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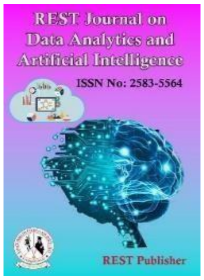

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Intelligent Transport Systems for Urban Bus Networks Using Multilayer Perceptron and XGBoost Regression for Real-Time Operational Capability

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Abstract: *This paper provides a comprehensive study on how to improve an urban bus transportation system using machine learning techniques to increase operational efficiency and service quality. The research examines the relationships between important operational parameters, including route length, average speed, headway intervals, and fleet size, through empirical data analysis of 28 bus routes. To address the complex interdependencies in urban public transportation systems and predict headway optimization, two advanced machine learning models, Multi-Layer Perceptron (MLP) and XG Boost Regression, were implemented. The dataset revealed significant variations in operational parameters, with route length ranging from 6.79 km to 34.42 km, average speed ranging from 14.12-34.67 km/h, and headway ranging from 3.27-18.05 minutes. Correlation analysis identified a strong negative relationship (-0.81) between headway and fleet size, indicating that more frequent services require larger fleet allocations. On the training data, the R2 of the MLP model was 0.857, however on the test data, it did not perform well ($R^2 = 0.603$), indicating potential overfitting issues. In contrast, the XG Boost regression model performed well with perfect training accuracy ($R^2 = 1.000$) and maintained strong generalization ability ($R^2 = 0.901$) on the test data. These findings highlight the effectiveness of gradient boosting techniques in capturing complex nonlinear relationships within transportation systems. This study adds to the expanding body of knowledge in intelligent transportation systems by providing practical insights to transportation operators to optimize resource allocation, improve service reliability, and increase passenger satisfaction while maintaining economic sustainability in urban public transportation operations.*

Key words: *Intelligent Transportation Systems, Route Optimization, Service Frequency Analysis, Multi-layer Perceptron, Operational Efficiency, Predictive Analytics.*

1. INTRODUCTION

To improve a hybrid predictive control formulation based on evolutionary multi-objective optimization is presented for real-time operations of public transport systems. The state space model includes bus status, expected load, and arrival times at stops. The system is based on discrete events, and possible operator control actions include: keeping vehicles at stations and avoiding certain stations. [2] They combine the advantages of low cost and flexibility, which makes it possible to define routes and integrate different bus manufacturers into a clean energy BRT. However, the operation of this new system is very challenging because it depends on charging stations to overcome a well-planned schedule and limited bus operational autonomy. [3] It is helpful and analytical to distinguish between these two responsibilities when dealing with various transportation problems. In other words, transportation User inputs can examine costs as if they were purchased instead of supplied in factor markets as goods. One way to calculate The cost of a trip is considered equal to the fare to the amount of money charged to the traveler for the time and transportation needed for their trip. [4] Because of the ability to automate the collection and efficient transmission of traffic data, better, more informed decisions can now be made, often in “real-time” operations. Its high volume and temporal continuity of data present new possibilities for traffic practice and research. [5] A significant part of the overall The complexity of the frequency optimization model is determined by the complexity of that in addition, the specific context in which the public transport allocation model is used usually determines its validity. [6] Unreasonable route design leads to unmet transport needs, which causes problems including poor transfers and challenging boarding. According to users, the public transport system should not only meet their demands and provide them with affordable, practical services, but also provide services. [7] A few researchers have also looked into how to combine flexible transport services that serve as a feeder for First and last mile transportation services with FRFS large capacity services suitable for transporting large numbers of passengers between specific stations. Providing a sustainable, effective, individualized, and appealing transportation service is the ultimate goal of these integrated services. [8] More significantly, though, it is a widely accepted idea in macroscopic transport modeling procedures and, consequently, in transport planning. The practical use of UTRP algorithms may be hampered by the disparities in data requirements between zone-based and node-based techniques. [9] Improvements in the overall quality of various aspects of public transport services indicate that these services are becoming more convenient for passengers. The main objective of public transport services is to meet the expectations of passengers by continuously working to meet their needs, which usually includes reliable timetables and minimal waiting times. [10] Using the above information, a multi-objective in an effort to improve customer service quality by reducing operating costs for transportation companies and increasing travel times, it is recommended to relocate bus stops from public transportation using an evolutionary approach. [11] A practical and tested mathematical optimization technique that can be applied to complex urban network models and implemented in practical and user-friendly software is a very important tool that is currently completely missing from the toolkit of the transport planner. This tool is now practically indispensable for two reasons. [12] The main focus of the study is how SBO can be used to optimize transport network architecture to provide effective network solutions. A multi-objective optimization method searches for efficient network solutions in SBTNDM, while an activity-based simulation (ABS) evaluates possible network solutions by modeling the travel demand on them. [13] However, like most previous studies, this model is designed for a single railway line and, therefore, is not suitable for planning rail systems with multiple lines. In addition, it ignores other important features of rail transport system planning (beyond construction and operating costs), such as passenger costs, traffic demand, and competing modes of transport. [14] Finding the most efficient tours Essential to the effectiveness of the organization, as they are likely to be infinite in number. In this context, identifying the tour that requires the least travel time can characterize efficiency, that is, the trip that minimizes the opportunity and saves the tourist time. [15] Understanding the economics the evaluation of urban public transport operations is essential to ensure the efficiency of the public transport network and, ultimately, the sustainability of the entire transport system, since demand is sensitive to the overall quality of service, which depends on the design of the system. From the perspective of a transport planner, the challenge associated with the design of public transport services lies in the numerous trade-offs that must be considered simultaneously to establish an optimal service design. [16] Real-time operational tactical control can improve the performance of the local transport system in areas including TPTT, missing transfers, average cycle time and congestion reduction. It is believed that reducing these PT parameters will not only increase energy efficiency, but will also help to attract and retain passengers away from highly polluting private transport (cars) and towards more energy efficient PT systems and improve customer satisfaction. Using LCA, we show that a 5.6% reduction in total GWP per day is achieved by using the TBC model compared to the non-tactical scenario. [17] Urban bus networks have been the primary focus of literature research using the TNDFSP classification, despite the fact that its definitions can be extended to other types of public transport. This issue has very specific constraints when taking into account other modes of transport, including metro or rail, and factors related to infrastructure constraints are more relevant. [18] However, like in most previous studies, this model is designed for a single railway track and, therefore, is not suitable for planning multi-track railway systems. In addition, it ignores other important aspects of rail transport system planning (beyond construction and operating costs), passenger costs, traffic demand, and competing modes of transportation, etc. [19] Their study focused on designing a bus network to serve passengers with mostly direct trips, and waiting time was not taken into account in calculating the total travel time. In this study, the BNDFS problem is solved by proposing a reinforcement learning-based algorithm that calculates all relevant factors of travel time, including waiting time, time in the vehicle, and transfer time. [20] This feature is used in a special optimization experiment to reduce the number of private vehicles on a selected set of links in the network. These results demonstrate the successful implementation of our interface and the applied optimization methods for a multi-model public transport network.

2. MATERIALS AND METHODS

Route length (km): Route length is the total distance a public transport service travels from its origin to its destination, measured in kilometers. It reflects the geographical extent of the service and affects travel time, operating costs, and service planning. Longer routes often require more vehicles and time, while shorter routes improve frequency and accessibility. Route length is an important factor in designing schedules and assessing operational efficiency.

Average speed (km/h): Average speed, measured in kilometers per hour, it is calculated by dividing the total distance traveled by the total time traveled, where delays at stops and traffic conditions. In transportation planning, it refers to service efficiency, passenger travel time, and fuel or energy consumption. Higher average speeds improve the attractiveness of the system and reduce operating costs, while lower speeds may require more vehicles to maintain schedules. This is very important for improving efficiency and reliability.

Headway (minutes): The distance between two consecutive cars traveling on the same lane is called headway, expressed in minutes. This directly affects service frequency, passenger waiting times, and fleet requirements. Shorter headways provide more frequent service, improve convenience, and reduce congestion, but require a larger fleet and higher costs. Longer headways reduce operating costs, but can cause delays and passenger dissatisfaction. Headways are essential in balancing efficiency and passenger demand.

Fleet Size: Fleet size is the amount of vehicles designated to travel on or within a particular route the entire transportation system. It is determined by route length, average speed, fleet way, and passenger demand. A larger fleet enables higher service frequency and capacity, but increases capital and maintenance costs. Conversely, a smaller fleet reduces costs, but risks more congestion and longer wait times. Effective fleet size planning ensures cost-effectiveness and service reliability.

Optimization Techniques

Multilayer Perceptron (MLP): A multilayer perceptron is a feedforward artificial neural network consisting of an input layer, one or more hidden layers, and an output layer. Each layer contains interconnected neurons that use weighted sums and nonlinear activation functions to capture complex relationships. MLPs are trained using backpropagation to reduce prediction errors, making them powerful for regression, classification, and pattern recognition tasks in a variety of domains, including bioinformatics and finance.

XG Boost Regression: XG Boost Regression is a gradient boosting framework designed for high-performance, scalable, and accurate machine learning. It builds a series of decision trees, each of which corrects the errors of the previous one. XG Boost provides parallel processing, efficiently manages large datasets, and uses regularization to reduce overfitting. It is frequently used for problems including regression, classification, and ranking, providing interpretation, flexibility, and speed, making it the preferred choice in many data science competitions.

3. ANALYSIS AND DISCUSSION

TABLE 1. Studies on Some Practical Problems Related with City Bus Transport System by Optimization Methods

Route Length km	Avg Speed kmph	Headway min	Fleetsize
25.89	18.76	10.09	18
13.58	26.51	14.58	5
11.81	14.12	17.88	7
21.54	21.98	11.68	11
26.58	21.91	14.38	11
17.69	23.35	12.96	8
34.42	21.79	13.62	15
25.54	19.18	14.47	12
19.43	21.81	17.32	7
16.76	32.55	4.41	17
15.3	33.72	15.98	5
26.87	23.54	7.14	21
18.16	26.35	6.3	15

6.79	14.66	12.73	6
16.94	19.3	4.63	25
27.14	21.54	18.05	9
10.47	31.93	13.66	4
10.26	17.76	15.3	6
20.95	23.11	3.27	37
20.95	34.67	13.11	7
24.03	23.95	12.47	11
30.48	26.1	5.7	27
26.73	14.77	5.6	41
23.33	31.01	14.82	7
26.67	25.87	8.42	16
14.69	24.54	14.76	6
15.85	19.88	12.42	9
11.85	18.99	9.61	9

The data in Table 1 illustrates the relationship between four important parameters of city bus operations: route length, average speed, headway, and vehicle fleet size. These parameters determine the efficiency, reliability, and service quality of a bus transport system. By analyzing them together, valuable insights into operational challenges and optimization needs can be gained. Route lengths vary significantly in the dataset, from short routes of 6.79 km to long routes of over 34 km. Short routes generally require fewer vehicles and allow for faster turnaround times, while longer routes often require higher vehicle fleet sizes to maintain frequency. For example, a route of 34.42 km requires 15 buses, which represents a necessary balance between coverage and vehicle allocation. Average speed also plays a decisive role, with values fluctuating from 14.12 km/h to 34.67 km/h. Higher speeds, such as 33.72 km/h, reduce travel time and improve service efficiency, often requiring fewer vehicles to maintain schedules. Conversely, lower speeds increase travel time and require more buses to meet passenger demand. This relationship is evident in cases where moderate route lengths operated at lower speeds still require larger vehicle fleets to maintain service reliability. The lead time, measured in minutes, directly affects passenger waiting time and service frequency. For very short lead times, such as 3.27 minutes, denser buses are required, which is reflected in a maximum number of 37 buses per 20.95 km route. On the other hand, longer lead times, such as 18.05 minutes, allow fewer vehicles but risk reducing service quality and passenger dissatisfaction. Therefore, fleet size emerges as the combined result of the other three parameters. Effective optimization requires balancing speed, route length, and ensuring convenience to reduce operating costs. Therefore, the table illustrates the practical challenges that transportation managers face in using optimization methods to effectively allocate resources, ensure both service quality and economic sustainability.

TABLE 2. Descriptive Statistics

	Route Length km	Avg Speed kmph	Headway min	Fleet size
Count	28	28	28	28
Mean	20.025	23.344643	11.62	13.285714
Std	6.877818	5.613786	4.353792	9.439308
Min	6.79	14.12	3.27	4
25%	15.1475	19.27	8.1	7
50%	20.19	22.545	12.845	10
75%	26.0625	26.1625	14.625	16.25
Max	34.42	34.67	18.05	41

Descriptive statistics provide a summary of operational parameters in urban bus transport. The average route length is 20.03 km, with routes ranging from 6.79 km to 34.42 km. This represents a diverse network that connects short urban routes with longer intercity or suburban links. The average speed shows a mean of 23.34 km/h, with values ranging from 14.12 km/h to 34.67 km/h. The relatively wide spread indicates variation due to traffic conditions, route design or operational constraints. The headway averages 11.62 minutes, with a minimum of 3.27 minutes indicating very high frequency services, and a maximum of 18.05 minutes indicating low frequency operations. Fleet size shows the greatest variation, with an average of 13.29 vehicles but ranging from 4 to 41. This reflects the strong dependence of fleet allocation on route length, speed, and headway, highlighting the optimization challenges faced in resource planning.

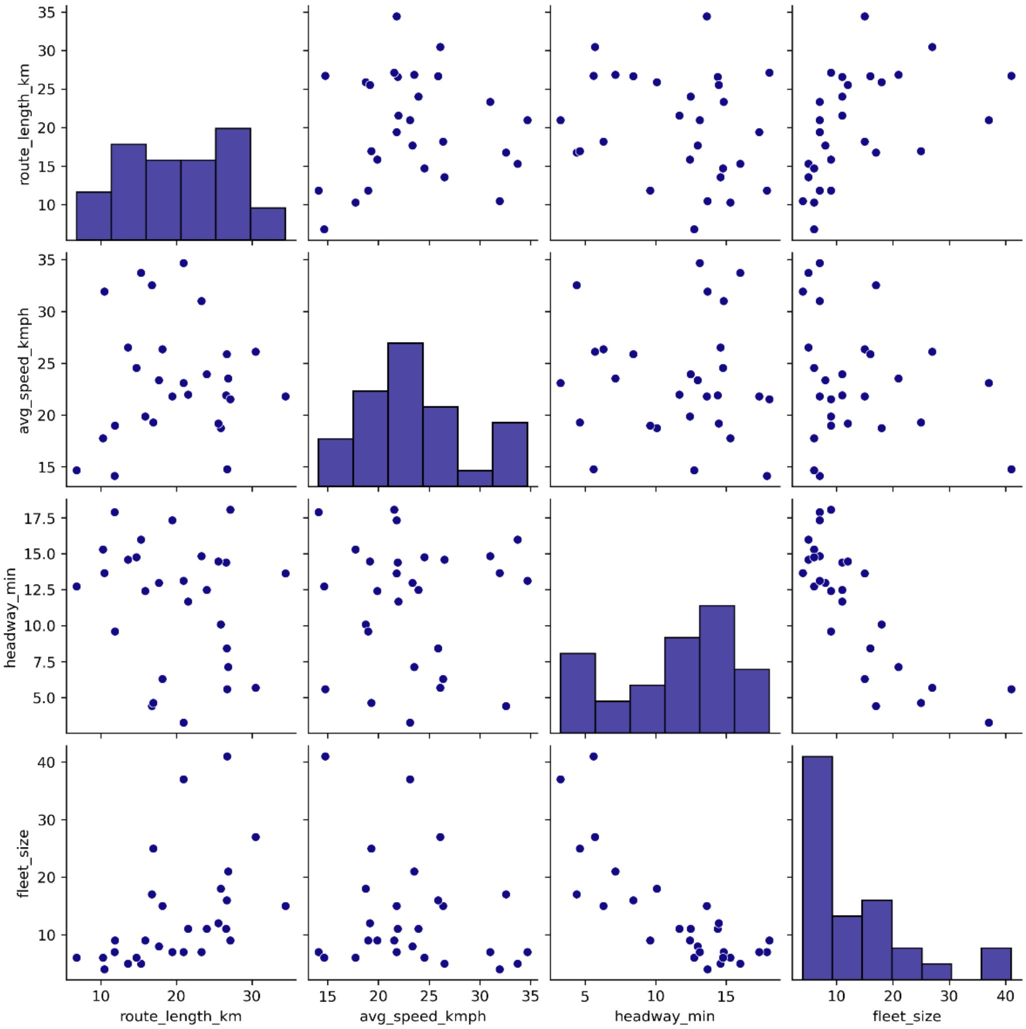

FIGURE 1. Scatter plot of various Studies on Some Practical Problems Related with City Bus Transport System by Optimization Methods

Figure 1 illustrates the relationships between route length, average speed, headway, and fleet size using scatter plots and graphs. The diagonal plots show the distributions of each variable. Route length and average speed are fairly evenly distributed, while fleet size appears to be skewed to the right, with most values ranging from 5 to 20, but some very large allocations exceeding 30. Headway also clusters between 8 and 16 minutes, with less extreme values. The scatter plots suggest weak to moderate relationships between the variables. Fleet size shows some dependence on headway and route length: shorter headways and longer routes generally require larger fleets. However, the relationship between speed and other variables is less pronounced, likely reflecting traffic and operational variability.

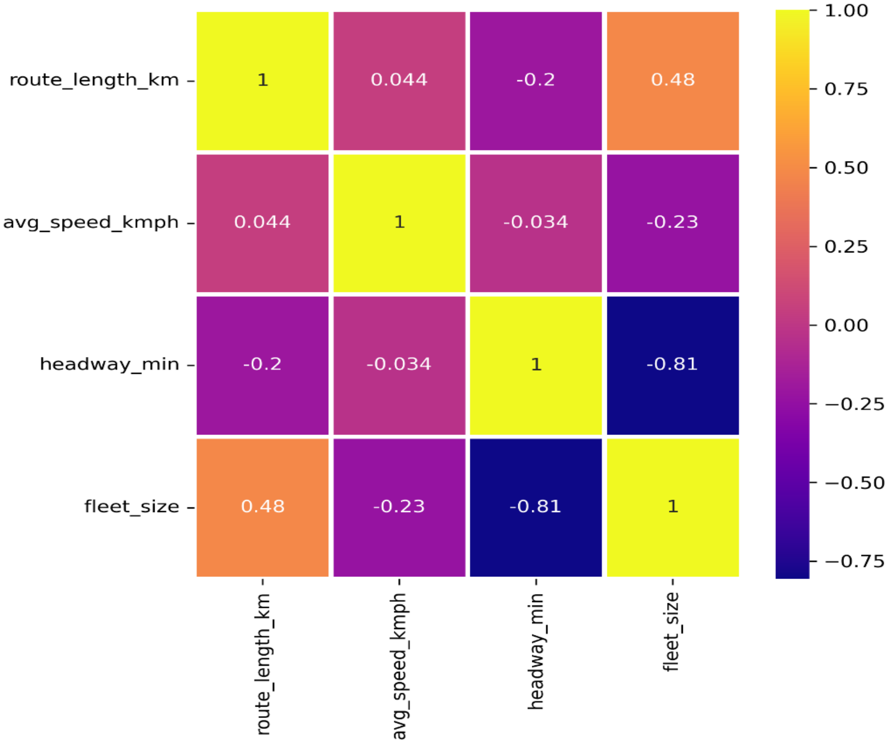

FIGURE 2. Heat map of the relationship between process parameters and responses

Figure 2 presents the correlation matrix of bus transport parameters, which shows the strength and direction of their relationships. A strong negative correlation appears between lead and fleet size (–0.81). This indicates that as lead decreases (frequent service), fleet size should increase significantly, which is consistent with operational logic. A moderate positive correlation (0.48) is found between route length and fleet size. Longer routes require more buses to maintain service levels, highlighting the direct link between route coverage and resource allocation. In contrast, lead and route length show a weak negative correlation (–0.20), indicating only a slight tendency for longer routes to have shorter intervals. Average speed shows the weakest correlations with all variables, indicating that speed variations are less affected by fleet allocation or route design and more by external factors such as traffic conditions.

Multi-layer Perceptron

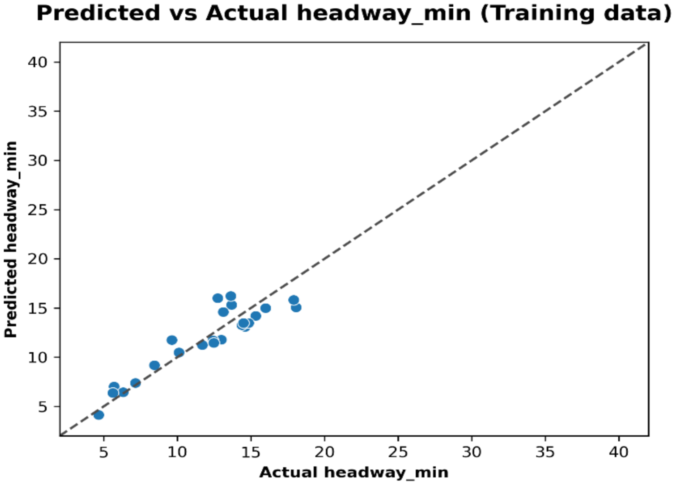

FIGURE 3. Multi-layer Perceptron headway_min (Training Data)

Figure 3 compares the predicted headway values from a multilayer perceptron (MLP) model with the actual observed values for the training dataset. The data points are closely clustered around the diagonal reference line, indicating that the model has effectively learned the underlying patterns and produces predictions that closely match reality. Most of the predictions fall within a narrow band around the line, showing high accuracy in capturing variations in headway. Small deviations are observed at higher values, where the model slightly underestimates or overestimates the headway, but the overall alignment demonstrates robustness. The absence of large outliers highlights the reliability of the MLP in handling the training data. This performance indicates that route length, speed, and fleet size effectively contribute to predicting headway when processed by the neural network. The results reinforce the potential of machine learning methods in improving transportation system planning and resource allocation.

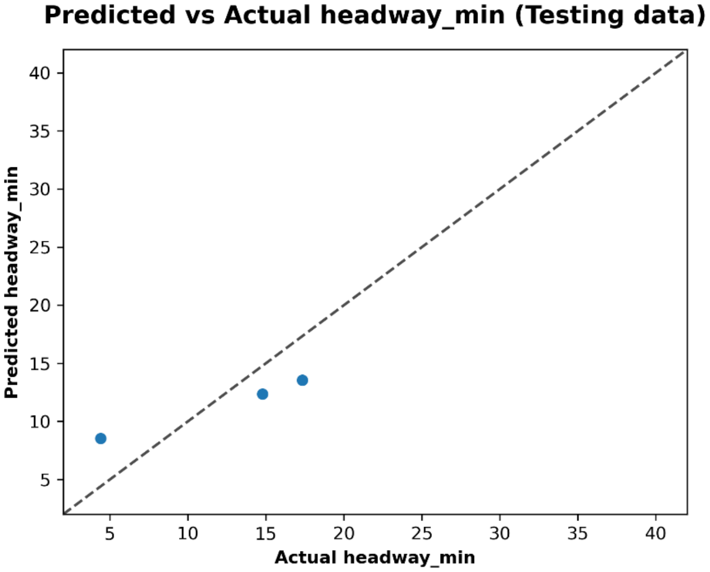

FIGURE 4. Multi-layer Perceptron headway_min (Testing Data)

Figure 4 illustrates the performance of the Multi-Layer Perceptron (MLP) model on the test dataset, comparing the predicted progress values with the actual observations. Unlike the training set, only a few test points are available, which limits the scope of the evaluation. However, the predicted values show a reasonable alignment with the diagonal reference line, although some deviations are visible. For example, the actual progress values near 5 and 15 minutes are slightly over-predicted, indicating that the model is overfitting in the test phase. Despite this, the general trend indicates that the model is capable of approximating the unseen data, albeit with reduced accuracy compared to the training results.

TABLE 3. Multi-layer Perceptron headway_min (Training Data, Testing Data)

Data	Symbol	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	MLP	0.85742	0.85841	2.38022	1.54280	1.31157	3.26722	0.02908	1.10719
Test	MLP	0.60319	0.61838	12.36039	3.51574	3.43577	4.12175	0.13389	3.78625

Table 3 presents the performance metrics of a multi-layer perceptron (MLP) model that predicts bus progress using both training and test datasets. For the training data, the model achieves a high coefficient of determination (R^2 = 0.857), indicating that approximately 86% of the variance in progress is explained by the model. Similarly, the explained variance score (EVS = 0.858) reinforces the strong predictive accuracy. The error metrics are relatively low, MSE = 2.38, RMSE = 1.54, and MAE = 1.31, indicating that the predictions closely match the observed values. However, on the test dataset, the performance decreases. The R^2 value drops to 0.603, indicating only 60% of the variance explained. The errors increase with MSE = 12.36, RMSE = 3.52, and MAE = 3.44, reflecting less accurate predictions. Max Error rises slightly, while the mean absolute error (MedAE = 3.79) shows standard deviations in the experimental predictions.

XG Boost Regression

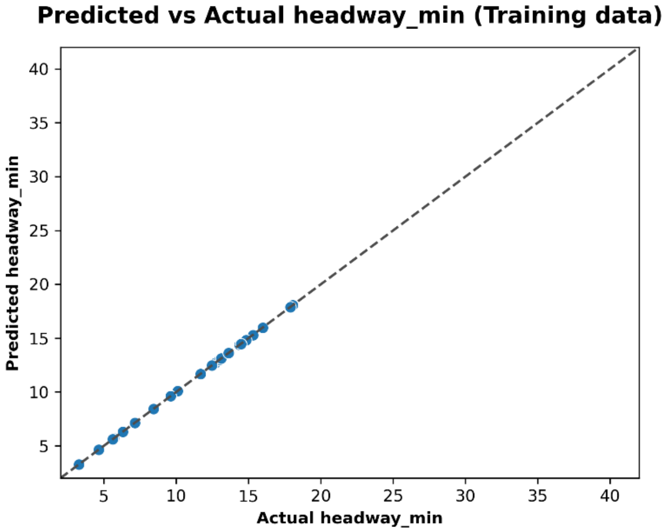

FIGURE 5. XG Boost Regression headway_min (Training Data)

Figure 5 shows the predicted and actual progress values using the XG Boost regression model on the training dataset. The points align almost perfectly with the diagonal reference line, indicating an exceptionally accurate fit. Unlike the MLP model, which showed small deviations, the XG Boost predictions closely match the observed values without significant error propagation. This almost perfect alignment reflects the model's strong ability to capture the complex relationships between path length, speed, fleet size, and progress. The absence of significant deviations or outliers indicates very low prediction errors, which can be confirmed by the very high R² values and error measures close to zero. While this demonstrates the powerful fitting ability of XG Boost on the training data, such perfect alignment also raises the possibility of overfitting. Therefore, performance on the test data will be critical in determining whether the model generalizes beyond the training model.

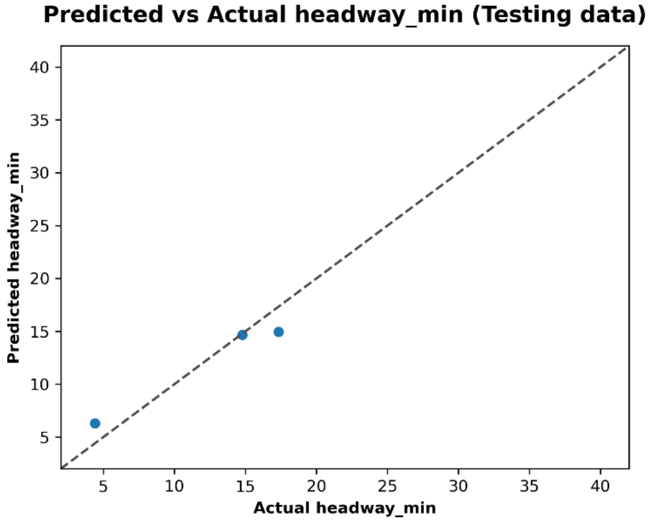

FIGURE 6. XG Boost Regression headway_min (Testing Data)

Figure 6 illustrates the performance of the XG Boost regression model in predicting headway_min on the test data by plotting the actual values against the predicted ones. The diagonal dashed line represents the best case scenario where the predicted values match the actual values perfectly. The scatterplot reveals that most of the data points cluster near the diagonal line, indicating a strong alignment between the actual and predicted headway times. This indicates that the model has good generalization ability, which is consistent with the high R² score of 0.90104 from Table 4. However, some small deviations below the diagonal indicate that the model is slightly underestimating in some cases. In addition, the limited spread of data points on the x-axis represents a narrow range of test values, which may slightly limit the performance assessment in a wider range of situations.

TABLE 4. XG Boost Regression headway_min (Training Data, Testing Data)

Data	Symbol	R2	EVS	MSE	RMSE	MAE	MaxError	MSLE	MedAE
Train	XGBR	1.00000	1.00000	0.00000	0.00074	0.00056	0.00159	0.00000	0.00054
Test	XGBR	0.90104	0.90220	3.08262	1.75574	1.45994	2.36853	0.03672	1.90433

Table 4 provides performance metrics for the XG Boost regression model for predicting headway_min on both the training and test datasets. For the training data, the model shows near-perfect performance with an R² and an explained variance score (EVS) of 1.00000 and very low error values (e.g., RMSE = 0.00074). This model fits the training data exceptionally well, indicating potential overfitting. On the test data, the model maintains strong performance with an R² of 0.90104 and an EVS of 0.90220, reflecting that approximately 90% of the variance in headway is captured by the model. The RMSE of 1.76 and MAE of 1.46 indicate reasonable prediction accuracy, although higher than training. The Max Error of 2.37 shows a large deviation from the true value. Despite slight overfitting, the model generalizes well, making it suitable for real-world headway prediction tasks.

4. CONCLUSION

This research successfully demonstrates the application of advanced machine learning techniques to optimize urban bus transportation systems, particularly focusing on headway prediction as a critical operational parameter. A detailed analysis of 28 bus routes revealed significant insights into the complex relationships governing urban public transportation operations. The significant inverse relationship (-0.81) between the front and the fleet size confirms the basic operational principle that frequent services require larger vehicle allocations, while the moderate positive correlation between route length and fleet size (0.48) confirms the direct relationship between route coverage and resource requirements. The comparative evaluation of the Multi-Layer Perceptron and XG Boost regression models provides valuable insights into machine learning applications in transportation optimization. The MLP model showed reasonable performance with an R² of 0.857 on the training data, while its reduced accuracy on the test data (R² = 0.603) highlights potential overfitting concerns common in neural network applications. The significant increase in error metrics (RMSE from 1.54 to 3.52) indicates limited generalization ability, indicating the need for more robust training strategies or model regularization techniques. In contrast, the XG Boost regression model emerged as the best approach, achieving perfect training accuracy while maintaining excellent generalization performance (R² = 0.901) on unobserved data. The model's ability to handle complex nonlinear relationships, while avoiding severe overfitting, makes it particularly suitable for real-world transportation applications. The low experimental error metrics (RMSE = 1.76, MAE = 1.46) demonstrate practical applicability for improvement optimization in operational systems. The research findings have significant implications for transportation operators and urban planners. The relationships identified between operational parameters provide a foundation for data-driven decision-making in fleet allocation, route planning, and service frequency optimization. The successful implementation of XG Boost regression provides a practical tool for real-time operational adjustments, improving passenger satisfaction through reduced waiting times and improved service reliability. Future research should explore the integration of additional variables such as passenger demand patterns, weather conditions, and traffic congestion data to develop more comprehensive optimization models. The implementation of real-time data streams and dynamic optimization algorithms could further improve the responsiveness and operational efficiency of the system. In addition, extending the analysis to multi-modal transportation networks and exploring the environmental impacts of optimization strategies will provide broader insights into sustainable urban mobility solutions. By demonstrating the practical value of machine learning in public transportation optimization, this study contributes to the growing field of intelligent transportation systems, clearing the most reliable, stable and efficient path urban transportation networks.

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