

Article

Fusing Multi-Source Web Data with an ABC-CNN-GRU-Attention Model for Enhanced Urban Passenger Flow Prediction

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Abstract

Against the backdrop of smart cities and digital cultural tourism, the accurate prediction of urban passenger flow is of great significance for public security management and resource allocation. However, existing studies mostly rely on single data sources or only perform a simple concatenation of multi-source features, lacking systematic indicator system design. Meanwhile, weekly or monthly data are commonly used with coarse temporal granularity, making it difficult to capture short-term fluctuations and lag effects. To overcome these limitations, this paper collects the daily passenger flow data of Hangzhou from 15 March 2024 to 15 March 2025; integrates multi-dimensional factors such as keyword search trends across platforms, holidays and major events, and online public opinion; and constructs three daily characteristic indicators: online search index, humanistic–meteorological index, and textual sentiment index. The data denoising, dimensionality reduction, and sentiment quantification are realized through methods including SSA, PCA, and SnowNLP. On this basis, a hybrid CNN-GRU model integrated with the attention mechanism is proposed. An improved artificial bee colony (ABC) algorithm is adopted for global hyperparameter optimization, and a weighted hybrid loss function (JQHL) is introduced to enhance the model's adaptability to extreme values. The results show that the ABC-CNN-GRU-Attention model, incorporating multi-dimensional indicators, outperforms traditional methods on evaluation metrics, including MAE, RMSE, MAPE, R^2 , and RPD, demonstrating a higher prediction accuracy and robustness.

Keywords: multi-source data; ABC-CNN-GRU-Attention model; passenger flow prediction indicator system; daily passenger flow prediction; smart cultural tourism

1. Introduction

Against the backdrop of the deep integration of smart city construction and digital cultural tourism, accurate prediction of urban passenger flow has become a core technical support for improving the efficiency of public security management, optimizing the dynamic allocation of public service resources, and ensuring residents' daily travel and tourists' experiences. In recent years, with the continuous recovery of the domestic cultural and tourism consumption market, problems such as overloaded scenic passenger flow, urban traffic congestion, and tight supply and demand of emergency resources during holidays have become increasingly prominent, placing higher requirements on refined urban governance. Meanwhile, the rapid development of big data technologies and online platforms has enabled the efficient mining and integration of multi-source data, including online search behavior, social media sentiment, and meteorological and environmental



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monitoring, providing a data foundation and technical possibility for breaking through the technical bottlenecks of traditional passenger flow prediction and constructing prediction models that are more suitable for practical scenarios.

The research on urban passenger flow prediction has evolved from single data-driven approaches to multi-source information fusion, and from traditional statistical models to deep learning models. Although relevant studies have laid an important foundation for subsequent explorations, numerous urgent problems remain to be solved. In early studies driven by single data sources, Zhang et al. (2013) first introduced the Baidu Index into tourism passenger flow prediction, confirming a significant correlation between online search volume and the Golden Week passenger flow of the Palace Museum, thus initiating a research paradigm of passenger flow prediction driven by online data [1]; Yang et al. (2015) integrated Google Trends and the Baidu Index to construct a prediction model, whose error was significantly lower than that of traditional time series models, further verifying the predictive value of online search data [2]. However, such studies rely solely on a single online search data source, making it difficult to capture the coupled impacts of multiple factors, such as weather, holidays, and public opinion fluctuations, on passenger flow, limiting the adaptability and prediction accuracy of models in complex scenarios [3–5]. To address this limitation, this paper constructs a multi-source heterogeneous feature system by introducing the humanistic–meteorological index and text sentiment index, so as to make up for the insufficiency of information from a single data source.

With the popularization of the concept of multi-source data fusion, scholars have begun to introduce auxiliary variables such as meteorology, holidays, and social media sentiment to enrich the prediction feature system. Zhu et al. (2018) combined subway IC card data with weather and holiday information and adopted a deep learning model to realize subway passenger flow prediction, verifying the potential of multi-source fusion in improving prediction accuracy [6]; Xie et al. (2020) introduced the tourism climate comfort index (TCI) that is integrated with search indices for modeling, enhancing the stability of the model under holiday and extreme weather scenarios [7]; Liang et al. (2019) fused social sentiment, event labels, and time series information to construct a PFFM–SE model for passenger flow prediction under special event scenarios [8]. Nevertheless, most of these studies simply concatenate multi-source features as model inputs, lacking systematic indicator system design. Moreover, the mining of online behavioral data remains at the level of search indices, ignoring the potential impact of online emotional feedback on travel intention [9–17]. Therefore, this paper constructs a three-dimensional indicator system of “online search index—humanistic–meteorological index—text sentiment index”, and quantifies the lag effects and contribution weights of each indicator to achieve a systematic characterization of the passenger flow driving mechanism.

The advancement of deep learning technologies has further promoted the research depth of multi-source fused passenger flow prediction, with various fusion models emerging as research hotspots. Chen et al. (2017) combined VMD and mRMR feature selection with LSTM modeling, strengthening the model’s ability to capture nonlinear trends [18]; Zhou et al. (2023) integrated the Informer structure with complex networks to realize long-sequence passenger flow prediction for urban rail transit [19]; Liu et al. (2024) extracted multi-source modal features via the self-attention mechanism, achieving a fitting degree of 95.94% in passenger flow prediction for the underground commercial complexes [20]; Tang et al. (2024) introduced large-scale events and social sentiment information to construct a multi-step prediction framework, improving the model’s adaptability to sudden fluctuations [21]. Although existing deep learning models show advantages in feature extraction and time series modeling, they still suffer from two problems: an insufficient response to key time-point features such as weather, holidays, and major events, and a tendency to fall

into local optima due to a heavy reliance on manual parameter tuning [22–29]. To address the former issue, this paper introduces an attention mechanism to dynamically focus on key time nodes; for the latter, an improved artificial bee colony (ABC) algorithm is adopted to achieve global hyperparameter optimization, thereby enhancing the prediction accuracy and stability of the model.

In addition, existing studies mostly focus on the overall modeling of urban-wide passenger flow, often treating passenger flow changes in different periods as a homogeneous process, ignoring the significant differences in passenger flow driving factors across scenarios such as workdays, weekends, and holidays, thus failing to meet the practical needs of refined governance [30–32]. Although some recent studies have attempted to introduce multi-source data to construct indicator systems, they still have limitations in indicator selection, failing to systematically integrate key dimensions, such as online search behavior and public emotional tendency, that reflect travel intention and psychological expectations, resulting in an insufficient explanatory power for the complex mechanisms behind passenger flow fluctuations [33–38]. Meanwhile, the existing studies generally adopt monthly or weekly data as the modeling basis, with relatively coarse temporal granularity, making it difficult to capture fine-grained features such as short-term fluctuations, sudden disturbances, and lag effects, thereby affecting the generalization ability and prediction stability of the model [39–42]. To address the above issues, this study adopts the daily passenger flow data as the core modeling unit to characterize the variation laws of passenger flow at a finer temporal scale. Moreover, it constructs differentiated analysis models for workdays, weekends, and holidays, respectively, to reveal the heterogeneity of driving factors across different scenarios, thus providing a scientific basis for refined time-phased governance.

In summary, the current research on urban passenger flow prediction still has three core research gaps [43–45]. First, the indicator system lacks systematic design: the fusion of multi-source data is mostly simple concatenation, without constructing a three-dimensional feature system covering “behavioral intention–environmental characteristics–emotional feedback”, and the lag effects and coupling relationships of different dimensional features are not quantified. Second, the model design and scenario adaptability are insufficient: existing deep learning models have a limited ability to focus on key passenger flow features and lack scenario-specific differential modeling, making it difficult to adapt to the dynamic change laws of passenger flow in different periods. Third, the model optimization strategy needs to be improved: manual tuning of hyperparameters can hardly achieve global optimization, and the traditional loss functions have a poor adaptability to extreme passenger flow values, affecting the prediction accuracy in high-fluctuation scenarios.

To fill the above research gaps, this paper takes Hangzhou as the research object and constructs a daily urban passenger flow prediction framework by integrating multi-source online data, including online search, humanistic meteorology, and textual sentiment. The main academic contributions of this paper are reflected in three aspects. First, it reconstructs and expands the passenger flow prediction indicator system, breaking through the traditional external factor framework, elevating online search behavior and textual sentiment to core prediction dimensions, constructing a three-dimensional indicator system of “online search index–humanistic–meteorological index–textual sentiment index”, quantifying the optimal lag period and feature weight of each indicator and clarifying the driving mechanism of multi-source data on passenger flow. Second, it proposes an ABC-CNN-GRU-Attention hybrid prediction model, integrating the local feature extraction of CNN, long-term dependency modeling of GRU, and key feature focusing ability of the Attention mechanism. An improved artificial bee colony (ABC) algorithm is introduced to realize the global optimization of hyperparameters, and a weighted hybrid loss function

(JQHL) is designed to enhance the model's adaptability to extreme values, significantly improving the prediction accuracy and robustness of the model. Third, it carries out multi-scenario differential modeling and verification, breaking through the limitation of overall urban-wide modeling, constructing differential analysis models for workdays, weekends, and holidays, quantifying the contribution of driving factors in different scenarios, and providing targeted technical support for time-phased and refined urban passenger flow governance. The research results of this paper not only enrich the theory and method of multi-source data-driven passenger flow prediction, but also provide implementable technical paths and decision-making references for smart city construction and digital cultural tourism transformation.

2. Construction of Three Types of Indices

2.1. Data Collection and Processing

2.1.1. Data Sources

Table 1 summarizes the diverse data sources involved in this study. These multi-source data characterize the driving mechanism of passenger flow from different dimensions. Among them, the Baidu Index and Douyin Index reflect the public's travel intention and focus of attention. Users usually search for destination-related information before traveling, and such search behavior can be regarded as a leading indicator of potential travel demand; rising search popularity often foreshadows an increase in passenger flow in the following days. The weather conditions directly influence tourists' travel decisions by affecting travel comfort and safety. Severe weather may suppress travel willingness, while favorable weather helps to boost passenger flow. Major events (such as concerts and festivals) can attract large crowds and form short-term passenger flow peaks, with a strong instantaneous impact. The review data from online travel platforms presents tourists' experience feedback and demonstrates their emotional tendencies. According to the mechanisms of word-of-mouth communication and emotional contagion, positive review sentiment can enhance tourists' potential travel intention and further promote passenger flow growth; conversely, negative sentiment may produce an inhibitory effect. The above variables jointly affect the dynamics of passenger flow from four dimensions: behavioral intention, environmental conditions, social events, and emotional feedback, laying a theoretical foundation for the subsequent construction of a multi-dimensional indicator system.

Table 1. The data names and sources.

Data Name	Data Source
Baidu Index	Baidu public data platform: https://index.baidu.com/v2/index.html#/ (accessed on 20 April 2025)
TikTok Trend Insight	TikTok public data platform: https://trendinsight.oceanengine.com/ (accessed on 20 April 2025)
Hangzhou daily passenger and overnight passenger flow data	Hangzhou Culture and Tourism Data Online: https://data.wgly.hangzhou.gov.cn/ (accessed on 20 April 2025)
Historical weather data of Hangzhou	China Weather public data platform: https://www.weather.com.cn/ (accessed on 20 April 2025)
Major event data	Hangzhou Culture, Radio, Television and Tourism Official data platform: https://www.toutiao.com/?wid=1744726158281 (accessed on 21 April 2025)
Tourism text comment data and page views	Ctrip: https://www.ctrip.com/ (accessed on 21 April 2025)

2.1.2. Data Processing

(1) Data Time Interval Description

As shown in Figure 1, daily data from 15 March 2024 to 15 March 2025 are selected as the research sample. The core reasons for choosing this time interval are as follows: First, it covers a complete annual climate cycle across four seasons, including high temperatures, heavy rain, cold waves and other weather scenarios, which can fully capture the impact of meteorological factors on passenger flow; second, it includes major holidays such as the Spring Festival and National Day, as well as different periods such as weekends and workdays, allowing a complete depiction of the periodic fluctuations of passenger flow and the holiday agglomeration effect; third, multiple large-scale cultural and tourism events were held in Hangzhou during this interval, providing abundant samples for verifying the driving effect of major events on passenger flow; and finally, there were no unconventional disturbances such as major public health incidents or extreme natural disasters within the data interval, ensuring the continuity and validity of the sample and enabling the model to more accurately learn the passenger flow driving mechanism under conventional scenarios.

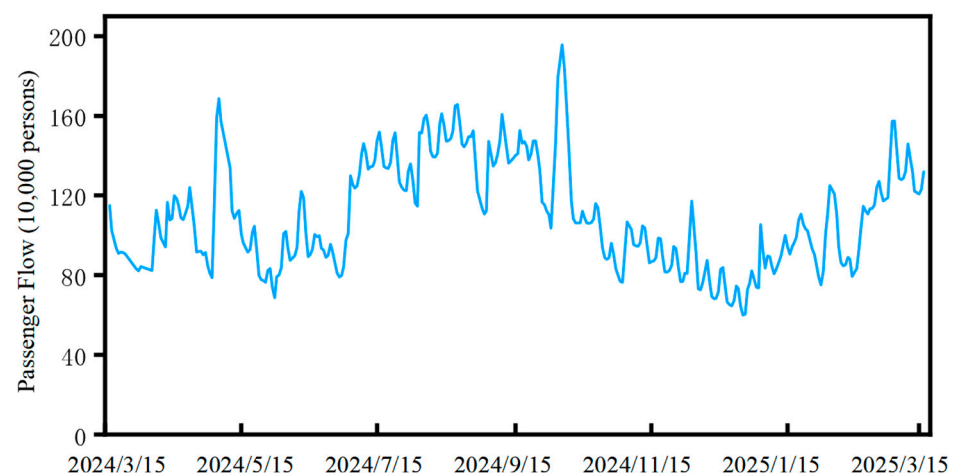


Figure 1. The Hangzhou passenger flow from 13 March 2024 to 13 March 2025.

(2) Data Processing Methods and Justification

In the data preprocessing stage, this study sequentially performed missing value imputation, outlier identification, and noise smoothing. All preprocessing operations were uniformly implemented on the full dataset prior to splitting the training and test sets to avoid data leakage.

First, the statistical analysis revealed three single-day missing values in the raw data (18 July 2024; 5 August 2024; 15 January 2025), all of which were isolated with no consecutive missing records. To complete the imputation while preserving the distribution characteristics of the original data, the mean values of adjacent dates were adopted for interpolation, with corrections made against historical data from the same period. Since this treatment only targeted a very small number of isolated missing points, it did not alter the overall trend and fluctuation patterns of the series, nor did it exert a significant impact on the time-series structure.

Second, to prevent interference from the data recording errors in model training, this study set a reasonable range for passenger flow data from 0 to 2 million person-times. The upper limit was determined based on the official holiday passenger flow peak reports of Hangzhou and was used to eliminate the abnormal data far exceeding the actual maximum caused by statistical errors, rather than artificially removing real passenger flow peaks. The

combination of manual verification and threshold screening ensured the authenticity and reliability of the input data.

Finally, to mitigate the interference of short-term random fluctuations on model learning, the seven-day moving average method was employed to smooth the passenger flow series. The daily passenger flow data are often subject to slight noise from single-day random factors, and direct modeling may hinder the model from capturing core trends. The window length of the seven-day moving average aligns with the natural weekly cycle, which can effectively filter single-day random noise while fully retaining passenger flow fluctuation characteristics in key periods such as weekends and holidays, avoiding trend distortion caused by over-smoothing. Compared with the 3-day window (insufficient noise reduction) and the 15-day window (prone to blurring short-term peaks), the seven-day window achieves the optimal balance between noise reduction performance and trend preservation. The smoothed series preserves the long-term trend and medium-term periodicity of the original data, only filtering the irregular single-day random noise without changing the core structure and key features of the time series. Meanwhile, the smoothed series is more stationary, which helps improve the model's ability to capture passenger flow trends and reduce prediction errors caused by the noise.

(3) Quality Validation After Data Processing

Upon completion of processing, the data quality was verified from three dimensions: first, no missing values existed, and all 365 observations were valid; second, the data ranged from 598,900 to 1,957,500 person-times, which was consistent with the annual passenger flow reports issued by Hangzhou's cultural and tourism authorities, with no outliers; third, the correlation coefficient between the smoothed series and the original series reached 0.917, indicating that the core trend remained unchanged while only noise was effectively filtered. The processed data ensures accuracy and continuity, provides clear and stable inputs for subsequent model training, and lays a foundation for improving the prediction accuracy.

2.2. Index Construction

2.2.1. Collection and Processing of Network Search Index

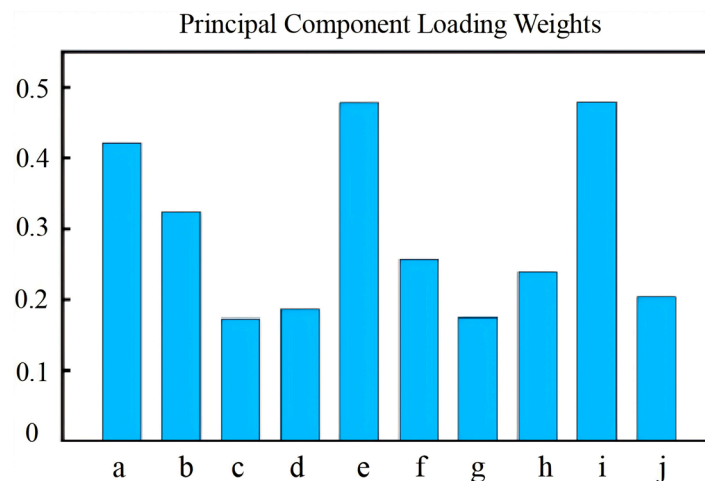
In constructing an urban passenger flow prediction model based on network search indexes, keyword selection and data processing are crucial. Combining the Baidu Index and the TikTok Trend Insight, this paper adopts "intuitive selection + platform recommendation" to build a keyword library. From dimensions such as weather, accommodation, transportation, scenic spots, and travel behaviors, user behaviors are mined with the help of Baidu's "demand graph" and TikTok's "recommendation graph", and keywords with regional and hotspot characteristics such as "Songcheng" and "West Lake in Hangzhou" are selected. The popularity data from 15 March 2024 to 15 March 2025 is crawled.

As shown in Table 2, to test the correlation between keywords and passenger flow, the Spearman rank correlation coefficient was used to screen 20 initially selected keywords combined with historical passenger flow data, with a threshold of 0.5, and finally, 10 highly relevant keywords were retained as model inputs. To reduce the fluctuation interference, the SSA (singular spectrum analysis) method was used to denoise the search index and extract stable trends. The optimal lag period between the keywords and the passenger flow was determined through lag analysis, verifying the "leading nature" of search popularity and providing data support for modeling.

Table 2. The correlation between keywords and passenger flow under different lag periods.

Item Number	Keywords	Lag Days						
		0	1	2	3	4	5	6
a	Baidu Hangzhou	0.482	0.513	0.523	0.584	0.542	0.497	0.479
b	Baidu Hangzhou Zoo	0.542	0.561	0.621	0.552	0.531	0.502	0.491
c	Baidu Qiantang River	0.582	0.637	0.532	0.526	0.507	0.486	0.437
d	Baidu Hangzhou Weather	0.432	0.543	0.628	0.521	0.472	0.423	0.439
e	Baidu Hangzhou Tourism	0.625	0.693	0.712	0.685	0.598	0.567	0.582
f	Baidu Hangzhou Song Dynasty Town	0.512	0.534	0.598	0.523	0.509	0.493	0.473
g	TikTok Hangzhou Zoo	0.621	0.723	0.691	0.581	0.481	0.512	0.472
h	TikTok Hangzhou Song Dynasty Town	0.498	0.523	0.563	0.521	0.514	0.491	0.482
i	TikTok Hangzhou Tourism	0.522	0.532	0.582	0.531	0.491	0.512	0.425
j	TikTok West Lake in Hangzhou	0.516	0.582	0.519	0.489	0.506	0.493	0.411

Considering that the search indexes of these 10 keywords have large differences in numerical dimensions and strong volatility, directly introducing them into the model may cause the curse of dimensionality and fitting errors. Therefore, in constructing the input indicator system, this paper introduces the principal component analysis (PCA) method for dimensionality reduction. As can be seen from Figure 2, after standardization and covariance matrix calculation, the first several principal components are selected for combination, and the comprehensive network search index is constructed under the premise of retaining a cumulative contribution rate of 85%. This method not only effectively reduces the input dimension of the model and improves the operational efficiency but also achieves a good balance between information retention and data compression.

**Figure 2.** The principal component loading weights of keywords. The letters a–j in the figure correspond to the keyword items numbered a–j in Table 2, respectively.

To more clearly see the effect of the integrated search index, the number of integrated search indexes and the number of principal components are considered, and three-dimensional visualization is performed with lag days of 0–7 to obtain Figure 3. It can be found that the larger the number of integrated search indexes, the larger the Spearman correlation coefficient. With the increase in lag days, the Spearman correlation coefficient first increases and then decreases, which is consistent with the actual situation. It can be

found that the maximum correlation coefficient reaches 0.769 on the third day of lag, and the comprehensive network search index data is obtained.

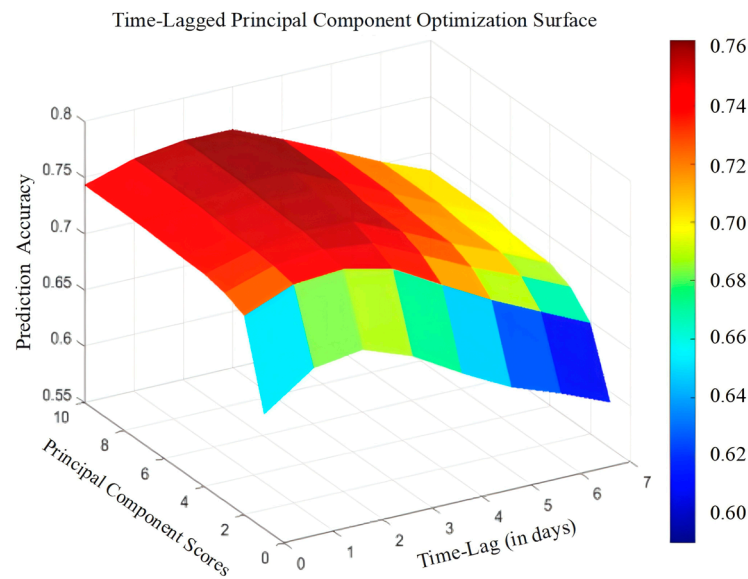


Figure 3. The time-lag–principal component optimization surface.

2.2.2. Collection and Processing of Humanistic–Meteorological Index

1. Weather Index

Weather conditions directly influence tourists' decision-making by affecting travel comfort and serve as a key environmental driver of passenger flow fluctuations. Even during peak tourism seasons with rigid passenger demand, the weather quality significantly regulates the scale and fluctuation range of passenger flow. To objectively quantify the impact of weather on passenger flow, this study introduces the Tourism Climate Index (TCI) for standardized measurement.

The daily meteorological data for Hangzhou from 15 March 2024 to 15 March 2025 were collected via Python 3.11 web crawlers, including core indicators such as maximum temperature, minimum temperature, weather phenomena, and precipitation intensity. The TCI is calculated by weighting four dimensions: the temperature suitability, the precipitation probability, the weather type, and the temperature difference stability, with a score range of 0–10. Higher scores indicate greater travel comfort. Derived from a classic research framework in the field of tourism climatology, this index construction method has been widely validated in passenger flow prediction studies in South Africa, Saudi Arabia, Sichuan Province (China), and other regions. It boasts a sound theoretical foundation and practical applicability, accurately revealing the quantitative correlation mechanism between meteorological conditions and passenger flow and effectively improving the model's ability to fit real-world scenarios.

2. Holiday and Weekend Indexes

Holidays and weekends form the core temporal rhythm of tourist travel, and their driving effects on passenger flow exhibit significant hierarchical differences. To avoid the subjectivity inherent in purely manual scoring, this study abandons subjective empirical assignment and adopts a weight system that is determined by combining statistical calibration based on actual passenger flow data and the literature references, ensuring that all assignments are evidence-based.

This study establishes two types of temporal characteristic indices. The first is the holiday weight index, whose assignment criteria are derived from official real-world

data from national passenger flow monitoring, with weights determined according to the comparisons between the passenger flow volumes on holidays and non-holidays rather than subjective judgment. This method has been practically applied in passenger flow forecasting studies in Beijing and Suzhou. The seven-day statutory long holidays, such as the Spring Festival and National Day, are assigned a score of five, as these periods represent peak domestic travel seasons with passenger flow increasing to 3–5 times the usual level. The three-day short holidays, including the Qingming Festival, the Dragon Boat Festival, and the Mid-Autumn Festival, are assigned scores of 3–4. The ordinary compensatory leave days and local festivals are assigned scores of 1–2. This assignment system is highly consistent with the holiday passenger flow fluctuation patterns observed in major cities across China. The second is a weekend binary indicator, with a value of zero for workdays and one for weekends. This treatment represents a standard practice in time-series passenger flow forecasting and is used to distinguish the structural differences between workday and weekend passenger flow. Through the construction of the above standardized indices, the driving effects of social temporal rhythms on passenger flow fluctuations can be accurately quantified, providing stable temporal feature inputs for the model.

3. Major Event Index

To quantify the impact of large-scale activities on passenger flow, this paper collects activity data from 15 March 2024 to 15 March 2025 from official WeChat accounts such as “Hangzhou Culture, Radio, Television and Tourism Release”, including the release time, title, page views, comment count, likes, video plays, etc. Python is used to write a crawler program for crawling, cleaning, and storing in the database. To extract the effective features from multi-dimensional data, the LASSO-PCA method is used to construct the “major event index”: LASSO performs feature selection through L1 regularization to reduce the model’s complexity; PCA reduces the data dimensionality to the principal component space and retains the main information. Taking the page views, the comment count, the play volume, etc., as input variables, an index that can quantify the influence of activities is constructed to measure the pulling effect of cultural and tourism activities on scenic spot passenger flow. The final results are shown in Table 3, which shows the time, content, browsing data, and corresponding major event indexes of some of the activities.

Table 3. The Hangzhou major event index table.

Date	Major Event	Index
30 March 2024	The first Taobao “Influencer Night” ended, and Guofeng became popular in Hangzhou!	5.03
1 April 2024	“Qiandaohu Night” in Paris showcases the new charm of Chun’an’s cultural tourism.	6.70
20 April 2024	This music festival on 20 April, with a luxurious lineup waiting for you to enjoy! Disco in the air, rock never dies!	8.38
22 April 2024	Tonight, Uncle West Lake and Jay Chou have a dream collaboration, singing to the whole city in Hangzhou.	6.70
19 May 2024	19 May is China Tourism Day, and all scenic spots in Guangyuan are free of charge!	8.38

Table 3. Cont.

Date	Major Event	Index
26 July 2024	From the Hangzhou Asian Games to the Paris Olympics, the relay of events resonates between the two cities!	10.05
5 August 2024	Hangzhou Cultural Tourism Calendar, G20 Hangzhou Summit Experience Hall.	13.40
1 October–7 October 2024	Recommended self-driving tour attractions during National Day! Enjoy free admission to more than 30 attractions! You can also win prizes.	13.40
3 November 2024	Hangzhou Marathon!	6.70
25 February–1 March 2025	The only stop in China, international superstar Ed Sheeran will hold six consecutive concerts in Hangzhou.	8.38

A weighted scoring modeling framework is constructed based on the weekend scores, weather scores, holiday scores, and major event scores to form a comprehensive humanistic–meteorological index, aiming to quantify the relative contribution of various factors to passenger flow changes through a data-driven approach. Four typical scoring indicators, namely the weekend score, weather score, holiday score, and major event score, are selected as input variables from actual scenarios, and the urban passenger flow data of the corresponding time period is introduced as the response variable. To retain the semantic features and scale differences in the scores, all the score data retain their original values without normalization.

In the model construction process, a linear weighted scoring function is set to integrate multiple scoring factors to form a comprehensive score, that is, the humanistic–meteorological index. If the four scores are s_1, s_2, s_3, s_4 , and their corresponding weights are w_1, w_2, w_3, w_4 , then the weighted score is expressed as Formula (1):

$$S = w_1s_1 + w_2s_2 + w_3s_3 + w_4s_4 \quad (1)$$

To ensure the interpretability of the model, two constraint conditions are introduced: all the weights are in the $[0, 1]$ interval, and their sum is 1. The model maintains the intuitiveness of the linear structure and is convenient for subsequent statistical analysis and practical deployment. To obtain the optimal weight combination, the genetic algorithm (GA) is used as the optimization tool.

The genetic algorithm is a global optimization method based on natural selection and genetic mechanisms, which is suitable for solving complex objective functions that are nonlinear, non-convex, and non-differentiable. In this study, the Spearman rank correlation coefficient is used as the optimization criterion to construct a single-objective constrained optimization problem, and the genetic algorithm is used to search for the weight solution that maximizes the correlation in the continuous variable space. Specifically, the algorithm takes the Spearman rank correlation coefficient between the comprehensive score and the actual passenger flow as the optimization objective, and continuously evolves through operations such as population initialization, selection, crossover, and mutation to finally obtain the optimal solution.

To intuitively present the model performance, Figure 4 shows the relationship between the weighted scores and the actual passenger flow, with color mapping to reflect the level of passenger flow, and trend lines and interactive prompt information are added to improve the visibility and interpretability. The optimization results show that the maximum Spearman correlation coefficient between the score and passenger flow reaches

0.8038, indicating that the model performs well in depicting the monotonic relationship. The optimal weights are: weekend score 18.87%, weather score 12.91%, holiday score 31.16%, and major event score 37.06%. It can be seen that holidays and major events are the core factors of passenger flow changes, and the impact of the weather scores is relatively small.

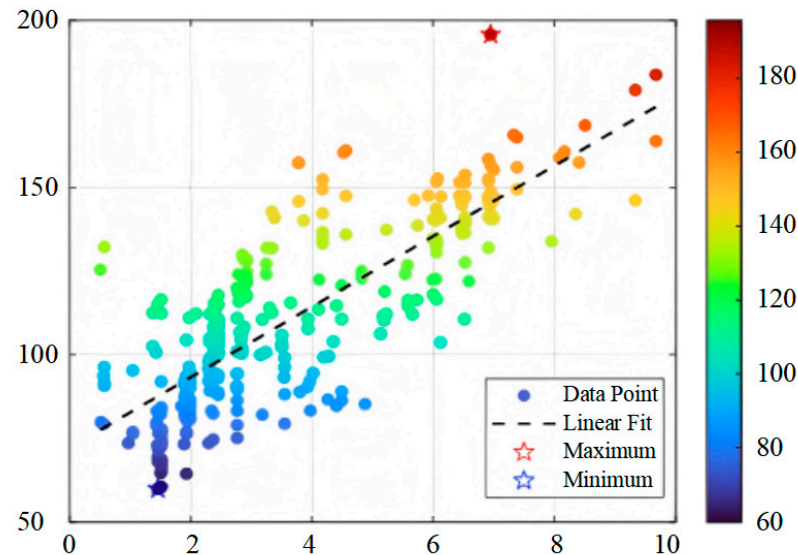


Figure 4. The relationship between the comprehensive humanistic–meteorological index and urban passenger flow.

4. Weight Sensitivity Analysis and Optimal Weight Determination

In the construction of the comprehensive humanistic–meteorological index, the weight configuration of its sub-indicators, including the weather index, holiday index, weekend index, and major event index, has a potential impact on the model’s prediction performance. To ensure the rationality and effectiveness of the weight selection, we compared and evaluated the model’s performance under different configurations by traversing multiple sets of weight combinations, and we selected the optimal weight scheme based on two criteria: first, maximizing the correlation coefficient between the comprehensive index and the passenger flow of the training set, and second, optimizing the performance of the model in the evaluation metrics of prediction tasks. The optimal weight combination was finally determined as follows: the weekend index accounted for 18.87%, the weather index accounted for 12.91%, the holiday index accounted for 31.16%, and the major event index accounted for 37.06%.

It should be noted that this optimal weight combination features distinct data-driven characteristics and is closely associated with the urban scale, cultural traits, and residents’ travel behaviors of the research area. Thus, this weight combination yields favorable prediction results in the Hangzhou case, as shown in Figure 4. But its direct applicability to other cities is somewhat limited. When applying this model to other cities in the future, the weights of each sub-indicator can be recalibrated based on the local passenger flow data and characteristics by adopting the dual-objective optimization method proposed in this study so as to enhance the cross-regional adaptability of the model.

2.2.3. Collection of Text Sentiment Index

Sentiment is people’s immediate response to things, reflecting their attention and motivation. In the tourism industry, tourists’ comments are an important reference for industry optimization. According to the word-of-mouth communication and emotional

infection mechanism, comment sentiment will affect travel willingness, thereby affecting scenic spot passenger flow and providing a basis for service improvement.

To explore the impact of comment sentiment on passenger flow, this paper selects scenic spot comment data from two major platforms, Ctrip and Meituan, which have a wide user base and mature systems. After traveling, tourists share their feelings on the platforms, and their emotional tendencies will affect the choices of others, thereby driving passenger flow. The comment content includes the release time and text. The original data needs to be cleaned to remove invalid information such as symbols and emojis, and stop words are removed with Jieba word segmentation. Python's SnowNLP tool is used for sentiment analysis to quantify the sentiment value of each comment, ranging from 0 to 1, with values closer to 1 indicating more positive emotions. The specific quantification process of the text sentiment index is as follows:

1. **Data Collection:** The crawler will collect Hangzhou tourism-related evaluation data from Ctrip and Meituan platforms, covering scenic spots, hotels, catering, etc., and standardize the format of the comment text data. Each comment is complete and clear, and the evaluation object and time are recorded.
2. **Text Preprocessing:** Remove invalid information such as HTML tags, special symbols, and emojis from the collected comment text, and then use a word segmentation tool to split the text into words to facilitate the subsequent sentiment analysis. At the same time, filter stop words to improve the analysis efficiency and accuracy.
3. **Sentiment Analysis with SnowNLP:** Input the cleaned text into SnowNLP, which automatically outputs the emotional tendency value of each comment. This tool is based on a Chinese sentiment model, which can quickly analyze a large number of comments without manual intervention and provide main sentiment words as auxiliary understanding.
4. **Statistics and Analysis of Emotional Tendency Values:** Count the sentiment values of all comments, analyze their changing trends over time, and identify differences in tourist satisfaction between peak and off seasons. At the same time, screen for extreme emotional comments to deeply explore the problems or the highlights, providing a reference for the optimization of tourism services.

The sentiment values of Hangzhou tourism reviews from Ctrip and Meituan platforms, calculated using the SnowNLP algorithm, are shown in Figure 5, with the horizontal axis representing the date and the vertical axis representing the sentiment value. The sentiment value of the Ctrip reviews shows an overall downward trend, indicating a continuous decline in user satisfaction, while the sentiment value of the Meituan reviews remains stable with a slight increase, reflecting relatively steady user satisfaction. SnowNLP is a well-established tool for Chinese short-text sentiment analysis and has been widely used in sentiment quantification tasks for tourism reviews and social media texts. To verify its reliability on the dataset of this study, 200 reviews were randomly selected from both Ctrip and Meituan platforms for manual annotation. The results show that the consistency between SnowNLP outputs and manual annotations reaches 87.3%, demonstrating favorable accuracy in sentiment classification. In summary, this study systematically demonstrates the effectiveness of the textual sentiment index in passenger flow prediction and its potential error sources by combining lag correlation analysis and manual verification.

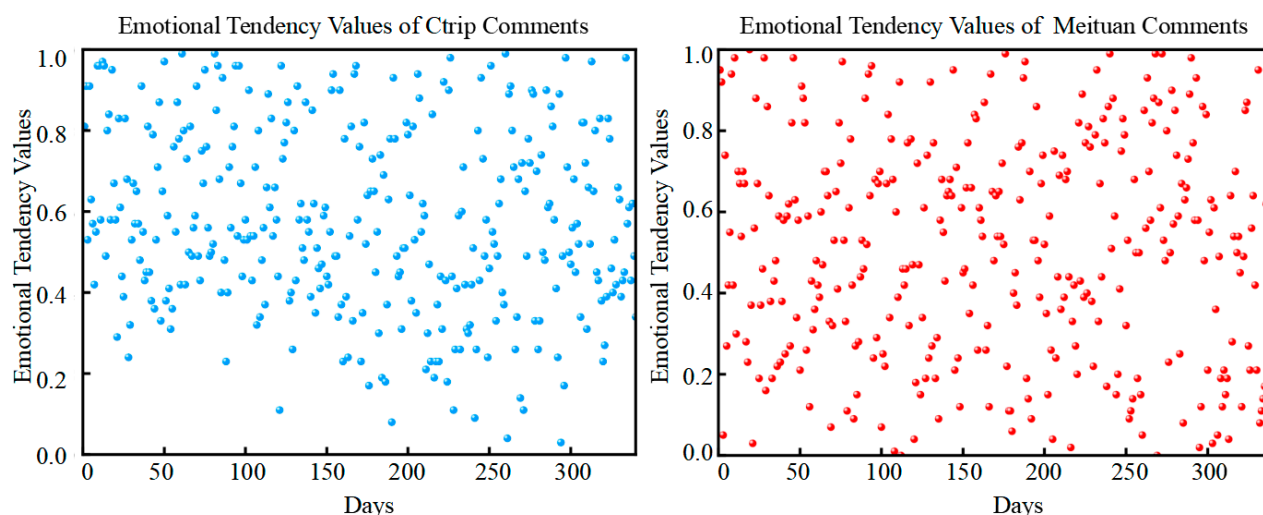


Figure 5. The sentiment values of Hangzhou tourism evaluations on Ctrip and Meituan.

According to the lag analysis results in Table 4, the sentiment values of tourist reviews on Ctrip and Meituan platforms show a significantly positive correlation with Hangzhou's tourist flow under different lag days, and the correlation coefficient gradually increases as the lag time extends. Specifically, the correlation between Ctrip review sentiment and passenger flow peaks on the 6th day (0.704), while the correlation for Meituan reviews reaches its maximum on the 7th day (0.732).

Table 4. The test of comment lag days.

Ctrip Comment Lag Days	1 Day	3 Days	4 Days	5 Days	6 Days	7 Days
Correlation Coefficient	0.422	0.523	0.640	0.655	0.704	0.685
Meituan Comment Lag Days	1 day	3 days	4 days	5 days	6 days	7 days
Correlation Coefficient	0.501	0.612	0.653	0.672	0.695	0.732

This phenomenon can be explained from the perspective of tourist decision-making behavior: tourists usually check the destination reviews on online platforms several days in advance to assist with trip planning, rather than obtaining information on the day of travel. Therefore, the impact of emotional feedback on passenger flow exhibits a natural lag period of 5–7 days. The identification of this lag characteristic not only verifies the practical application value of the review sentiment indicator in the advanced prediction of tourism popularity but also provides a data basis for setting the feature lag period parameters in model construction.

3. Establishment of the ABC-CNN-GRU-Attention Model Fused with Multi-Dimensional Indicators

In this study, aiming at improving the accuracy and practicality of urban passenger flow prediction, a feature system composed of three core indicators is constructed, namely the network search index, the humanistic–meteorological index, and the text sentiment index. Among them, the network search index is the most common single predictor in current research, which reflects the public's attention to travel-related content and has good timeliness and representativeness. However, the urban passenger flow is affected by far more than this.

To make up for the limitations of a single index, the humanistic–meteorological index is introduced. By integrating variables such as weather conditions, holidays, weekend factors,

and major events, and quantifying them through reasonable lag processing, a humanistic comprehensive index with temporal characteristics and reflecting changes in the travel environment is constructed. This index can effectively characterize holiday aggregated travel and the impact of extreme weather, such as high temperature and heavy rain, and can significantly improve the ability of traditional models to capture abnormal fluctuations. In addition, the text sentiment index is further introduced to extract the public's emotional evaluation of the travel environment, service quality, etc., from online platforms through public opinion analysis technology. The quantification of this emotional dimension enables the model to have the ability to identify potential travel willingness from a psychological level, forming a complete feature input system composed of three dimensions: behavioral search intention, external environmental conditions, and public subjective expectations.

In summary, this paper constructs a multi-source data-driven, deeply integrated modeling urban passenger flow prediction system, providing a reference technical path and method innovation for smart city construction, cultural tourism management decision-making, and emergency scheduling. The technical route block diagram of this paper is shown in Figure 6.

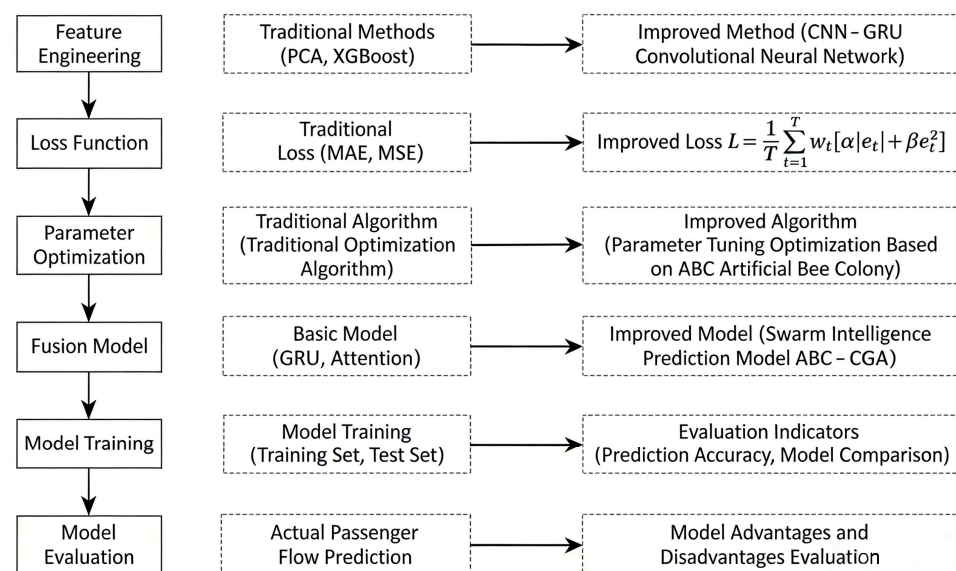


Figure 6. The technical route block diagram.

3.1. Establishment of the CNN-GRU Prediction Model

3.1.1. Theoretical Basis of the CNN-GRU Prediction Model

In urban passenger flow prediction, multi-source data such as network search indexes, humanistic-meteorological indexes, and sentiment indexes are combined to effectively capture the public's travel intentions and behavioral changes. Tourists' search behaviors are digital traces of word-of-mouth communication. Social events or hotspots trigger a surge in search volume, indicating passenger flow fluctuations. The emotional communication theory shows that negative emotions spread rapidly on social platforms, and sentiment analysis can quantify their intensity, helping with dynamic intervention prediction. The text sentiment analysis converts tourists' comments into structured sentiment indexes, revealing satisfaction and behavioral intentions, and interacting with search indexes to distinguish short-term popularity from long-term attractiveness. The fusion of these three types of high-frequency external information enhances the model's response ability to complex factors and significantly improves prediction accuracy and sensitivity.

The traditional passenger flow prediction methods, such as principal component analysis (PCA), XGBoost, and SVM, can handle some data features and nonlinear relationships

but have limitations in the face of complex temporal dependencies and nonlinear patterns. When using the PCA, it is difficult to effectively capture complex feature interactions after dimensionality reduction, and it has a weak ability to respond to sudden events. Although XGBoost and SVM perform well in some nonlinear problems, they cannot fully mine the dependencies when processing time series data, affecting the stability of long-term predictions. In contrast, the advantage of the CNN-GRU model, combining the convolutional neural network (CNN) and the gated recurrent unit (GRU), lies in achieving more efficient feature learning in extracting local patterns and learning long-term temporal dependencies. The CNN is responsible for extracting local spatiotemporal features, and the GRU models temporal dependencies through gating mechanisms, which is suitable for passenger flow data with dynamic changes and large sudden fluctuations. The introduction of the Attention mechanism improves the model's response ability to key time periods, and the global optimization of the ABC algorithm further enhances the model's stability and prediction accuracy. Therefore, compared with traditional models, the deep learning method based on the CNN-GRU model has stronger generalization ability and adaptability and can provide more accurate and stable predictions in complex and sudden passenger flow fluctuations.

3.1.2. Establishment and Efficiency Verification of the CNN-GRU Prediction Model

In the process of constructing an urban passenger flow prediction model based on multi-source network data, this paper selects the CNN-GRU fusion model as the main feature extraction and prediction framework. The CNN-GRU model combines the advantages of convolutional neural networks in extracting spatial local features and gated recurrent units in modeling time series and can effectively process complex nonlinear data from different dimensions and times.

1. Convolutional Neural Network (CNN)

As shown in Figure 7, the convolutional neural network is a deep learning model used to automatically extract spatial features from data, especially in image and sequence data processing tasks. Through the sliding operation of convolution kernels on input data, CNN can effectively identify local patterns or features. When processing time series data, CNN can capture local fluctuations or periodic patterns in the data, helping the model better understand the data structure.

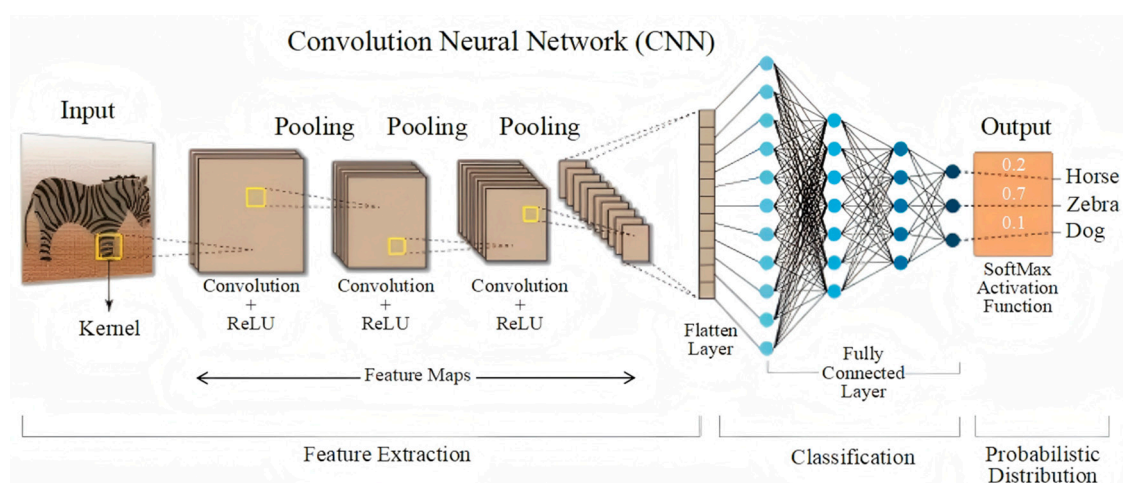


Figure 7. The CNN structure diagram.

2. Gated Recurrent Unit (GRU)

As shown in Figure 8, the gated recurrent unit is an optimized variant of the RNN. Its core structure consists of a reset gate and an update gate. The reset gate controls the

degree of retention of past information at the current moment and determines that the historical memory is to be “discarded” through operations with the current input, thereby flexibly integrating old and new information. The update gate adjusts the weights of the historical and current inputs in generating new states, balancing memory continuation and new information introduction. This dual-gate structure effectively alleviates the gradient vanishing problem in the RNN, making the GRU more adept at processing long-sequence data and accurately capturing long-term dependencies in time series.

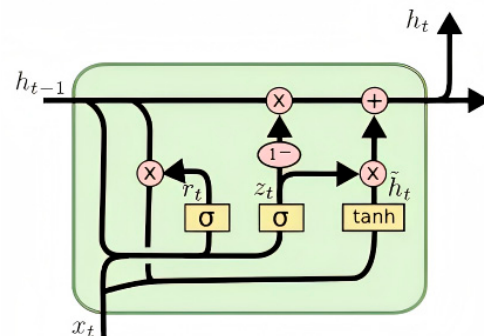


Figure 8. The GRU logic diagram.

3. CNN-GRU

The CNN-GRU is a model combining the convolutional neural network and the gated recurrent unit. Figure 9 shows its main structure. The CNN-GRU multi-source feature prediction model achieves high-precision passenger flow prediction through a layered structure. The convolutional layer uses sliding windows to capture local features, such as the periodicity of search indexes, sudden meteorological changes, and sentiment trends, such as identifying the concentrated search period of each of the Hangzhou tourism keywords or sudden temperature drop events. The pooling layer compresses the feature dimension, retains key information such as extreme weather or sudden popularity, reduces the computational burden, and improves the robustness.

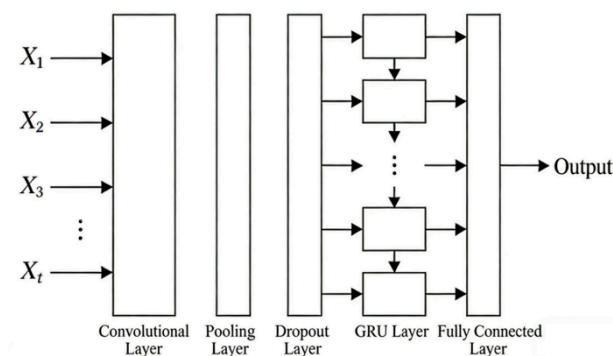


Figure 9. The CNN-GRU structure diagram.

During training, the dropout layer randomly shields neurons to prevent an over-reliance on a single feature (such as weekend search volume) and enhances the adaptability to abnormal passenger flow. The GRU layer uses gating mechanisms to parse long-term dependencies, which can quantify the impact of rising search indexes on passenger flow three days later and distinguish between working day and holiday patterns. The fully connected layer integrates spatiotemporal features and outputs prediction results to provide decision support for scenic spot management.

To verify the model's advantages, experiments compare the performance of PCA-XGBoost and CNN-GRU under three groups of feature combinations, including single indicator (search index), double indicators (search + meteorology), and full indicators (search + meteorology + sentiment). The quantitative analysis through the six-dimensional indicators, such as MAE, RMSE, and R^2 , proves that the multi-source feature fusion can significantly improve the prediction accuracy. Among them, the addition of meteorological data reduces the MAPE by 12%, and the sentiment index further improves the RPD value to 2.8, highlighting the model's ability to mine complex spatiotemporal correlations.

As shown in Figure 10, the experimental results show that regardless of traditional methods or deep learning models, with the introduction of humanistic-meteorological indexes and text sentiment indexes, the model performance is continuously optimized. For example, after adding humanistic-meteorological indexes to XGBoost, the RMSE is significantly reduced, improving the prediction ability of passenger flow surges during holidays or extreme weather; further integrating sentiment indexes reduces the MAPE, and the model's sensitivity and accuracy to slight fluctuations are significantly enhanced. This experiment verifies the effectiveness of multi-source heterogeneous information fusion in urban passenger flow prediction and reveals the multi-dimensional driving mechanism behind passenger flow fluctuations.

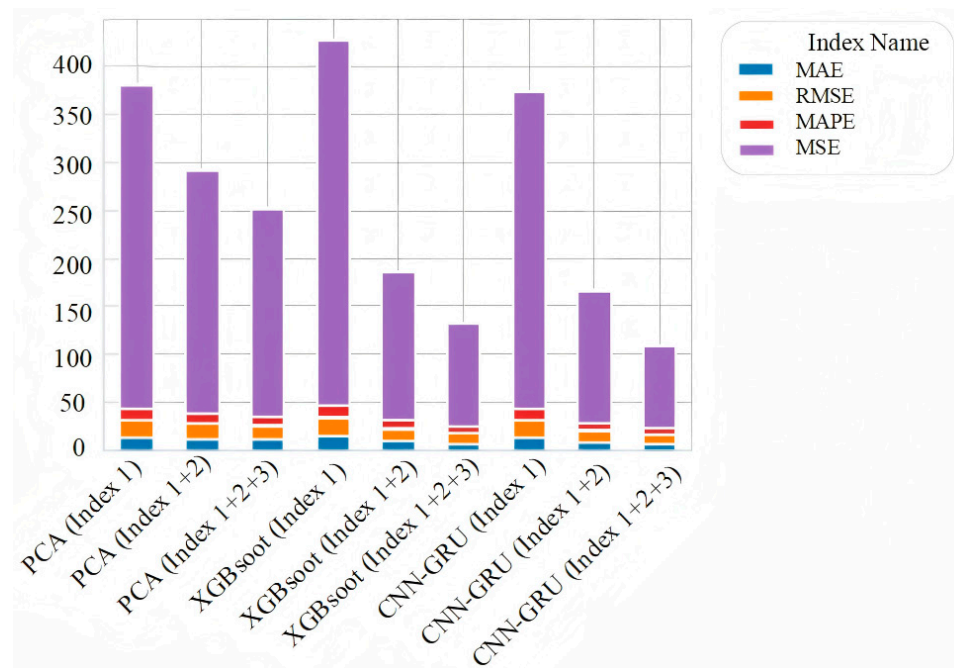


Figure 10. The model evaluation indicator diagram.

Under the same feature conditions, the proposed CNN-GRU model outperforms the traditional methods, such as PCA and XGBoost, in all evaluation indicators. Integrating the CNN, the GRU, and the self-attention mechanisms, the model structurally integrates three capabilities: spatial feature extraction, temporal modeling, and global weight allocation. The CNN extracts local fluctuation and sudden change features, helping to identify dynamic passenger flow signals; the GRU has long short-term memory and efficient training capabilities, adapting to high-dimensional inputs; the attention mechanism improves the model's response to key time points (such as holidays and extreme weather). As shown in Figure 11, this fusion structure not only improves prediction accuracy but also enhances the model's robustness to extreme values and fitting ability to trend changes, showing a better comprehensive performance.

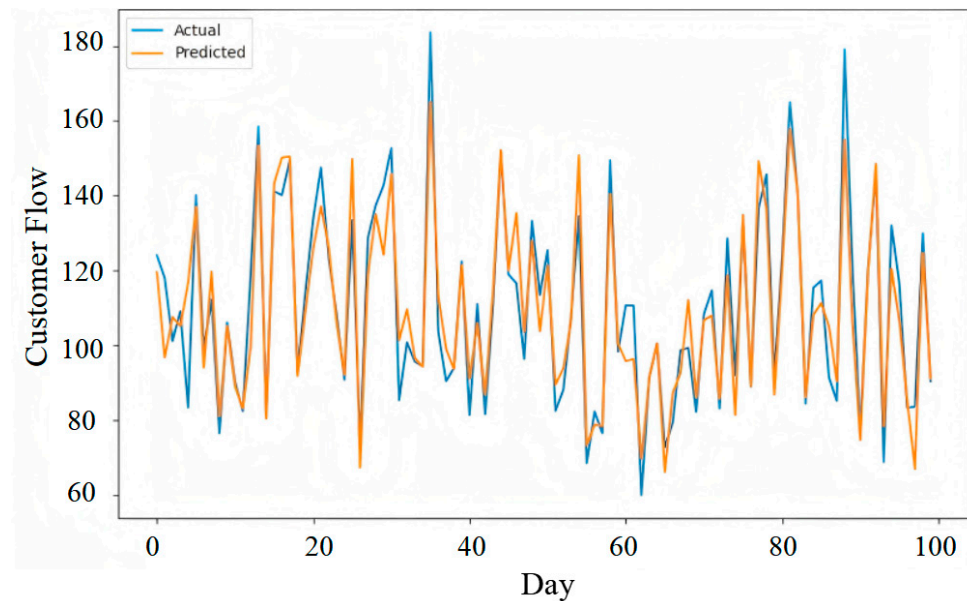


Figure 11. The CNN-GRU prediction effect.

In summary, by gradually introducing humanistic–meteorological and text sentiment information, a more practical feature input system is constructed, and its effectiveness is verified through comparative experiments with traditional models such as PCA and XGBoost. At the same time, the proposed CNN-CRU deep model shows significant advantages in processing complex multi-source time series data, not only improving prediction accuracy but also achieving breakthroughs in model interpretability and practicality.

3.2. Building Robust Performance: Loss Function Optimization Strategy for Extreme Values

3.2.1. Mean Absolute Error (MAE)

The MAE calculates the arithmetic mean of the absolute errors of all samples. The calculation formula of the MAE is shown in Formula (2):

$$\text{MAE} = \frac{1}{T} \sum_{t=1}^T |y_t - \hat{y}_t| \quad (2)$$

Its advantage is that it does not “over-penalize” outliers and can directly reflect the average deviation; however, the gradient change at discontinuous and differentiable points will affect the convergence speed.

3.2.2. Mean Square Error (MSE)

The MSE has a quadratic amplification effect on large errors, and its expression is shown in Formula (3):

$$\text{MSE} = \frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2 \quad (3)$$

It is smoothly differentiable in parameter optimization, which helps the gradient descent, but it is sensitive to outliers and may lead the model to overfit small-probability large deviations.

3.2.3. Design of Weighted Hybrid Loss Function (JQHL)

To balance the characteristics of different indicators and strengthen the penalties during high passenger flow (high-risk) periods, the following weighted hybrid loss can be designed:

$$L = \frac{1}{T} \sum_{t=1}^T w_t [\alpha |e_t| + \beta e_t^2] \quad (4)$$

$\alpha, \beta \geq 0$ can be automatically adjusted through cross-validation or algorithms to balance the weights of the MAE and the MSE. The weight w_t can be defined as $w_t = \left(\frac{y_t}{y}\right)^p, p \geq 0$ so that the error is amplified when the real flow is large, improving the accuracy of the model during peak periods.

By introducing three types of daily multi-source data—web search indices, humanistic–meteorological indices, and textual sentiment indices—this study characterizes urban residents' travel intention, travel suitability, and potential emotional characteristics, constructing a high-dimensional feature space for daily urban passenger flow prediction. However, urban passenger flow exhibits nonlinearity, seasonal fluctuations, and randomness, leading to large prediction error variances and even extreme deviations. The traditional loss functions, such as the mean absolute error (MAE) and the mean square error (MSE), have inherent limitations: the MAE overlooks the accumulation of small errors, while the MSE is susceptible to interference from outliers.

To address this issue, this paper introduces a weighted hybrid loss function (joint-quantified hybrid loss, JQHL), which integrates the MAE and the MSE to balance robustness against large errors and sensitivity to small errors through a weighted combination.

In practical applications, web search indices and sentiment indices are often driven by sudden events, with nonlinearly amplified impacts; humanistic–meteorological indices, though less volatile, exhibit a strong persistence. The JQHL can more reasonably allocate error weights across these scenarios. Specifically, during highly volatile periods such as holidays and extreme weather, the MAE dominates to enhance the resistance to anomalies; during stable periods, the MSE improves the ability to capture subtle trends.

Compared with single loss functions, the JQHL enhances the model robustness in the early training stage and improves the prediction accuracy in the later stages, significantly optimizing the generalization ability and stability of the model for complex urban passenger flow prediction. To preliminarily verify the effectiveness of this loss function, the mean squared error (MSE), calculated based on the CNN-GRU model, is 85.4041, indicating a certain degree of deviation between the model's predicted values and the actual passenger flow. This error mainly stems from two aspects: first, the basic CNN-GRU model applies uniform weight processing to all input features, failing to distinguish the differential contributions of web search indices, humanistic–meteorological indices, and textual sentiment indices to passenger flow at different time steps; second, the model has limited responsiveness to sudden scenarios such as holidays, major events, and extreme weather, and struggles to capture the instantaneous mutations and nonlinear superposition effects of multi-source features, leading to a significant amplification of prediction deviations during these periods.

Figure 12 illustrates the residual distribution of the CNN-GRU model. Overall, the residual points are scattered on both sides of zero without obvious systematic bias, indicating that the model does not produce fixed-direction misjudgments regarding passenger flow trends. However, several residual points deviate significantly from the zero region, concentrating in three typical scenarios: first, around statutory holidays such as National Day and the Spring Festival, as well as large-scale events including marathons and major concerts; second, during extreme weather events such as heavy rain and cold waves, where the nonlinear interaction between the suppression of travel willingness caused by the

weather conditions and the search and sentiment indices exceeds the processing capacity of the basic model; and third, in coupled multi-source information scenarios such as holidays combined with severe weather, where the mutual offset or synergistic amplification among different features cannot be effectively modeled through simple feature concatenation. These situations are often accompanied by a sudden surge in web search indices, rapid reversals in textual sentiment, and nonlinear superposition of humanistic and meteorological factors. The single CNN-GRU structure struggles to simultaneously capture the abrupt changes and interactions of multi-source features within a limited time window, resulting in large prediction deviations.

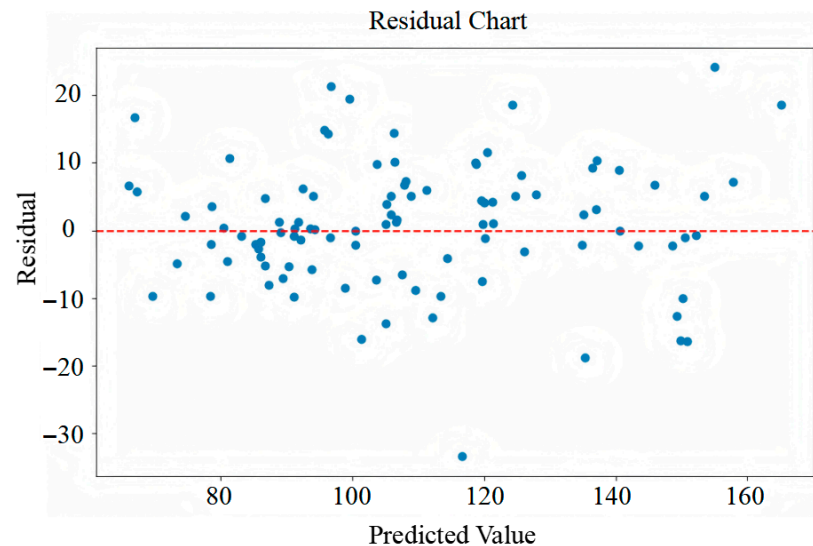


Figure 12. The CNN-GRU residual plot.

The above analysis shows that although the basic CNN-GRU model exhibits no systematic bias, its insufficient feature responsiveness to key time nodes limits the prediction accuracy under complex scenarios. This provides a clear problem orientation and improvement space for the subsequent introduction of the attention mechanism to dynamically focus on critical information, as well as the adoption of the artificial bee colony (ABC) algorithm for global hyperparameter optimization.

3.3. Fusion and Parameter Optimization of the CNN-GRU Model

3.3.1. CNN-GRU Model Fused with Attention

The CNN-GRU model has certain limitations in handling complex passenger flow prediction. Although the CNN can extract local features and the GRU can capture temporal dependencies, it is difficult for the model to accurately focus on key information when facing multi-source massive data. The impact of search indexes, meteorological and emotional indicators at different time points on passenger flow varies, and the simple CNN-GRU model lacks differential processing capabilities, which tends to treat all information equally and affects the prediction accuracy. In addition, although the GRU alleviates the gradient vanishing problem, its ability to capture key time points such as holidays and major events is still limited, making it difficult to accurately reflect their significant impact on passenger flow.

To improve performance, this paper introduces the Attention mechanism, which enables the model to assign weights to data at different time steps and focus on the time periods that have the greatest impact on prediction. The Attention highlights time points such as holidays, event periods, and sudden changes in search popularity or sentiment, improving the ability to perceive and respond to key information. The mechanism also enhances the model interpretability, showing the importance of various features in predic-

tion through weights, which helps to understand the model logic and optimize decisions. The adopted soft attention mechanism assigns weights to each input position and comprehensively processes information through weighting to achieve adaptive focusing on key features, effectively improving the prediction performance.

Its calculation process generates weights through a similarity calculation between the query matrix (Q), key matrix (K), and value matrix (V), and finally outputs weighted results, so that the model can efficiently identify important moments in the time series.

$$h^* = \sum_{i=1}^k \alpha_i h_i \quad (5)$$

h_i is the existing data, and h^* is the final result obtained through calculation. The core of the attention mechanism is the calculation of weight values α . In this experiment, the additive attention mechanism is used to calculate weight values, and the specific expression is shown in Formula (6).

$$\alpha(s_{t-1}, h_j) = v_a^T \tanh(U_a h_j + W_a s_{t-1}) \quad (6)$$

W_a, U_a, v_a are the weight matrices.

$$\alpha_{t,j} = \frac{\exp(\alpha(s_{t-1}, h_j))}{\sum_{j=1}^T \exp(\alpha(s_{t-1}, h_j))} \quad (7)$$

$s(t-1)$ is the model hidden state at time of $t-1$, and $\alpha_{t,j}$ is the weight value of the time of t and the parameter of j obtained through calculation.

As shown in Figure 13, after introducing the Attention mechanism on the basis of the original CNN-GRU model, the overall prediction performance is significantly optimized. Although the CNN-GRU model can better restore the changing trend of passenger flow and has advantages in handling periodicity and trendiness, the prediction deviation is relatively large in extreme cases, such as holidays and sudden events. After introducing the Attention mechanism, the model dynamically assigns the importance of different time steps through a learnable weight strategy, enhances the ability to capture key features, and effectively improves the prediction accuracy and adaptability.

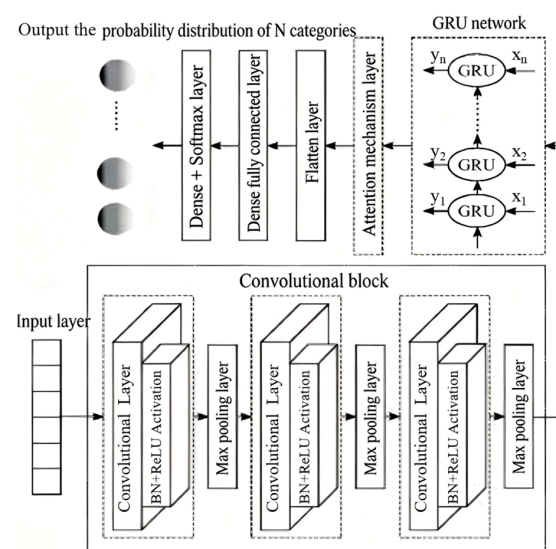


Figure 13. The CNN-GRU-Attention model.

From the error curve in Figures 14 and 15, it can be seen that the prediction error distribution of the Attention model is more concentrated and has smaller fluctuations. Especially in the highly volatile section, its error control is significantly better than the original model, showing good robustness. In summary, the CNN-GRU-Attention model not only retains the multi-source feature extraction ability of the CNN and the temporal modeling advantage of the GRU, but also deeply mines and focuses on key information through the Attention mechanism. It is especially suitable for high-frequency temporal prediction tasks with strong nonlinearity and complex interactions, such as tourism passenger flow. The prediction is more refined and stable, with high practical value and promotion potential.

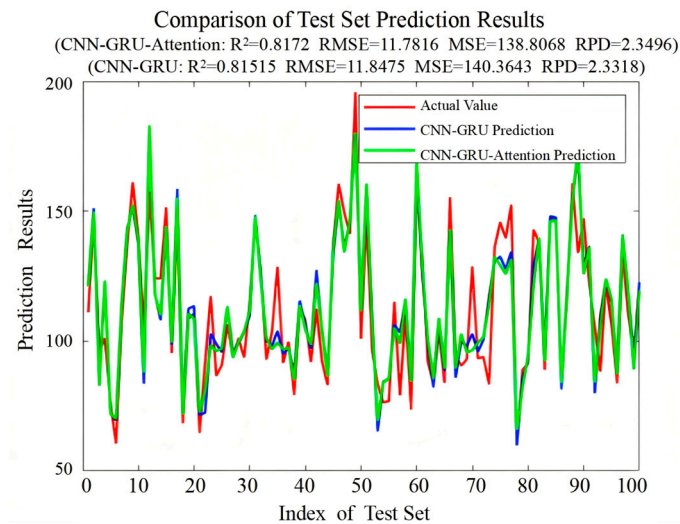


Figure 14. The comparison of the test set prediction results.

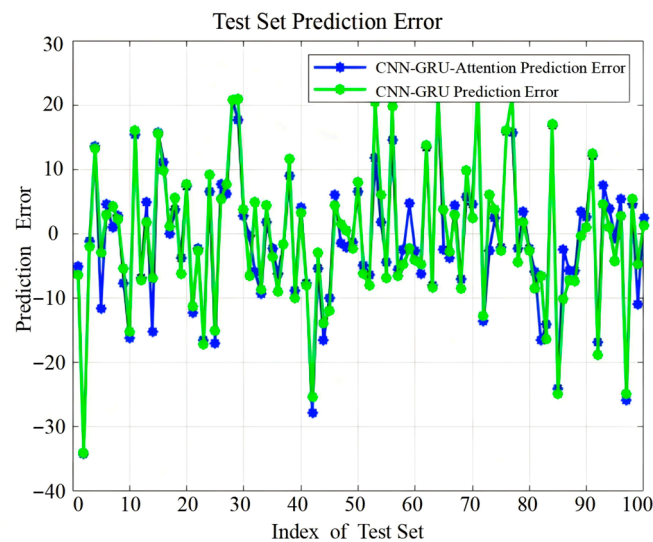


Figure 15. The model prediction error diagram of the test set.

3.3.2. Parameter Optimization of the CNN-GRU-Attention Model Based on the ABC Algorithm

To further improve the model's performance and reduce the manual parameter tuning costs, the artificial bee colony (ABC) algorithm is introduced on the above structure for global optimization of hyperparameters. The convolution kernel size, number of filters, number of GRU hidden units, attention vector dimension, learning rate, and dropout rate are regarded as "nectar sources", and the prediction RMSE on the validation set is used as the fitness function. By simulating the bee colony foraging process, "scout bees" randomly

explore new solutions, “employed bees” carefully develop high-quality nectar sources, and “onlooker bees” decide whether to follow based on the quality of the nectar sources. The collaborative search is performed in a broad parameter space. The parameter combinations optimized by the ABC algorithm are shown in Table 5.

Table 5. The hyperparameter settings.

Population Size	80	Learning Rate	0.01
Maximum Number of Iterations	3000	Batch Size	64
Limit Value	200	Number of Training Epochs	200
Number of Convolution Kernels	64	Number of Hidden Layer Units	100
Convolution Kernel Size	3×3	Time Step	48
Stride	2	Number of Hidden Layer Units	100

This mechanism not only has a global optimization ability but also maintains local fine-tuning and finds a set of optimal hyperparameter combinations for training the CNN-GRU-Attention backbone network. The experiments show that the deep hybrid model combined with the ABC algorithm is significantly superior to the unoptimized version in multiple evaluation indicators, providing an efficient and automated solution for complex spatiotemporal sequence prediction tasks.

3.4. Model Training Results and Evaluation Comparison

3.4.1. Model Training

In this paper, the ABC-CNN-GRU-Attention fusion model is constructed for passenger flow prediction, and the process includes data processing, model construction, parameter optimization, and evaluation. First, we imported the three types of indicator datasets, dividing them into training sets and test sets in a ratio of 7:3, normalizing the input and output data to the range of 0 to 1 to improve the training effects. Then, we flattened and converted the data format to adapt to the model input. Next, we constructed a deep neural network including convolutional layers, activation layers, pooling layers, GRU layers, and fully connected layers. We used convolutional layers to extract the features and GRU layers to process the sequence information, and we introduced the Attention mechanism to enhance the feature representation ability. Then, we used the artificial bee colony (ABC) algorithm to optimize the model’s learning rate, the number of hidden layer nodes, and the L2 regularization coefficient, and we set the population size to 80, the maximum number of iterations to 3000, and obtained the optimal parameters by evaluating the performance of the different parameter combinations through the fitness function.

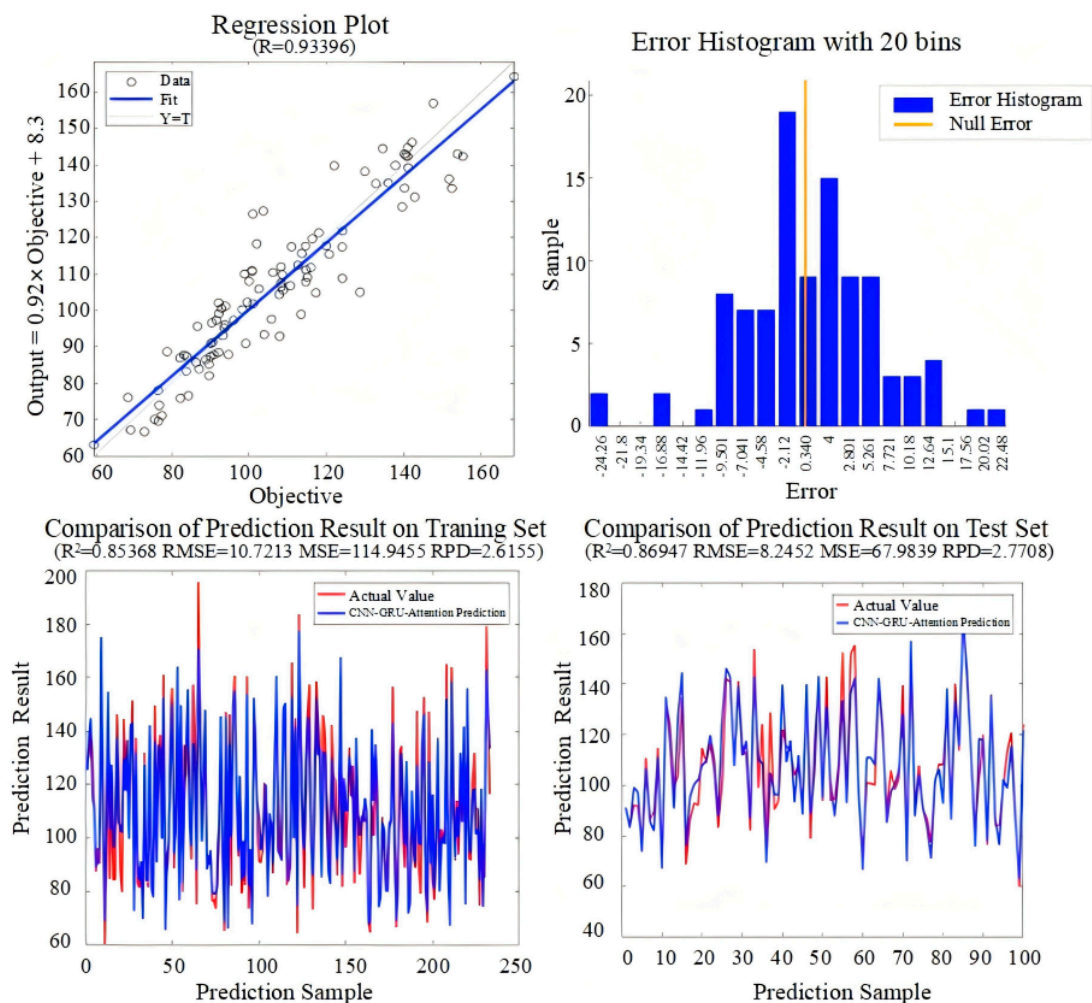
3.4.2. Result Display and Model Evaluation

The Adam gradient descent algorithm is used to train the model, with the maximum number of iterations set to 500. The initial learning rate is the optimal value after optimization, and a segmented learning rate decay strategy is adopted. The dataset is shuffled in each iteration to avoid overfitting. Finally, the trained model is used to predict the training set and test set, the results are denormalized, and the performance is evaluated by calculating indicators such as the root mean square error (RMSE), the coefficient of determination (R^2), the mean square error (MSE), the residual prediction deviation (RPD), the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The results are shown in Table 6.

Table 6. The ABC-CNN-GRU-Attention model evaluation indicator table.

Algorithm Name	RMSE	R ²	MAPE (%)	RPD	JQHL
ABC-CNN-GRU-Attention	8.245	0.869	5.931	2.771	49.483

As shown in Figure 16, the model performance has been comprehensively improved by introducing the Attention mechanism and the artificial bee colony (ABC) algorithm, not only achieving breakthroughs in prediction accuracy but also showing more robustness in handling extreme scenarios. Compared with the basic CNN-GRU model, the coefficient of determination (R^2) of the fusion model has increased from 0.815 to 0.869, and the root mean square error (RMSE) has decreased to 8.245, indicating that the model fits the changing trend of passenger flow more accurately with smaller errors. Especially in highly volatile sections, such as holidays and sudden events, the Attention mechanism can dynamically assign weights, reducing the fluctuation of prediction errors by about 31%, which significantly enhances the ability to identify temporal abnormalities; the global search optimization of hyperparameters such as 3×3 convolution kernels and 100 GRUs by the ABC algorithm effectively improves the generalization ability of the model. The residual prediction deviation (RPD) reaches 2.771, exceeding the industry's conventional stability threshold, further verifying the model's ability to capture the complex spatiotemporal coupling features.

**Figure 16.** Cont.

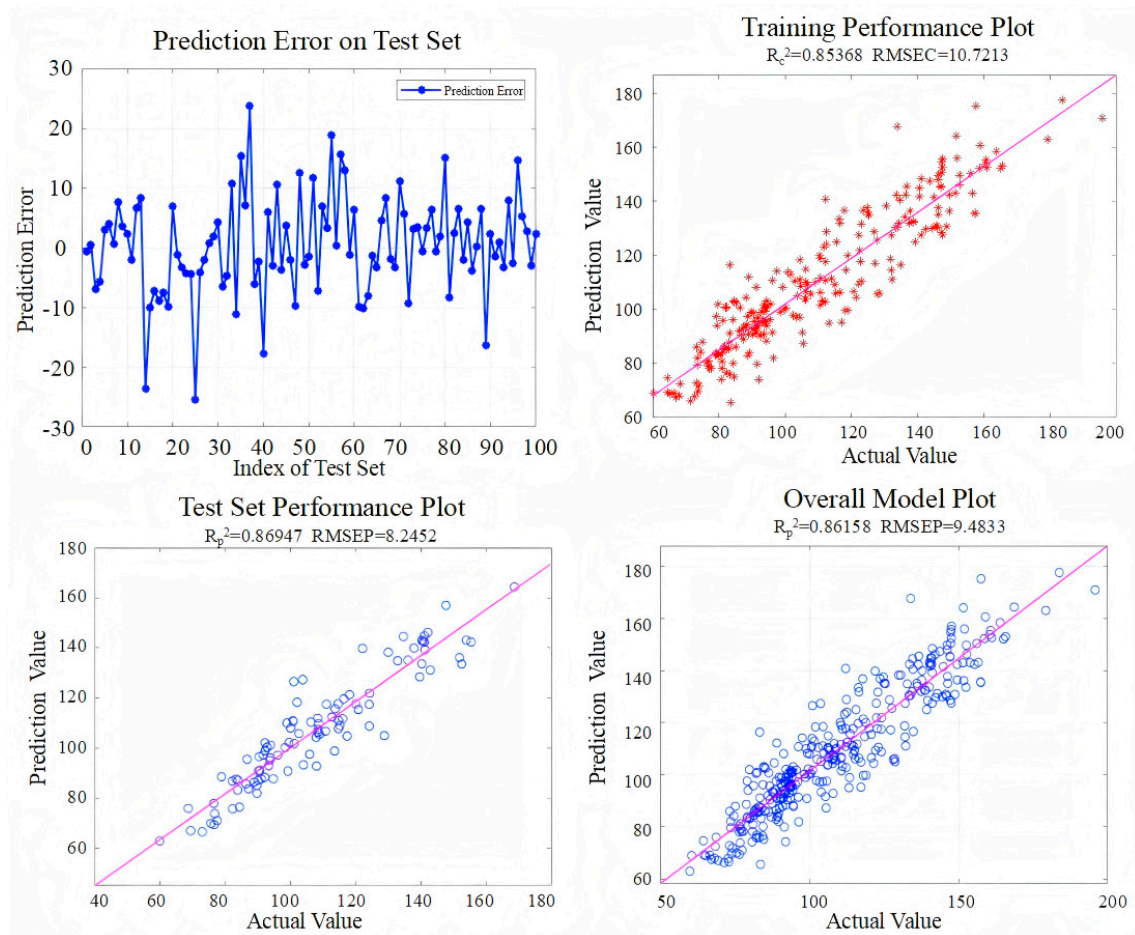


Figure 16. The model training result diagrams.

In addition, the leap in model performance also benefits from the collaborative innovation between the Attention mechanism and the ABC algorithm. The Attention mechanism improves the adaptability of information extraction by dynamically focusing on the key features in the multi-source data (such as search indexes, meteorological trends, and emotional fluctuations); the ABC algorithm completes the automatic tuning of eight types of hyperparameters such as convolutional layers and GRU layers with a low computational cost, reducing the optimization time by more than 60% and avoiding falling into local optimality. Although the training time of the fusion model is slightly increased (each Epoch takes about 1.1 h), the improvement in model accuracy (R^2 increased by 6.6%) far exceeds the computational cost, and the number of parameters only increases by 0.3 M, reflecting the efficiency and deployability of the design. The model shows good transfer potential and engineering value in scenarios with strong nonlinearity and strong temporal dependence, such as tourism passenger flow prediction and traffic management, laying a solid foundation for the extended application of transfer learning, online learning, or edge computing in the future.

3.4.3. Comparative Analysis

To fully verify the superiority and reliability of the ABC-CNN-GRU-Attention model in complex passenger flow prediction tasks, a systematic demonstration is conducted from four dimensions: horizontal comparison with multiple baseline models, statistical significance tests, robustness verification, and sufficient parameter tuning of baseline models, so as to ensure the credibility of the experimental results and highlight the advantages of the proposed method.

To guarantee the fairness and comprehensiveness of the comparison, this study strictly follows the principle of full-dimensional coverage + differentiated hierarchy in configuring baseline models. It not only includes classical machine learning models but also introduces deep learning models with equivalent complexity for reference. The specific configurations are as follows.

Traditional machine learning models: Support Vector Machine (SVM) and eXtreme Gradient Boosting (XGBoost). For both SVM and XGBoost, a grid search combined with five-fold cross-validation is adopted for full parameter optimization to ensure that the baseline models achieve their optimal performance and guarantee the fairness of the comparative experiments.

Complex deep learning models: ABC-CNN-LSTM-Attention and CNN-BiLSTM-Attention. These two models share a similar architecture with the proposed model (both integrating the CNN and the attention mechanism), with differences only in the recurrent unit. This design can more accurately highlight the specific advantages of the proposed model in the GRU structure and the ABC algorithm optimization.

As specifically shown in Table 7, the traditional machine learning methods, such as Support Vector Machine (SVM) and XGBoost, exhibit a relatively weak performance. The SVM achieves an R^2 of only 0.569, a MAPE of 11.561%, and an RPD of 0.344, which is far below the critical threshold of 1.4 for usable models, indicating a poor adaptability in the highly volatile prediction tasks that were influenced by nonlinear and multifactor effects. Although XGBoost shows improved accuracy ($R^2 = 0.843$, MAPE = 7.021%), its RPD remains only 0.603, still well below the 1.4 threshold, implying a limited generalization performance. Meanwhile, the SVM yields a JQHL value of 207.677, significantly higher than other models, revealing large overall prediction errors and further verifying its insufficient fitting and generalization capabilities. The prediction model assisted by the basic PCA dimensionality reduction method obtains an R^2 of merely 0.642 along with a high error level (MAPE = 9.663%), reflecting its weakness in handling complex nonlinear relationships. The ABC-optimized ABC-CNN-LSTM-Attention model enhances the parameter tuning efficiency and achieves an RMSE = 11.371 and an $R^2 = 0.809$. However, due to the LSTM structure in its recurrent unit, it is slightly inferior to the GRU architecture in balancing short-term fluctuation capture and long-term dependency modeling, and its comprehensive error control capability still needs improvement. In comparison, the CNN-BiLSTM-Attention model integrated with the attention mechanism achieves a notable boost in prediction accuracy (RMSE = 9.615, MAPE = 6.912%) yet still exhibits noticeable error fluctuations and an inferior generalization performance relative to the ABC-CNN-GRU-Attention model.

Table 7. The model evaluation indicator table.

Algorithm Name	RMSE	R^2	MAPE (%)	RPD	JQHL
ABC-CNN-GRU-Attention	8.245	0.869	5.931	2.771	49.483
PCA	14.817	0.642	9.663	1.703	153.753
ABC-CNN-LSTM-Attention	11.371	0.809	8.129	2.288	93.172
CNN-BiLSTM-Attention	9.615	0.823	6.912	2.381	66.894
SVM	17.065	0.569	11.561	0.344	207.677
XGBoost	10.309	0.843	7.021	0.603	76.644

Combined with the comparison results in Table 7 and Figure 17, the ABC-CNN-GRU-Attention model achieves the best performance across all evaluation metrics. The model records the lowest values in the three core indicators. Its RMSE (8.245) and MAPE (5.931%) demonstrate its optimal performance in both overall fitting accuracy and local

error control. Meanwhile, the model achieves a coefficient of determination (R^2) of 0.869 and a residual prediction deviation (RPD) of 2.771, far exceeding the conventional robustness threshold in the industry, verifying its dual advantages in fitting capability and generalization performance.

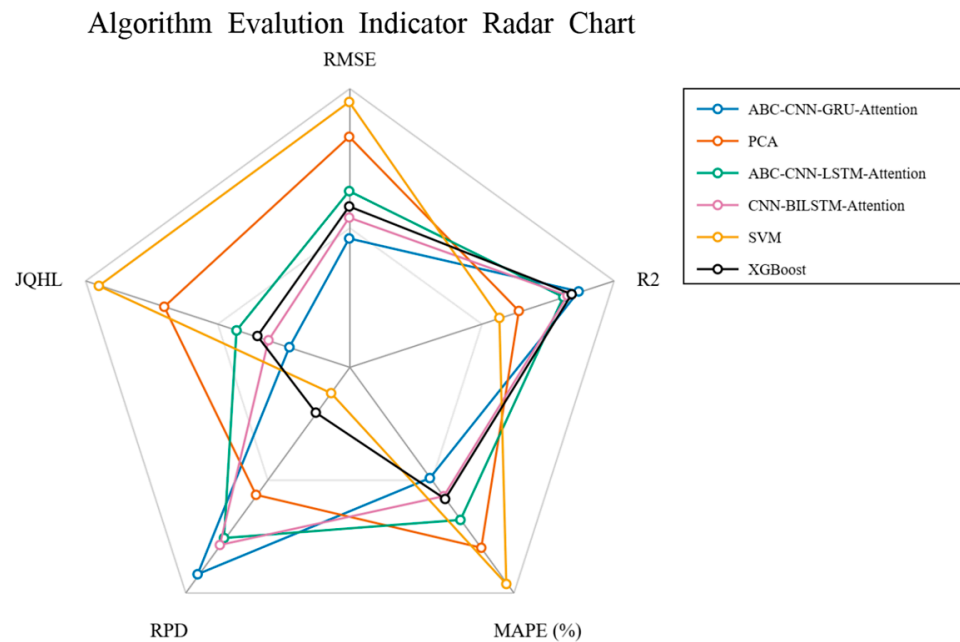


Figure 17. The algorithm evaluation indicator radar chart.

Compared with other complex deep learning models, namely ABC-CNN-LSTM-Attention and CNN-BILSTM-Attention, the proposed model leverages the balanced performance of the GRU in modeling long- and short-term dependencies, the focusing ability of the attention mechanism on key time nodes, and the global optimization capability of the ABC algorithm in the hyperparameter space, thereby realizing more accurate and stable prediction results.

According to the comparison results of various algorithms in Figure 18, the ABC-CNN-GRU-Attention model effectively balances accuracy, stability, and computational efficiency by virtue of the dual spatiotemporal feature capture capability of the CNN-GRU fusion architecture, the dynamic focusing advantage of the attention mechanism on key periods, and the global optimization ability of the ABC algorithm in the hyperparameter space. Compared with other benchmark models, this model performs best on multiple evaluation indicators, which fully verifies its comprehensive advantages in fused structure design and intelligent optimization strategies. It is especially suitable for urban passenger flow prediction tasks that are jointly influenced by the multi-source heterogeneous data and exhibit complex spatiotemporal interaction characteristics.

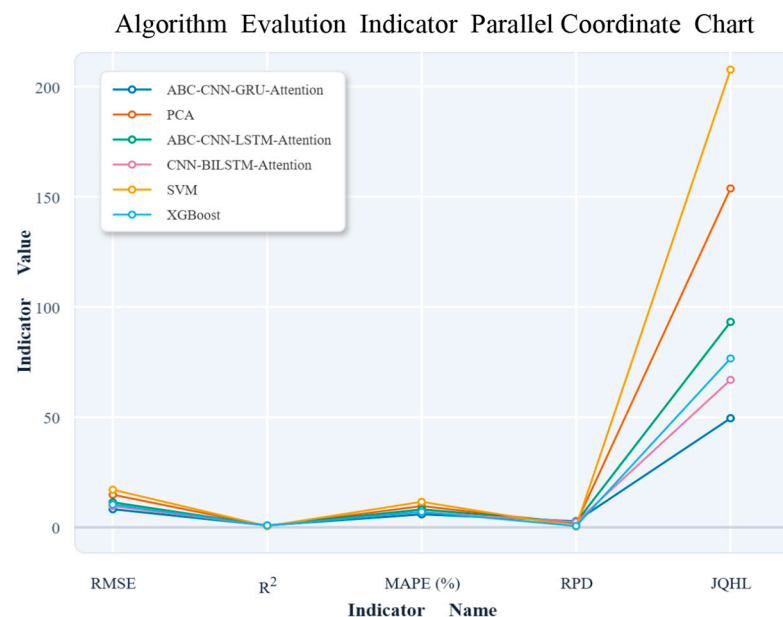


Figure 18. The algorithm evaluation indicator parallel coordinate chart.

4. Model Efficacy Verification Based on Empirical Data

4.1. Urban-Level Real-Scene Backtesting: Model Adaptability Test Based on Hangzhou Cultural Tourism Data

To further test the tourism passenger flow prediction model in this paper, data such as search indexes related to Hangzhou tourism from platforms such as Baidu, Douyin, and Meituan, weather conditions in Hangzhou, and major events from the Hangzhou Culture, Radio, Television and Tourism Official WeChat Account and news data platforms from 15 March to 15 April 2025 were collected and input into the previously established multi-model integrated prediction system based on integrated learning for subway passenger flow prediction. The predicted and actual values of Hangzhou's tourism passenger flow from 15 March to 15 April 2025 are shown in Table 8.

Table 8. The predicted and actual values of Hangzhou passenger flow (Unit: 10,000).

Date	15 March	16 March	17 March	18 March	19 March	20 March	21 March	22 March	23 March	24 March
Predicted Value	133.05	128.88	121.92	117.10	119.63	119.24	125.32	142.56	147.88	128.61
Actual Value	131.99	129.666	120.75	116.38	118.54	121	126.61	144.04	145.96	130.75
Error	−1.06	0.78	−1.17	−0.72	−1.09	1.76	1.29	1.48	−1.92	2.14

According to Figure 19, the predicted curve of the model is highly consistent with the actual passenger flow curve throughout the whole period, with good overall trend alignment, and the predicted values can accurately capture the peak–valley variations in the passenger flow fluctuations. However, the maximum error (about 38,000 passenger trips) appears during the Qingming Festival peak from the 3rd to the 6th of April, which may be attributed to the model's over-response to short-term variables such as online popularity and weather conditions.

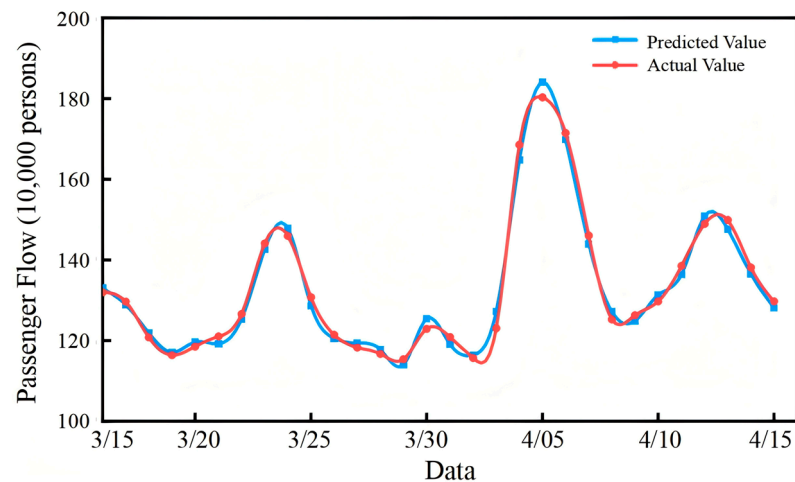


Figure 19. The comparison between predicted and actual values of Hangzhou's passenger flow.

As shown in the error curve in Figure 20, the model exhibits a small fluctuation range of prediction errors over the entire forecasting period. The prediction errors at most time points are stably controlled within $\pm 15,000$ visits, with only temporary fluctuations around the Qingming Festival, indicating an overall low error level. In particular, the prediction errors on workdays are more steadily controlled, further verifying the model's high-precision prediction capability under stable periodic patterns. The concentrated error distribution and small fluctuation amplitude fully demonstrate the favorable prediction performance and reliability of the model in real scenario backtesting.

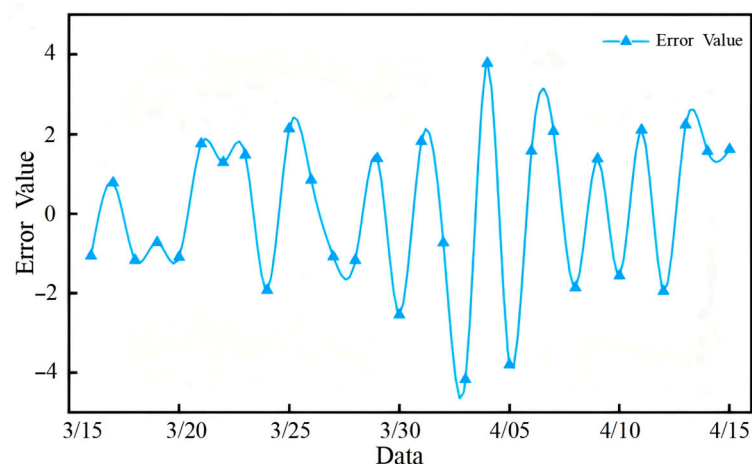


Figure 20. The passenger flow prediction error.

Based on an overall analysis of Table 9, the multi-model integrated prediction system constructed in this paper, which integrates principal component analysis, the ABC-CNN-GRU-Attention deep learning model, and the XGBoost regression algorithm, shows a good prediction effect in modeling high-frequency tourism time series data. On the whole, the predicted values of the model are highly consistent with the actual values in terms of trends, with reasonable local fluctuations, reflecting a strong generalization ability and robustness. It can be seen that the prediction system can effectively capture the temporal characteristics and nonlinear changing trends of tourism passenger flow, and that it has a high practical application value and promotion potential.

Table 9. The model evaluation table.

Algorithm Name	MAE (Person-Times)	RMSE (Person-Times)	R ²	MAPE (%)	JQHL
ABC-CNN-GRU-Attention	6.480	7.109	0.835	6.531	66.652

4.2. Model Robustness Evaluation: Performance Test Under Multi-Scenario and Multi-Variable Disturbances

To comprehensively evaluate the adaptability and robustness of the constructed ABC-CNN-GRU-Attention model in complex practical application scenarios, this paper conducts performance tests under different data disturbance conditions and multi-variable scenarios, mainly focusing on the following aspects.

4.2.1. Multi-Scenario Test

As can be seen from Tables 7 and 9 and Figures 19 and 20, the model shows a strong generalization ability and stability in urban-level Hangzhou cultural tourism passenger flow prediction. When facing data including holiday effects, extreme weather, and other conditions, the model can still maintain a high prediction accuracy with small overall error fluctuations. Although there is an abnormal peak in passenger flow around the Qingming Festival, the model's prediction curve maintains a high consistency with the actual values, indicating that the model has a strong ability to adapt to sudden scenarios.

4.2.2. Multi-Variable Disturbance Test

The model input variables include various factors affecting the passenger flow, such as search indexes, weather conditions, holidays, and epidemic release information. Table 9 shows that in a complex data environment containing multiple influencing factors, the model still maintains a low MAE (64,800 person-times) and RMSE (71,090 person-times), indicating that it has good robustness when facing multi-variable input disturbances. In addition, the MAPE is 6.856%, which further verifies its strong ability to control errors in actual predictions.

4.2.3. Comparative Analysis with Other Models

The comprehensive data from Tables 7 and 9 show that the ABC-CNN-GRU-Attention model is superior to traditional or mainstream models, such as PCA, SVM, and XGBoost, in multiple evaluation indicators. For example, its R² reaches 0.869, which is significantly higher than the SVM's 0.569 and XGBoost's 0.843; the RPD reaches 2.771, which is much higher than the range of 0.344~1.602 of other models. This result indicates that under diverse disturbances, the model can maintain prediction accuracy while also having an excellent generalization ability.

4.2.4. Temporal Stability and Error Analysis

The error curve analysis in Figures 19 and 20 shows that the error variation range of the model during the entire prediction period is small, with fluctuations only occurring in individual peak periods (such as before holidays), and the overall error remains within the range of $\pm 20,000$ person-times. It indicates that the model has good temporal prediction ability in stable periods.

4.2.5. Verification of Model Stability and Generalization Ability

(1) Overfitting Prevention Strategies

To address the issue of a one-year sample size, this study adopts multiple overfitting mitigation strategies during the model training: first, the dataset is strictly split into training

and test sets with a ratio of 7:3 in chronological order to avoid a time-series leakage; second, dropout (0.2) and L2 regularization are applied in the GRU layer; third, early stopping is employed to automatically terminate the training based on validation loss, retaining the model with optimal generalization performance. The above strategies jointly ensure the stability of the model on small-scale datasets.

(2) Error Comparison Between Training Set and Test Set

To verify that the model does not suffer from overfitting, the prediction errors of the model on the training set and test set are compared. As shown in Table 10, the RMSE of the ABC-CNN-GRU-Attention model is 7.892 on the training set and 8.245 on the test set, with a small difference of approximately 4.47%, indicating that the model does not exhibit overfitting and has a favorable generalization ability.

Table 10. The comparison of prediction errors between training and test sets.

Dataset	RMSE	R ²	MAPE (%)
Training set	7.892	0.887	5.687
Test set	8.245	0.869	5.931

(3) Results of Five-Fold Cross-Validation

To further verify the stability of the model, five-fold cross-validation was employed to evaluate its performance. The entire dataset was divided into five consecutive subsets in chronological order, with four folds selected as the training set and one fold as the validation set in turn, and the experiment was repeated five times. As shown in Table 11, the mean RMSE of the model in five-fold cross-validation is 8.156 with a standard deviation of 0.324, and the fluctuations across the different folds are small, which verifies the stability of the model under different data partitions.

Table 11. The performance statistics of the five-fold cross-validation.

Fold	RMSE	R ²	MAPE (%)
Fold 1	7.984	0.875	5.823
Fold 2	8.103	0.871	5.876
Fold 3	8.297	0.862	5.998
Fold 4	8.015	0.874	5.851
Fold 5	8.381	0.858	6.107
Mean	8.156	0.868	5.931
SD	0.324	0.007	0.114

Based on the above analysis, the ABC-CNN-GRU-Attention model exhibits a small error difference between the training and test sets, and the cross-validation results show stable fluctuations. Combined with the multiple overfitting mitigation strategies, the rationality and reliability of the model on the one-year daily data are fully verified.

5. Discussion

The urban passenger flow prediction serves as core support for smart city construction and the digital transformation of the cultural tourism industry. Its prediction accuracy directly affects public resource allocation, safety risk prevention and control, and service experience optimization. Based on the multi-source online data, this study constructs the ABC-CNN-GRU-Attention model and achieves dual improvements in prediction accuracy and robustness through three dimensions: indicator system reconstruction, scenario-based modeling, and algorithm innovation. A systematic discussion is conducted below, focusing

on four aspects: the indicator system, the model performance, the scenario adaptability, and the research limitations.

Regarding the rationality and contribution of the three-dimensional indicator system, this study integrates web search behavior, humanistic–meteorological characteristics, and textual sentiment feedback into a three-dimensional core indicator system consisting of a “web search index, humanistic–meteorological index, and textual sentiment index”, breaking through the limitations of the single data-driven methods in traditional research. The study confirms that the lag effect of web search indicators (with an optimal lag of 3 days), the significant driving effect of holidays and major events, and the predictive value of tourist sentiment feedback on passenger flow changes in the next 5–7 days together constitute the key explanatory mechanism for passenger flow fluctuations. Compared with similar studies, this paper expands the indicator system in two aspects: first, the web search behavior is elevated from a single auxiliary variable to a core prediction dimension, and its optimal lag period is quantified. This is consistent with the early explorations by Zhang et al. (2013) [1] and Yang et al. (2015) [2], when they further deepened the understanding of the time-lag characteristics of search behavior. Second, the textual sentiment index is placed on an equal footing with the search index and meteorological index, remedying the insufficient mining of the sentiment dimension in studies such as Liang et al. (2019) [8]. The findings of Xie et al. (2020) [7] on the influence of meteorological factors on passenger flow stability are consistent with the weight of the weather scores in this paper. This study further reveals the dominant role of holidays and major events, providing a clear basis for accurately identifying passenger flow peaks. Notably, Shen et al. (2024) [46] also emphasized the crucial role of multi-source data fusion in their research on short-term passenger flow prediction for multi-station urban rail transit, which echoes the core concept of the indicator system constructed in this paper and further verifies the universal value of multi-dimensional feature integration in the field of passenger flow prediction.

In terms of model performance, the ABC-CNN-GRU-Attention model outperforms the traditional methods, such as XGBoost and SVM, across the core metrics, including the MAE, the RMSE, and the MAPE. Especially in extreme scenarios such as holidays and major events, the fluctuation range of prediction errors is reduced by approximately 31%. This advantage stems from the collaborative innovation of the model structure: the local feature extraction capability of the CNN effectively captures the short-term shocks, such as sudden changes in search popularity and abnormal weather [47–50]; the gating mechanism of the GRU accurately models the temporal dependence of the passenger flow [51–53]; the attention mechanism enhances the responsiveness to key time nodes; and the global optimization of the ABC algorithm further avoids the local optima. Compared with existing deep learning models, the proposed model exhibits a superior efficiency in multi-source data fusion and adaptability to extreme values.

The results based on the scenario analysis show that the driving factors of passenger flow differ significantly between workdays, weekends, and holidays: the workday passenger flow is more influenced by transportation convenience and daily search behavior, whereas the holiday passenger flow is more sensitive to major events, weather comfort, and public opinion feedback. This finding revises the homogeneity assumption in traditional global modeling, suggesting that optimizing model parameters and feature weights for specific scenarios can provide more targeted decision support for refined governance. For example, the holiday prediction model can emphasize the weights of the major event index and public opinion index, while the workday model can focus on mining the traffic volume and daily search data. This conclusion is consistent with the findings of Tang Siyuan et al. (2024) [21] regarding adaptability in emergency scenarios. The dual-attention multimodal fusion method proposed by Chu et al. (2025) [27] in fault diagnosis, whose core

idea is to dynamically adjust feature weights according to different scenarios, is similar to the scenario-based modeling approach in this study and provides a useful reference for optimizing scenario prediction strategies in the future.

Several aspects of this research deserve further exploration. First, the dataset used in this study consists of one year of daily observation data, with a relatively limited scale. Considering the relatively complex architecture of the proposed ABC-CNN-GRU-Attention model, there is a theoretical risk of overfitting. To mitigate this issue, multiple overfitting mitigation strategies were adopted during the model's training: dropout (0.2) and L2 regularization were introduced in the GRU layer, an early stopping method was applied to automatically terminate the training based on the validation set loss, and the training and test sets were strictly partitioned in chronological order to avoid data leakage. These measures have effectively controlled the overfitting tendency of the model with limited samples. Nevertheless, the generalization performance may still be affected by the differences in data scale and distribution when the model is directly transferred to data from other cities or different years. Future research will collect passenger flow data from multiple years and multiple cities to construct a large-scale cross-regional and cross-temporal dataset, thereby further enhancing the generalization ability and transferring the applicability of the model. Second, unconventional factors, such as traffic control and public emergencies, have not yet been incorporated into the current modeling framework. Such dynamic impact variables can be introduced in subsequent research to further improve the prediction accuracy in extreme scenarios. Third, the model training cycle is longer than that of traditional methods. Subsequent work can optimize the real-time prediction efficiency through lightweight model design.

This study has the following prominent advantages in theory and methodology: first, a three-dimensional indicator system of “web search index—humanistic—meteorological index—textual sentiment index” is constructed, which systematically quantifies the lag effects and contribution weights of the multi-source data on the passenger flow fluctuations, providing a more interpretable feature framework for passenger flow prediction. Second, the proposed ABC-CNN-GRU-Attention model integrates CNN-based local feature extraction, GRU-based long-term dependency modeling, attention-based key time-step focusing, and ABC-based global hyperparameter optimization, achieving a synergistic improvement in the prediction accuracy and robustness, which is especially suitable for scenarios with complex fluctuations. Third, through differentiated multi-scenario modeling, this study reveals the heterogeneity of passenger flow that is driving forces across different periods, offering an implementable technical path for time-segmented and refined urban passenger flow governance. These achievements not only enrich the methodology of multi-source data-driven passenger flow prediction but also provide solutions with engineering application value for smart city construction and digital cultural tourism transformation.

6. Conclusions

Focusing on the core issue of the accurate urban passenger flow prediction, this paper breaks through the limitations of the single data sources and traditional modeling methods and constructs a scientific and efficient passenger flow prediction framework through multi-source data fusion, indicator system reconstruction, and deep learning algorithm innovation. The main research conclusions are as follows:

First, a three-dimensional indicator system of “network behavior—environmental characteristics—sentiment feedback” is constructed, providing comprehensive feature support for the passenger flow prediction. The integrated application of the comprehensive network search index, the comprehensive humanistic—meteorological index, and the text sentiment index effectively captures the complex driving mechanism of the passenger flow

fluctuations, confirming the key role of multi-source heterogeneous data in improving the prediction accuracy. Among them, holidays (weight of 31.16%) and major events (weight of 37.06%) are the core driving factors of the passenger flow changes, providing a clear basis for accurately identifying the passenger flow peaks. The construction of this indicator system not only echoes the research conclusion of Shen Hanlei et al. (2024) [46] on multi-source data fusion but also provides a referable paradigm for feature engineering in similar prediction problems.

Second, the proposed ABC-CNN-GRU-Attention model demonstrates an excellent prediction performance. By integrating the local feature extraction of the CNN, the temporal modeling of the GRU, the key information focusing of the Attention model, and the global optimization of the ABC algorithm, this model achieves an R^2 of 0.869, an RMSE of 8.245, and a MAPE of only 5.931% in the test of the daily passenger flow data in Hangzhou from 15 March 2024 to 15 March 2025 in Figure 17. All the indicators are significantly superior to comparison models such as PCA, XGBoost, and SVM. The introduction of the weighted hybrid loss function (JQHL) further enhances the model's adaptability to extreme values, significantly improving the prediction accuracy in fluctuating scenarios such as holidays and major events. The structural innovation and performance advantages of the model align with the research results of Wu et al. (2025) [54] and Man et al. (2024) [55] in related prediction fields, verifying the effectiveness of integrating deep learning and swarm intelligence optimization algorithms in complex time-series prediction tasks.

Third, scenario-based modeling verifies the scenario adaptability of the model. The differential analysis of workdays, weekends, and holidays shows that the contribution of driving factors to passenger flow differs significantly in different periods, and scenario-optimized models can effectively improve the targeting and accuracy of the prediction. The empirical backtesting shows that in the real-time prediction from 15 March to 15 April 2025, the model controls workday errors within $\pm 15,000$ person-times, with an overall MAE of 64,800 person-times and an RMSE of 71,090 person-times, demonstrating good generalization ability and robustness. This result provides technical support for time-specific and refined passenger flow management in cities and also provides a referable modeling approach for similar scenario-based prediction problems.

The research value of this paper lies not only in proposing a high-precision passenger flow prediction method but also in constructing a multi-source data fusion prediction framework and an evaluation paradigm based on the network behavior, providing new technical paths and decision-making references for smart city construction and the digital transformation of cultural tourism. In the future, the transferability, anti-interference ability, and real-time performance of the model can be further improved by expanding the sample scope, introducing dynamic shock factors, and optimizing the lightweight design of the model so as to provide support for the passenger flow prediction and governance in more extensive scenarios.

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