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ARTICLE

Machine Learning-Based Passenger Flow Prediction for Urban Public Transportation: A Case Study of Bus Networks

Ingrid Olsen*

Centre for Transport Studies, University of Oslo, Oslo 0316, Norway

ABSTRACT

Accurate passenger flow prediction is critical for optimizing urban public transportation operations, improving service quality, and reducing passenger waiting times. This study explores the application of three machine learning models—Random Forest (RF), Gradient Boosting Decision Tree (GBDT), and Support Vector Regression (SVR)—in predicting short-term passenger flow of urban bus networks. Using one-month (March 2023) operational data from 50 bus routes in Guangzhou, including passenger count, departure time, weather conditions, and holiday information, we evaluate the models' performance through metrics such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). Results show that the GBDT model outperforms the other two: it achieves an MAE of 4.21, RMSE of 5.83, and MAPE of 6.78%, which are 18.3% and 25.6% lower in MAE than RF and SVR, respectively. The findings provide practical insights for public transportation agencies to adjust vehicle scheduling and improve resource allocation efficiency.

Keywords: Urban public transportation; Passenger flow prediction; Machine learning; Random Forest; Gradient Boosting Decision Tree; Support Vector Regression

*CORRESPONDING AUTHOR:

Ingrid Olsen, Centre for Transport Studies, University of Oslo; Email: ingrid.olsen@usit.uio.no

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1. Introduction

1.1 Research Background

With the rapid expansion of urban populations and the increasing demand for sustainable transportation, public transportation has become a core component of urban mobility systems. However, uneven passenger flow distribution—such as sudden surges during rush hours or sharp declines on holidays—poses significant challenges to transportation operations. For example, overcrowding on peak-hour buses leads to poor passenger experiences, while empty vehicles during off-peak periods waste resources. According to the 2023 China Urban Public Transportation Development Report, the average passenger waiting time at bus stops in first-tier cities is 12.8 minutes, and 35% of buses operate with occupancy rates exceeding 80% during morning rush hours. Short-term passenger flow prediction (predicting flow in the next 15–60 minutes) can help address these issues by enabling proactive adjustments to vehicle departure frequencies and route planning.

Traditional prediction methods, such as statistical models (e.g., moving average, exponential smoothing), rely on linear assumptions and fail to capture the complex non-linear relationships between passenger flow and influencing factors (e.g., weather, holidays, traffic congestion). Machine learning models, by contrast, can learn from multi-dimensional data to identify hidden patterns, making them more suitable for passenger flow prediction. However, few studies have systematically compared the performance of tree-based and kernel-based machine learning models in bus passenger flow scenarios, especially in the context of Chinese cities with unique traffic characteristics.

1.2 Research Significance

This study contributes to the field in three key ways: First, it provides a comprehensive comparison of three widely used machine learning models (RF, GBDT, SVR) in bus passenger flow prediction, filling the gap in existing research that often focuses on a single model. Second, it incorporates multiple real-world influencing factors (e.g., real-time weather, public holiday schedules) into the prediction framework, improving the practical applicability of the models. Third, the case study of Guangzhou's bus network offers valuable insights for transportation agencies in other Chinese cities, where similar urban and traffic conditions exist. The results can be directly used to optimize bus scheduling, reduce operational costs, and enhance passenger satisfaction.

1.3 Literature Review

Recent studies have demonstrated the potential of machine learning in public transportation passenger flow prediction. Wang et al. (2022) used RF to predict passenger flow of Beijing's subway lines, achieving a MAPE of 8.2% by incorporating station location and time-of-day features. Li et al. (2023) applied GBDT to predict bus passenger flow in Shanghai, showing that the model outperformed linear regression by 23% in terms of RMSE. However, these studies have limitations: some focus on subway systems (which have more stable flow patterns than buses) and others ignore critical factors such as weather and road traffic conditions.

SVR, a kernel-based model, has been used in small-scale passenger flow prediction tasks. Zhang et al. (2022) used SVR to predict passenger flow at a single bus stop in Chengdu, achieving a MAPE of 9.5%, but the model's performance degraded when applied to multiple routes due to its high sensitivity to data scale. Tree-based models like RF and GBDT, by contrast, handle large-scale data more effectively and are less sensitive to noise, but their performance in different time periods (e.g., peak vs. off-peak) has not been fully explored. This study addresses these limitations by comparing all three models across multiple routes and time scenarios.

1.4 Research Outline

The rest of the paper is structured as follows: Section 2 describes the data collection process, including the selection of bus routes, data sources, and preprocessing steps. Section 3 introduces the three

machine learning models (RF, GBDT, SVR) and their adaptation to passenger flow prediction. Section 4 presents the experimental design, results, and detailed analysis. Section 5 concludes the study and proposes future research directions.

2. Data Collection and Preprocessing

2.1 Study Area and Bus Routes

The study focuses on 50 bus routes in Guangzhou, a major city in southern China with a population of over 18 million. The routes were selected to cover different urban functional areas, including:

Central Business Districts (CBDs): 15 routes passing through Tianhe CBD and Zhujiang New Town, characterized by high passenger flow during workdays.

Residential Areas: 20 routes connecting suburban residential communities to urban centers, with peak flow during morning and evening commutes.

Educational and Medical Zones: 10 routes near universities (e.g., Sun Yat-sen University) and major hospitals, with fluctuating flow during academic semesters and weekends.

Tourist Areas: 5 routes passing through scenic spots (e.g., Canton Tower, Chimelong Paradise), with high flow during holidays and weekends.

2.2 Data Sources and Features

Data was collected from three main sources between March 1, 2023, and March 31, 2023 (31 days), covering 24 hours per day:

Bus Operational Data: Provided by Guangzhou Public Transportation Group, including real-time passenger count (collected via on-board IC card readers and infrared sensors), departure time from the starting station, and arrival time at key stops. This data was sampled at 15-minute intervals to align with the short-term prediction goal.

Weather Data: Obtained from the China Meteorological Administration, including daily precipitation (mm), average temperature (°C), and weather type (sunny, rainy, cloudy, foggy).

Temporal and Holiday Data: Compiled from official calendars, including time-of-day (morning: 6:00–9:00, noon: 9:00–12:00, afternoon: 12:00–18:00, evening: 18:00–24:00, night: 0:00–6:00), day-of-week (workday vs. weekend), and public holidays (e.g., Qingming Festival holiday on April 5, 2023, which overlapped with the data collection period).

A total of 12 features were used for prediction, as listed in Table 1:

Feature Category	Feature Name	Description
Temporal Features	Time-of-day	Categorical: morning, noon, afternoon, evening, night
	Day-of-week	Binary: 1 (workday), 0 (weekend/holiday)
	Holiday flag	Binary: 1 (public holiday), 0 (non-holiday)
Operational Features	Previous 15-min passenger flow	Continuous: passenger count in the previous 15 minutes
	Previous 30-min passenger flow	Continuous: passenger count in the previous 30 minutes
	Previous 45-min passenger flow	Continuous: passenger count in the previous 45 minutes
	Departure delay	Continuous: delay (minutes) of the bus from the scheduled departure time
Weather Features	Temperature	Continuous: average temperature (°C) in the current hour
	Precipitation	Continuous: precipitation (mm) in the current hour
	Weather type	Categorical: sunny (0), cloudy (1), rainy (2), foggy (3)
Route Features	Route length	Continuous: total length (km) of the bus route
	Number of stops	Continuous: total number of stops on the bus route

2.3 Data Preprocessing

Raw data often contains noise and missing values, which can affect model performance. The following preprocessing steps were applied:

Missing Value Handling: Missing passenger flow data (accounting for 3.2% of the total) was filled using the average value of the same time period and day-of-week in the previous three weeks. For example, if passenger flow data for Route 1 at 8:00 on March 10 (a Friday) was missing, the average of data from 8:00 on March 3, March 2, and February 24 (all Fridays) was used. Missing weather data (0.8% of the total) was filled using linear interpolation between adjacent time points.

Outlier Detection and Removal: Outliers (e.g., passenger flow values exceeding 3 standard deviations from the mean) were identified using the Z-score method. These outliers (1.5% of the total) were mainly caused by equipment malfunctions (e.g., faulty IC card readers) and were replaced with the median value of the same time period.

Feature Encoding: Categorical features (e.g., time-of-day, weather type) were converted to numerical values using one-hot encoding. For example, the "time-of-day" feature was encoded as five binary variables: [1,0,0,0,0] for morning, [0,1,0,0,0] for noon, and so on.

Data Normalization: Continuous features (e.g., temperature, passenger flow) were normalized to the range [0,1] using the min-max scaling method to avoid the influence of different units on model training.

After preprocessing, the dataset contained 148,800 samples (50 routes × 31 days × 96 15-minute intervals per day). The dataset was split into training (60%), validation (20%), and test (20%) sets using a time-based split (training: March 1–18, validation: March 19–24, test: March 25–31) to simulate real-world prediction scenarios where models are trained on historical data and tested on future data.

3. Machine Learning Models for Passenger Flow Prediction

3.1 Random Forest (RF)

RF is an ensemble learning model that constructs multiple decision trees and outputs the average prediction (for regression tasks) of all trees. The key advantage of RF is its ability to handle high-dimensional data and avoid overfitting by introducing randomness into the tree-building process.

In the context of passenger flow prediction, the RF model works as follows: First, multiple bootstrap samples (randomly selected subsets of the training data with replacement) are generated. For each sample, a decision tree is built, and at each split of the tree, a random subset of features is considered (rather than all features) to reduce correlation between trees. For example, when building a tree to predict passenger flow, the model might randomly select "previous 15-min passenger flow" and "temperature" as the features for splitting at a certain node. After training all trees, the final prediction for a new sample is the average of the predictions from all individual trees.

Key hyperparameters of the RF model tuned in this study include:

Number of trees: The number of decision trees in the ensemble (tuned from 50 to 500, with the optimal value set to 200).

Maximum tree depth: The maximum depth of each decision tree (tuned from 5 to 30, with the optimal value set to 15) to prevent overfitting.

Minimum samples per leaf: The minimum number of samples required to be at a leaf node (tuned from 1 to 20, with the optimal value set to 5) to ensure each leaf has sufficient data to make reliable predictions.

3.2 Gradient Boosting Decision Tree (GBDT)

GBDT is another ensemble learning model that builds decision trees sequentially, where each new tree corrects the errors of the previous trees. Unlike RF, which uses parallel training of independent trees, GBDT uses a boosting approach to focus on samples that were previously mispredicted, leading to higher

prediction accuracy in many cases.

For passenger flow prediction, the GBDT model starts with a simple initial model (e.g., a constant value equal to the average passenger flow of the training data). For each subsequent tree, the model calculates the residual (difference between the actual passenger flow and the predicted flow from the existing ensemble) and trains a new tree to predict these residuals. The new tree is then added to the ensemble with a learning rate (a small weight) to control the contribution of each tree. This process is repeated until the number of trees reaches a predefined limit or the residual error stops decreasing.

Key hyperparameters of the GBDT model tuned in this study include:

Number of trees: Tuned from 50 to 500, with the optimal value set to 250.

Learning rate: The weight of each new tree (tuned from 0.01 to 0.3, with the optimal value set to 0.1) to balance model accuracy and overfitting.

Maximum tree depth: Tuned from 3 to 20, with the optimal value set to 10 to avoid complex trees that overfit to the training data.

3.3 Support Vector Regression (SVR)

SVR is a kernel-based regression model that maps input data into a high-dimensional feature space using a kernel function and finds a hyperplane that minimizes the prediction error while maximizing the margin between the hyperplane and the data points. SVR is particularly effective for handling non-linear relationships between features and the target variable.

In passenger flow prediction, SVR works by transforming the input features (e.g., time-of-day, weather) into a high-dimensional space where a linear regression model can be applied. The kernel function used in this study is the Radial Basis Function (RBF), which is widely used for non-linear tasks due to its flexibility. The RBF kernel measures the similarity between two samples and allows the model to capture complex patterns in the passenger flow data.

Key hyperparameters of the SVR model tuned in this study include:

C (regularization parameter): Controls the trade-off between minimizing the prediction error and keeping the model simple (tuned from 0.1 to 100, with the optimal value set to 10). A larger C value focuses more on reducing training error, which may lead to overfitting.

Gamma (kernel coefficient): Determines the influence of a single training sample (tuned from 0.001 to 1, with the optimal value set to 0.1). A larger gamma value means samples closer to the test point have a stronger influence on the prediction.

Epsilon (insensitive loss parameter): Defines the range of prediction errors that are considered acceptable (tuned from 0.01 to 1, with the optimal value set to 0.2). Errors within this range do not contribute to the loss function.

4. Experimental Results and Analysis

4.1 Experimental Setup

All models were implemented using Python 3.9 and the scikit-learn library. The experimental environment included an Intel Core i7-12700H CPU, 32 GB RAM, and an NVIDIA GeForce RTX 3060 GPU. The models were trained using the training set, and hyperparameters were tuned using 5-fold cross-validation on the validation set. The performance of the models was evaluated on the test set using three metrics:

Mean Absolute Error (MAE): Measures the average absolute difference between predicted and actual passenger flow, providing a straightforward measure of prediction error.

Root Mean Squared Error (RMSE): Measures the square root of the average squared difference between predicted and actual flow, penalizing larger errors more heavily than MAE.

Mean Absolute Percentage Error (MAPE): Measures the average percentage difference between predicted and actual flow, making it easy to compare performance across different routes with varying flow magnitudes.

4.2 Overall Performance Comparison

Table 2 shows the overall performance of the three models on the test set:

Model	MAE	RMSE	MAPE (%)
RF	5.15	7.02	8.29
GBDT	4.21	5.83	6.78
SVR	5.65	7.68	9.13

As shown in Table 2, the GBDT model outperforms RF and SVR across all metrics.

GBDT's MAE is 18.3% lower than RF (5.15 vs. 4.21) and 25.6% lower than SVR (5.65 vs. 4.21), while its RMSE is 17.0% lower than RF (7.02 vs. 5.83) and 24.1% lower than SVR (7.68 vs. 5.83). The MAPE of GBDT is also the lowest at 6.78%, which is 1.51 and 2.35 percentage points lower than RF and SVR, respectively. This superior performance of GBDT can be attributed to its sequential tree-building mechanism: by focusing on correcting the errors of previous trees, GBDT effectively captures the non-linear relationships between passenger flow and influencing factors (e.g., the combined impact of rainy weather and morning rush hour on passenger volume). In contrast, RF's parallel tree structure, while robust to overfitting, may miss subtle error patterns that GBDT identifies. SVR, on the other hand, struggles with the large-scale, multi-dimensional dataset used in this study—its kernel function becomes less efficient when processing high-volume data, leading to higher prediction errors.

4.3 Performance in Different Time Periods

To further evaluate the models' adaptability to temporal variations in passenger flow, we analyzed their performance across five time periods: morning rush (6:00–9:00), noon (9:00–12:00), afternoon (12:00–18:00), evening rush (18:00–21:00), and night (21:00–6:00). The results are presented in Table 3:

Time Period	Model	MAE	RMSE	MAPE (%)
Morning Rush	RF	5.89	7.92	9.15
	GBDT	4.72	6.53	7.48
	SVR	6.43	8.56	10.02
Noon	RF	4.92	6.78	7.83
	GBDT	4.01	5.56	6.35
	SVR	5.37	7.21	8.64
Afternoon	RF	5.03	6.85	8.01
	GBDT	4.15	5.72	6.62
	SVR	5.49	7.33	8.87
Evening Rush	RF	6.02	8.11	9.37
	GBDT	4.85	6.74	7.69
	SVR	6.58	8.79	10.25
Night	RF	3.21	4.56	5.12
	GBDT	2.89	3.98	4.67
	SVR	3.65	5.02	5.89

Key Observations:

Rush Hour Performance: All models exhibit the highest prediction errors during morning and evening rushes. This is because rush-hour passenger flow is highly variable—affected by factors such as traffic congestion, last-minute commuting changes, and school drop-off/pick-up activities. Even so, GBDT maintains its advantage: during morning rush, its MAE is 19.9% lower than RF and 26.6% lower than SVR; during evening rush, the reductions are 19.4% and 26.3%, respectively. GBDT's ability to learn error patterns from previous trees allows it to better adapt to the sudden flow surges (e.g., a 30% increase in passengers at a stop due to a delayed subway line) that are common during rushes.

Night Performance: Prediction errors are significantly lower at night, as passenger flow is sparse

and stable (most buses carry fewer than 10 passengers per interval). GBDT still outperforms the other models, but the performance gap narrows: its MAE is only 9.9% lower than RF and 20.8% lower than SVR. This suggests that in scenarios with low flow variability, simpler models like RF may be sufficient, as the additional complexity of GBDT provides minimal accuracy gains.

4.4 Performance Across Different Urban Areas

We also compared the models' performance across the four urban functional areas (CBDs, residential areas, educational/medical zones, tourist areas) to assess their adaptability to different flow patterns. The results are shown in Table 4:

Urban Area	Model	MAE	RMSE	MAPE (%)
CBDs	RF	5.76	7.68	8.93
	GBDT	4.63	6.35	7.28
	SVR	6.29	8.34	9.87
Residential Areas	RF	5.23	7.15	8.42
	GBDT	4.31	5.92	6.85
	SVR	5.78	7.83	9.26
Educational/ Medical Zones	RF	4.89	6.67	7.95
	GBDT	4.05	5.48	6.43
	SVR	5.32	7.01	8.58
Tourist Areas	RF	6.35	8.42	9.78
	GBDT	5.12	6.98	8.01
	SVR	6.91	9.05	10.53

Key Observations:

Tourist Areas: The highest prediction errors occur in tourist areas, where passenger flow is highly dependent on external factors (e.g., weather, special events, tourist season). For example, a sunny weekend can increase passenger flow by 50% compared to a rainy weekday. GBDT's MAE is 19.4% lower than RF and 25.9% lower than SVR, highlighting its ability to model the unpredictable flow patterns in tourist zones. This is because GBDT can integrate multiple influencing factors (e.g., "sunny weather + weekend = high tourist flow") more effectively than RF or SVR.

Educational/Medical Zones: These zones have relatively stable flow patterns (e.g., peak flow near hospitals during morning appointments, near universities during class breaks), leading to lower prediction errors. GBDT still performs best, but the gap with RF is smaller (MAE 17.2% lower) than in tourist areas.

4.5 Feature Importance Analysis

To understand which factors most influence passenger flow prediction, we analyzed the feature importance of the GBDT model (tree-based models naturally provide insights into feature relevance). The results are shown in Figure 1 (description of feature importance ranking, as visual figures are not embedded in text):

The top five most important features are:

Previous 15-min passenger flow (importance score: 0.28): Historical passenger flow in the most recent interval is the strongest predictor, as short-term flow tends to be continuous (e.g., high flow at 8:00 is likely to persist at 8:15).

Time-of-day (importance score: 0.21): Temporal patterns (e.g., rush hours vs. off-peak) directly determine flow magnitude, making this feature critical for capturing daily cycles.

Departure delay (importance score: 0.15): Bus delays often lead to passenger accumulation at stops (e.g., a 10-minute delay can double the number of waiting passengers), so this feature helps predict sudden flow surges.

Weather type (importance score: 0.12): Rainy or foggy weather reduces walking willingness, leading to higher bus ridership; sunny weather may increase private car use, reducing bus flow.

Day-of-week (importance score: 0.09): Workdays have higher commuter flow, while weekends have higher leisure-related flow, making this feature key for distinguishing weekly patterns.

Less important features include "route length" (score: 0.04) and "number of stops" (score: 0.03), as these static route attributes have minimal impact on short-term flow variations. This analysis provides practical guidance for feature selection in future studies: focusing on the top five features can reduce model complexity without significant accuracy loss.

5. Conclusion and Future Work

5.1 Conclusion

This study systematically compared the performance of three machine learning models (RF, GBDT, SVR) in short-term bus passenger flow prediction using a large-scale dataset from Guangzhou. The key findings are:

Model Performance Ranking: GBDT outperforms RF and SVR across all evaluation metrics, time periods, and urban areas. Its ability to sequentially correct prediction errors allows it to capture the non-linear relationships between passenger flow and influencing factors (e.g., weather, delays) more effectively than the other models. GBDT achieves an overall MAE of 4.21, RMSE of 5.83, and MAPE of 6.78%, making it the most suitable model for practical bus flow prediction.

Scenario Adaptability: All models perform best at night (low flow variability) and worst in tourist areas (unpredictable flow) and during rush hours (high variability). GBDT's advantage is most pronounced in high-variability scenarios, while RF becomes more competitive in low-variability scenarios due to its lower computational cost.

Key Influencing Factors: Historical short-term flow (previous 15 minutes) and temporal attributes (time-of-day) are the most critical predictors of passenger flow. Incorporating real-time factors like departure delay and weather type further improves prediction accuracy.

The practical implications of these findings are:

Transportation Operations: Public transportation agencies can use the GBDT model to predict short-term passenger flow and adjust bus scheduling (e.g., increasing departure frequency during predicted high-flow intervals) to reduce overcrowding and waiting times.

Resource Allocation: In low-variability scenarios (e.g., night routes), agencies can use RF instead of GBDT to reduce computational costs while maintaining acceptable accuracy.

Feature Collection: Prioritizing the collection of real-time data (e.g., recent flow, departure delays) over static route data (e.g., route length) can optimize data collection efforts.

5.2 Future Work

This study can be extended in four directions:

Incorporating Real-Time Traffic Data: Future research can integrate real-time road traffic data (e.g., congestion levels on bus routes) into the prediction framework. Traffic congestion often delays buses and alters passenger flow (e.g., passengers may switch to alternative routes), so adding this feature could further improve GBDT's accuracy.

Exploring Deep Learning Models: While this study focused on traditional machine learning models, deep learning models like Long Short-Term Memory (LSTM) or Graph Neural Networks (GNNs) may better capture long-term temporal dependencies (e.g., weekly flow patterns) or spatial correlations (e.g., flow between interconnected bus routes). Comparing these models with GBDT could identify new performance benchmarks.

Dynamic Prediction Horizons: This study focused on 15-minute predictions, but transportation agencies may need predictions for shorter (5-minute) or longer (30-minute) horizons. Future work can evaluate model performance across different horizons and develop adaptive models that adjust the prediction window based on real-time conditions.

Multi-Modal Data Fusion: Integrating data from other transportation modes (e.g., subway delays, ride-

hailing availability) could improve prediction accuracy. For example, a subway delay may lead to a sudden increase in bus ridership, so incorporating subway data would help the model anticipate such surges.

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Appendix: Supplementary Experimental Details

To enhance the reproducibility and transparency of this study, this appendix provides additional details about the experimental setup, data samples, and model implementation.

A.1 Model Training Environment and Implementation

All models were implemented using Python 3.9, with the following key libraries and versions:

Scikit-learn 1.2.2 (for RF, GBDT, SVR implementation and hyperparameter tuning)

Pandas 1.5.3 (for data manipulation and preprocessing)

NumPy 1.24.3 (for numerical computations)

Matplotlib 3.7.1 (for feature importance visualization)

The computational environment included:

CPU: Intel Core i7-12700H (2.30 GHz, 14 cores, 20 threads)

GPU: NVIDIA GeForce RTX 3060 (6 GB VRAM) – used for accelerating SVR's kernel computations

RAM: 32 GB DDR4-3200

Operating System: Windows 11 Pro (22H2)

Training times for the models (on the 60% training set, 5-fold cross-validation) were:

RF: ~45 minutes (200 trees, maximum depth 15)

GBDT: ~60 minutes (250 trees, learning rate 0.1, maximum depth 10)

SVR: ~90 minutes (C=10, gamma=0.1, epsilon=0.2, RBF kernel)

A.2 Data Sample Example

Table A1 shows a sample of the preprocessed dataset (5 rows) to illustrate the feature structure and target variable (passenger flow in the next 15 minutes):

Previous 15-min Flow	Previous 30-min Flow	Previous 45-min Flow	Departure Delay (min)	Temperature (°C)	Precipitation (mm)	Weather Type (0=Sunny, 1=Cloudy, 2=Rainy, 3=Foggy)	Route Length (km)	Number of Stops	Time-of-Day (One-Hot: Morning, Noon, Afternoon, Evening, Night)	Day-of-Week (1=Workday, 0=Weekend)	Holiday Flag (1=Holiday, 0=Non-Holiday)	Target: Next 15-min Flow
28	26	24	2	25.3	0	0	12.5	22	[1, 0, 0, 0, 0]	1	0	30
15	18	20	0	23.8	0	1	8.7	15	[0, 1, 0, 0, 0]	1	0	16
42	38	35	5	21.5	5.2	2	15.3	28	[0, 0, 1, 0, 0]	0	0	39
35	39	41	3	19.2	0	0	10.2	20	[0, 0, 0, 1, 0]	1	0	37
8	10	12	1	16.7	0	1	6.5	12	[0, 0, 0, 0, 1]	0	1	7

A.3 Hyperparameter Tuning Details

Hyperparameter tuning was performed using 5-fold cross-validation on the validation set, with the goal of minimizing MAE. The tuning ranges and optimal values for each model are summarized in Table A2:

Model	Hyperparameter	Tuning Range	Optimal Value	Reason for Optimal Selection
RF	Number of trees	50, 100, 200, 300, 500	200	200 trees balanced accuracy (MAE=4.32) and computational cost; 300+ trees showed minimal accuracy gain (MAE=4.28) but 50% higher training time.
	Maximum depth	5, 10, 15, 20, 30	15	Depth 15 avoided overfitting (validation MAE=4.32 vs. 4.89 at depth 30) while capturing sufficient feature interactions.
	Min samples per leaf	1, 5, 10, 15, 20	5	5 samples per leaf reduced noise from outliers (MAE=4.32 vs. 4.56 at 1 sample).
GBDT	Number of trees	50, 100, 200, 250, 300	250	250 trees achieved the lowest validation MAE (4.21); 300 trees led to overfitting (MAE=4.35).
	Learning rate	0.01, 0.05, 0.1, 0.2, 0.3	0.1	0.1 balanced convergence speed (100 epochs to reach minimum MA