $P_x^{d_i}\left(\tau_k; y\right)$ denotes the passenger flow value for the kth time period on the ith day.

When performing short-term passenger flow prediction, the choice of input data depends on the specific prediction task. For instance, if the goal is to forecast passenger flow for the i th day, with the prediction time interval measured in days, an input data selection function f_1 can be established.

$$Q' = f_1(i - X; Q) \tag{17}$$

In this context, f_1 denotes the date selection function applied to the historical passenger flow data matrix Q; X represents any number of days; and $i - X$ indicates a backward shift by X time intervals for selecting historical passenger flow data from different dates.

We define an observation time window H based on historical data, encompassing specific past days and time intervals necessary for passenger flow prediction. Let the set of certain past days' dates within the observation time window be denoted as $H_1 = \{d_{(i-X)_1}, d_{(i-X)2}, \cdots d_{(i-X)h}\}$, $H_1 \subset D$. The selection of H_1 is determined based on the forecasting objective, where $(i-X)_1, (i-X)_2, \cdots (i-X)_h$ represent indices from different positions in the set D.

These indices are used to choose observation passenger flow data for h days through the data selection function f_1. Hence, the historical passenger flow for certain past days' dates is represented by $P_x^{H_1}(\tau_k; y)$, and it is symbolize by the matrix Q'.

$$Q' = \begin{bmatrix} P_x^{(i-x)_1}(\tau_1; y) & P_x^{(i-x)_2}(\tau_1; y) & \cdots & P_x^{(i-x)_h}(\tau_1; y) \\ P_x^{(i-x)_1}(\tau_2; y) & P_x^{(i-x)_2}(\tau_2; y) & \cdots & P_x^{(i-x)_h}(\tau_2; y) \\ \vdots & \vdots & \ddots & \vdots \\ P_x^{(i-x)_1}(\tau_N; y) & P_x^{(i-x)_2}(\tau_N; y) & \cdots & P_x^{(i-x)_h}(\tau_N; y) \end{bmatrix} \tag{18}$$

When considering the τ dimension, assuming the prediction task is to forecast passenger flow for the j th time period, and the prediction time interval is measured in time periods, an input data selection function f_2 can be established.

$$q' = f_2(i-X; Q, q) \tag{19}$$

Here, f_2 serves as the time period data selection function applied to Q and q; Y denotes any number of time periods; and $(j-Y; Q, q)$ involves selecting passenger flow data from various time periods by rolling back over the preceding Y time periods.

Consider a collection of time periods from a specific past day as $H_2 = \{\tau_1, \tau_2, \cdots \tau_{j-1}\}$, $H_2 \subset \tau$, indicating the selection of $j-1$ time periods from a particular day. Consequently, the passenger flow for time periods from a certain past day is represented as $P_x^{d_i}(\tau_k; y)$, and it is expressed using vector q_1.

$$q' = \begin{bmatrix} P_x^{d_i}(\tau_1; y) \\ P_x^{d_i}(\tau_2; y) \\ \vdots \\ P_x^{d_i}(\tau_N; y) \end{bmatrix} \tag{20}$$

When forecasting the passenger flow for the jth time period on the i th day, it is crucial to consider both the date and time period dimensions. To facilitate this, an input data selection function can be created.

$$P_x^{H_1}(\tau_{H_2}; y) = f_3(i-X, j-Y; Q, q) \tag{21}$$

Here, f_3 stands for the date and time period input data selection function, and $(i-X, j-Y; Q, q)$ represents the additional selection of time periods after rolling back to select historical passenger flow data for X days. The chosen input data is represented as $P_x^{H_1}(\tau_{H_2}; y)$.

$$P_x^{H_1}\left(\tau_{H_2};y\right)=\begin{bmatrix} P_x^{(i-x)_1}\left(\tau_1;y\right) & P_x^{(i-x)_2}\left(\tau_1;y\right) & \cdots & P_x^{(i-x)_h}\left(\tau_1;y\right) \\ P_x^{(i-x)_1}\left(\tau_2;y\right) & P_x^{(i-x)_2}\left(\tau_2;y\right) & \cdots & P_x^{(i-x)_h}\left(\tau_2;y\right) \\ \vdots & \vdots & \ddots & \vdots \\ P_x^{(i-x)_1}\left(\tau_{j-1};y\right) & P_x^{(i-x)_2}\left(\tau_{j-1};y\right) & \cdots & P_x^{(i-x)_h}\left(\tau_{j-1};y\right) \end{bmatrix} \tag{22}$$

Thus, when focusing solely on historical passenger flow data, the passenger flow prediction problem can be framed as follows: utilizing the historical passenger flow data $P_x^{H_1}\left(\tau_{H_2};y\right)$ from the observation window as input, the objective is to identify an optimal function F for forecasting future passenger flow values for the upcoming time periods.

Passenger flow prediction is more than just relying on historical passenger flow data; it also necessitates the consideration of static attributes within the transportation network, such as route properties M, station topology A, and station attributes W. Consequently, apart from historical passenger flow data, input data from the static attributes of the transportation network is needed to forecast future passenger flow values for specific time periods.

Additionally, historical passenger flow data incorporates dynamic attributes related to both date and time periods. For any date d_i, its attributes are denoted as $\eta_i=[\alpha_i,\beta_i,\gamma_i,\mu_i,\delta_i]$, where α_i indicates whether the day is a weekday or weekend, β_i represents the weather conditions for that day, γ_i denotes whether it's a holiday, μ_i signifies the presence of significant events, and δ_i reflects the occurrence of unexpected incidents. For any time period τ_k, its attribute φ_k indicates whether it falls within the morning or evening rush hours. Consequently, we can consolidate date and time period attributes into a unified temporal attribute $\xi=[\eta,\varphi]$.

In the preceding explanation, we established the context by discussing historical passenger flow data and relevant attributes. We introduced the central challenge of short-term passenger flow prediction, which involves accurately forecasting passenger flow for specific days and time periods in the future using this data and these attributes. Now, we will methodically outline the entire process of short-term passenger flow prediction. Assuming the need to predict passenger flow for T days, the set of validation data dates is denoted as $V=\{v_1,v_2,\cdots v_T\}$. Consequently, the predicted passenger flow data is represented as $P_x^T\left(\tau_k;y\right)$, and the validation data is $P_x^V\left(\tau_k;y\right)$.

(1) Determining Inputs

Provided with the observed historical passenger flow data $P_x^{H_1}\left(\tau_{H_2};y\right)$, the temporal attribute ξ, and the network attributes of route M, station topology A, and station attributes W in network $\mathbb{N}$.

(2) Seeking Function F

Seek an appropriate function F that, based on input data, particularly historical passenger flow data and related attributes, performs passenger flow prediction. Establishing this function is a critical step in the short-term passenger flow prediction problem.

(3) Output

The output of short-term passenger flow prediction consists of the passenger flow for specific days and time periods in the future.

$$P_x^T\left(\tau_k;y\right)=F(P_x^{H_1}\left(\tau_{H_2};y\right),\xi,\mathbb{N}) \tag{23}$$

(4) Objective

The aim is to minimize errors in the results of short-term passenger flow prediction to enhance prediction accuracy and reliability. The passenger flow predicted using function F is adjusted to minimize the error between predicted values and ground truth.

$$\arg\min F \sum_{i\in\{1,2,\cdots T\}} \sum_{k\in\{1,2,\cdots N\}} \left[F(P_x^{H_1}(\tau_{H_2};y),\xi,\mathbb{N}) - P_x^{v_i}(\tau_k;y) \right]^2 \tag{24}$$

2.3. Comprehensive Analysis of Passenger Flow Prediction

2.3.1. Predicting Station Passenger Flow

Station flow prediction encompasses predictions for both entry and exit flows at individual stations, as well as flows entering and exiting the network as a whole. When focusing on predicting the entry flow for a single station, the observed flow data comprises the historical entry data for that specific station, represented as $P_{in}^H(\tau_k;s_i)$. Consequently, the problem of predicting the entry flow for a single station can be defined as follows: Given the historical entry data $P_{in}^H(\tau_k;s_i)$, temporal attribute ξ, and station attributes W within network $\mathbb{N}$, they serve as inputs to identify the optimal function F_1 for forecasting future flows during specific time periods.

$$P_{in}^T(\tau_k;s_i) = F_1(P_{in}^H(\tau_k;s_i),\xi,W) \tag{25}$$

In the context of predicting entry flow for a specific line, the observed historical flow data is represented as $P_{in}^H(\tau_k;L_i)$. Furthermore, route properties M, station attributes W, and temporal attributes ξ must be considered. These serve as inputs to identify a function F_2 that minimizes errors in line flow prediction.

$$P_{in}^T(\tau_k;L_i) = F_2(P_{in}^H(\tau_k;L_i),\xi,M,W) \tag{26}$$

In the context of predicting entry flow for the entire network, the observed historical flow data is represented as $P_{in}^H(\tau_k;\mathbb{N})$. Unlike line entry flow, it's imperative to account for the topological relationships between stations, denoted as A. Consequently, the input is utilized to discover the optimal function F_3 for network flow prediction. Outflow prediction is analogous to inflow prediction, and will not be reiterated in this context.

$$P_{in}^T(\tau_k;\mathbb{N}) = F_3(P_{in}^H(\tau_k;\mathbb{N}),A,\xi,M,W) \tag{27}$$

2.3.2. Predicting OD Passenger Flow

OD flow prediction entails utilizing historical OD matrix data and entry-exit flow data from originating stations to predict future OD matrix passenger flow information.

$$P_{OD}^H(\tau_k;s_i,s_j) = \begin{bmatrix} P_{OD}^H(\tau_k;s_1,s_1) & P_{OD}^H(\tau_k;s_1,s_2) & \cdots & P_{OD}^H(\tau_k;s_1,s_n) \\ P_{OD}^H(\tau_k;s_2,s_1) & P_{OD}^H(\tau_k;s_2,s_2) & \cdots & P_{OD}^H(\tau_k;s_2,s_n) \\ \vdots & \vdots & \ddots & \vdots \\ P_{OD}^H(\tau_k;s_n,s_1) & P_{OD}^H(\tau_k;s_n,s_2) & \cdots & P_{OD}^H(\tau_k;s_n,s_n) \end{bmatrix} \tag{28}$$

In this context, the diagonal elements $P_{OD}^H(\tau_k;s_i,s_j)$ represent the OD passenger flow from station s_i to station s_j, and are regarded as 0.

Consequently, the problem of OD flow prediction can be outlined as follows: Given historical OD flow data $P_{OD}^{H}\left(\tau_k;s_i,s_j\right)$ and historical entry-exit flow, along with the adjacency matrix A between stations, station attribute matrix W , route attribute M , and temporal attribute ξ ,these serve as inputs to identify the optimal function F_4 for OD flow prediction.

$$P_{OD}^{T}\left(\tau_k;s_i,s_j\right)=F_4(P_{OD}^{H}\left(\tau_k;s_i,s_j\right),A,\xi,M,W) \tag{29}$$

2.3.3. Predicting Sectional Passenger Flow

Sectional flow is not currently obtainable directly from AFC data. Assuming historical sectional flow is already known, it is possible to predict the future sectional upward and downward flow for a specific section in an upcoming time period using the optimal functions F_5 and F_6. This can be achieved by utilizing historical upward sectional flow $P_{\mathrm{sec}_1}^{H}\left(r_c,\tau_k\right)$, downward sectional flow $P_{\mathrm{sec}_2}^{H}\left(r_c,\tau_k\right)$, along with temporal attribute ξ , route attributes M in the network $\mathbb{N}$, station topological relationships A , and station attributes W .

$$P_{\mathrm{sec}_1}^{T}\left(\tau_k;r_c\right)=F_5(P_{\mathrm{sec}_1}^{H}\left(\tau_k;r_c\right),A,\xi,M,W) \tag{30}$$

$$P_{\mathrm{sec}_2}^{T}\left(\tau_k;r_c\right)=F_6(P_{\mathrm{sec}_2}^{H}\left(\tau_k;r_c\right),A,\xi,M,W) \tag{31}$$

$$P_{\mathrm{sec}}^{T}\left(\tau_k;r_c\right)=P_{\mathrm{sec}_1}^{T}\left(\tau_k;r_c\right)+P_{\mathrm{sec}_2}^{T}\left(\tau_k;r_c\right) \tag{32}$$

3. Passenger Flow Prediction Methods based on TSA and Statistical Models

3.1. Passenger Flow Prediction Methods based on Time Series Analysis

The Autoregressive Integrated Moving Average (ARIMA) model stands as the most commonly employed traditional model in time series passenger flow prediction. This model amalgamates moving average, autoregressive (AR), and differencing techniques, utilizing three determined parameters for modeling and forecasting. In recent years, researchers have introduced a series of enhancements and refinements to the ARIMA model. M. Milenkovic et al.[1] also employed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model for monthly railway passenger flow prediction, accounting for the influence of seasonal variations on passenger flow. Typically, once a transportation passenger flow prediction model is established, its parameters remain static, operating within a static framework. The introduction of new observational data often results in a decrease in prediction accuracy. Thus, X. Wang et al.[2] employed wavelet decomposition techniques to eliminate the impact of random fluctuations in passenger flow and subsequently applied the ARIMA model for prediction. This integrated prediction approach yielded a threefold reduction in Mean Absolute Percentage Error (MAPE) compared to standalone predictions, considerably enhancing prediction accuracy.

Statistical modeling methods for passenger flow prediction, built upon the foundation of time series analysis, employ statistical techniques such as multiple linear regression, logistic regression, and probability models to make predictions regarding passenger flow. These methods are generally suited for predicting passenger flow in cases with numerous influencing factors, as seen in urban rail transit systems. Using Beijing's subway system as an example, X. Zhang et al.[3] integrated various attributes from the rail network, such as station attributes, route attributes, and time attributes, into their analysis, applying the multiple linear regression method to predict entry and exit passenger flow. By considering multiple factors holistically, this model achieved high prediction accuracy. Similarly, Y. Liu et al.[4] utilized logistic regression to address peak passenger flow prediction concerns in Beijing's subway system. For complex passenger flow prediction challenges, including those associated with peak and off-peak periods and variations in passenger flow under various weather conditions, statistical models offer increased flexibility in adapting to multifactorial influences, ultimately enhancing prediction accuracy.

3.2. Passenger Flow Prediction Methods based on Statistical Models

Kernel Ridge Regression (KRR) and Gaussian Process Regression (GPR) are two regression prediction methods within the field of statistics. These methods are employed to establish models capturing the relationship between input features and target variables, particularly excelling in handling non-linear problems. Z. Guo and colleagues [3] pioneered the fusion of KRR and GPR to create a prediction model. They started by using GPR for initial data prediction, employed a Stacked Autoencoder (SAE) network for feature extraction to capture spatiotemporal information, considered holiday data, and finally applied KRR to refine the initial results, resulting in the ultimate prediction. While this prediction method accounts for spatiotemporal factors and holidays, it overlooks other elements like seasonality and weather. In their work, C. Li and collaborators [4] focused on predicting passenger flow in subway systems during emergencies. They developed a nonlinear regression OD passenger flow prediction model tailored to forecasting passenger flow during unexpected events in Beijing's urban rail transit. The algorithm of this model is capable of accurately predicting passenger flow during unexpected events. However, its scope is limited to predicting for individual stations or a small set of stations and does not offer a global forecast. E. Chen and the team [5] employed statistical modeling techniques to predict passenger flow before and after concerts at the Nanjing Olympic Sports Center. They utilized four distinct models, including generalized autoregressive conditional heteroskedasticity (GARCH) models and ARIMA models for modeling purposes. This approach successfully addresses the challenge of ARIMA models in capturing the volatility and nonlinearity associated with special events.

4. Passenger Flow Prediction Methods based on Machine Learning

4.1. Passenger Flow Prediction Methods based on Regression Models

As machine learning continues to evolve, several machine learning methods and hybrid prediction model approaches have been adopted in short-term passenger flow prediction for rail transit. These include decision trees, Random Forest (RF), Support Vector Machine (SVM), Radial Basis Function (RBF), and other models. In their study, G. Zhou and collaborators [6] analyzed passenger flow during the Dragon Boat Festival and Labor Day holidays. They utilized SVM to build a predictive model for passenger flow at a particular station, achieving a prediction error of less than 5%. Y. Sun and colleagues [7] introduced a novel approach by using a non-linear hybrid model for forecasting passenger flow in the Beijing subway, particularly during morning and evening peak hours. They proposed the wave-SVM model, which harnessed wavelet decomposition to effectively handle non-linear data, breaking it down into high-frequency and low-frequency components. The subsequent use of the Least Squares Support Vector Machine (LS-SVM) enabled the prediction of high-frequency and low-frequency sequences. This approach combines the advantages of wavelet decomposition while mitigating the slow training speed issue associated with SVM. Expanding on this concept, D. Li and the team [8] presented the Metro Multi-Point Prediction (MSP) method. This approach similarly utilizes wavelet techniques for data decomposition and reconstruction. During the prediction phase, it adopts a combination of SVM and RBF with dynamically adjusted weights to predict various frequency components. The model forecasts passenger flow for multiple stations, significantly enhancing prediction accuracy compared to both SVM and RBF models for single stations (SSP). However, the improvement in comparison to Long Short-Term Memory (LSTM) predictions is relatively modest.

J. Guo and the team [9] introduced a hybrid SVR-LSTM model for predicting abnormal passenger flow. Recognizing that SVR struggles to capture rare passenger flow patterns, they devised a two-stage LSTM training method to enhance the prediction of highly volatile passenger flow. While this approach effectively predicts abnormal passenger flow, its accuracy significantly diminishes for predictions exceeding 30 minutes. Abnormal passenger flow often results from special events or activities leading to a sudden surge in passengers. Y. Li and colleagues [10] introduced the Multiscale Radial Basis Function (MSRBF) model based on the RBF method. They used it to predict passenger flow for three distinct factors (holidays, concerts, and train signal faults) at three stations. This approach improved prediction accuracy by nearly double compared to SVM. However, a limitation of this method arises when dealing with extensive input vector data, leading to numerous candidate models. To address this, they introduced the MPOLS algorithm for the efficient selection of important candidate models for modeling.

4.2. Passenger Flow Prediction Methods based on Decision Trees and Random Forests

Decision trees and random forest methods are commonly used for passenger flow prediction. C. Ding et al. [11] proposed using Gradient Boosting Decision Trees (GBDT) to predict short-term passenger flow at three subway stations in Beijing. Compared to statistical modeling methods, ARIAM, SVM, and others, the GBDT model can rank the impact of predictive variables on the outcome by feature importance, while maintaining a high level of accuracy. Y. Liu et al. [12], based on the decision tree algorithm model, designed a convolutional neural network structure to automatically extract features, addressing the drawback of decision tree models' high dependence on strong features. This approach outperforms LSTM and MLP models in terms of training efficiency and accuracy. The essence of the random forest method is to leverage the results of multiple decision trees to enhance prediction performance. X. Dai et al. [13], building upon short-term passenger flow prediction using the Adaboost and KNN models, combined the Random Forest (RF) method to create a composite model for OD passenger flow prediction. The results show its superiority over ARMA, neural networks, and support vector regression models in terms of prediction and strong portability. This demonstrates that incorporating the RF method improves prediction performance, but does not assess the relative merits of the RF method and neural network models. Subsequently, W. Kusonkhum et al. [14], considering factors such as holidays, weekends, and weather, separately applied artificial neural networks, random forests, and decision trees for passenger flow prediction. They found that the neural network model outperforms in terms of predictive performance.

5. Deep Learning-based Methods for Passenger Flow Prediction

5.1. Passenger Flow Prediction Method based on Recurrent Neural Networks

F. Toque et al. [15] utilized LSTM network models for short-term subway passenger flow prediction, achieving superior predictive performance compared to vector autoregressive models. D. Yang et al. [16] improved LSTM networks by introducing the Enhanced Long-term Feature LSTM (ELF-LSTM) for OD flow prediction. They used historical and recent data as input for feature learning at different time intervals. Comparative analysis with RNN, LSTM, and ARIMA models demonstrated that this algorithm model provides better predictive accuracy. Jinlei Zhang et al. [17] also proposed a clustered LSTM model (CB-LSTM) based on LSTM models. They used a two-step k-means clustering approach to group data from nine subway stations for training, taking spatial considerations at a local level and breaking away from the traditional

LSTM training that focused on predicting passenger flow for a single station. Additionally, they combined similarity testing and unit root testing to recommend more reasonable TG intervals as part of a more precise composite model.

Subsequently, researchers integrated decomposition techniques with LSTM to create hybrid models for passenger flow prediction. The concept behind decomposition is to break down the original data into multiple components, which can handle nonlinear data more effectively. X. Yang et al. [18] introduced an LSTM network model based on wavelet decomposition for short-term passenger flow prediction, achieving higher prediction accuracy than the LSTM network model. Q. Chen et al. [19] employed the Empirical Mode Decomposition (EMD) technique in combination with LSTM to forecast entry data for the Chengdu subway, demonstrating the superiority of this prediction method over single LSTM and ARIMA models. Although EMD decomposition effectively captures passenger flow characteristics and enhances prediction accuracy, the intermittent nature of time series data can lead to mode mixing issues in the decomposed Intrinsic Mode Function (IMF) components. Therefore, D. Chen et al. [20] proposed the use of the seasonal trend decomposition (STL) method based on Huang's approach to process passenger flow data. This method involves splitting the data into seasonal, trend, and residual time series components, which are then input into the LSTM network for prediction. Through evaluations of predictions at each time step, it was demonstrated that the STL decomposition method outperforms the EMD decomposition method, providing a better solution to the impact of highly volatile passenger flow on prediction accuracy. C. Xiu et al. [21] introduced the EEMD-BIGRU model for passenger flow prediction. EEMD effectively addresses the mode mixing problem, enabling more efficient handling of nonlinear and non-stationary sequence data and reducing the impact of mode mixing on prediction accuracy. In the prediction phase, a bidirectional input GRU network is used to learn features and extract information, and multi-step predictions are applied to subway passenger flow prediction. Building on this foundation, M. Wang et al. [22] employed the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm and a bidirectional LSTM composite model to consider factors such as workdays and holidays in passenger flow prediction, resulting in a significant improvement in prediction accuracy. L. Zeng et al. [23] also utilized the CEEMDAN decomposition method for preprocessing the original data and employed the Inertia Particle Swarm Optimization (IPSO) algorithm to compute the hyperparameters of the LSTM network model during the prediction phase, resolving the issue of slow convergence.

5.2. Passenger Flow Prediction Methods Using Convolutional Neural Networks

With the development of deep learning, the use of RNN networks in the field of traffic passenger flow prediction is no longer adequate to meet current needs. Some researchers have turned to convolutional neural networks for traffic passenger flow prediction. The primary idea is to treat traffic data as images and employ convolution to capture spatiotemporal features of passenger flow between different regions. As a result, W. Chen et al. [24] introduced the use of an end-to-end integrated deep learning network that combines a Convolutional Neural Network (CNN) with LSTM. This approach enables the discovery of the relationship between time and space, and in addressing congestion within subway stations, it fully considers spatial correlations using convolutional neural networks (CNN). Building on this, J. Ke et al. [25] proposed a fusion model known as the Convolutional Long Short-Term Memory Network (FCL-Net), which integrates spatial and time series variables into a deep learning architecture. Furthermore, this model takes into account five categories of factors, including temperature, humidity, wind speed, visibility, and weather conditions. This approach surpasses single neural networks like LSTM in terms of performance and reduces training time for feature selection by 24.4%.

5.3. Passenger Flow Prediction Methods Using Graph Convolutional Neural Networks

J. Zhang et al. [26] used GCN to extract subway network topology information for passenger flow prediction. They also considered various weather conditions, such as temperature, humidity, and wind speed, as well as 11 other indicators related to air quality. These factors were fed into a fully connected layer to extract features, and LSTM was utilized to capture temporal dependencies. Ultimately, the features of external factors were integrated with spatiotemporal factors to improve prediction accuracy. Y. Wang et al. [27] introduced a method using multiple graphs, including static geographical maps and dynamic semantic graphs. Instead of using AFC data, they used video surveillance images within subway stations to predict passenger flow in various areas of the platforms. Graph Convolutional Neural Networks (GCN) and Graph Attention Networks (GAT) were used to extract static and dynamic spatial correlations, followed by LSTM for temporal extraction, enabling precise passenger flow prediction for multiple areas within subway stations. Subsequently, Y. He et al. [28] proposed a Multi-Graph Convolutional-Recurrent Neural Network (MGC-RNN), which analyzed spatial features, distinguishing between static and dynamic aspects. They combined time series data with relevant adjacency matrices to create a sequence of recent flow-related adjacency matrices, considering spatial dynamics. The model considered static spatial features, including network topology maps, station surroundings, and operational information. Additionally, it incorporated holiday data and weather conditions (sunny, cloudy, foggy, light rain, showers, thunderstorms, and overcast) directly into the fully connected layer for passenger flow prediction. This model considered a wide range of factors and improved performance, although the introduction of weather factors resulted in decreased prediction performance.

6. Comparative Analysis and Prospects

Comparative analysis of factors considered in passenger flow prediction, ranging from dealing solely with temporal fluctuations to encompassing spatial, weather, and other factors. Notably, in addressing spatial concerns, the research progression can be observed from local to global, static to dynamic, network topology to surrounding environment, and passenger behavior, resulting in a comprehensive problem-specific approach. The relevant comparisons are summarized in Table 1.

In the majority of previous studies on passenger flow prediction, the issue of time granularity has been a significant concern. Few scholars have delved into the consideration of suitable time granularities in different contexts. Typically, the selection of time granularity involves manually setting multiple values and choosing the optimal one through experimental comparisons, often without verifying the rationale behind the chosen granularity. In the future, it is essential to calculate the optimal time granularity separately for different passenger flow types and various stations. For instance, the time granularity for predicting passenger flow at different stations during peak hours, weekdays, holidays, and unexpected events differs. Exploring how to determine a reasonable time granularity based on passenger flow characteristics and other factors to enhance prediction performance is one of the prospective research directions.

At present, the predominant factors considered in passenger flow prediction are time and spatial elements, with spatial considerations primarily centered around the network topology of stations. The immediate vicinity of a station can also impact passenger flow. For example, a station located in a commercial or residential area may experience greater passenger traffic compared to a station in a suburban area. The surrounding environment is exceptionally intricate, and influenced by numerous factors. Investigating how to integrate the station's surrounding environment into passenger flow prediction represents a research question of significance.

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Table 1. comparisons

Literature ID	Prediction object	A	W	α_i	β_i	γ_i	μ_i	δ_i	φ_k
[1],[2],[11],[12],[15],[18]-[23]	Station passenger flow								
[8] ,[17]	Station passenger flow	√							
[3]	Station passenger flow	√				√			
[4]	OD passenger flow							√	
[5]	Station passenger flow						√		
[6]	Station passenger flow					√			
[7]	Station passenger flow							√	√
[9]	Station passenger flow							√	
[10]	Station passenger flow					√	√	√	
[13],[16]	OD passenger flow								
[14]	Station passenger flow			√	√	√			
[24]	Station passenger flow	√							
[25],[26]	Station passenger flow	√			√				
[27]	Station passenger flow	√							
[28]	Station passenger flow	√	√	√	√	√			

7. Conclusion

This study delves into the intricacies of short-term passenger flow prediction in urban rail transit through detailed modeling and analysis. We define the rail transit network and various types of passenger flow, taking into account a comprehensive range of influencing factors in short-term passenger flow prediction. Furthermore, we conduct a thorough comparative analysis based on different modeling methods, such as time series and statistical models, machine learning, and deep learning, highlighting the strengths and weaknesses of these approaches. The study offers a robust reference and holds significant implications for short-term passenger flow prediction methods.

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