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Daily Ridership Forecasting for Urban Public Bus Transportation

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Abstract

Effective operational planning in public transit systems (PTS) needs estimates of future ridership as one of the inputs. The forecasting of passenger demands is challenging in PTSs due to changes travel behavior, presence of multi-seasonality data, influence of external events, etc. and often limited availability of historical data. In this study, riderhip forecasting has been performed for urban bus transport network. A set of statistical and machine learning models were selected based on literature review, data characteristics of PTS demand data, and our past studies ins same domain. A real-life large dataset on 110 routes of an urban public bus network has been used for experimental analysis. Further, several calendar-related and operations-related new variables were derived to help better model the travel patterns. These variables include the long weekend indicator, route direction indicator along with typical, day of the week, week of the year, month, weekend indicator, holiday indicator. Using selected forecasting methods, the 1-day, 7-day, and 28-day ahead forecasts were generated and performance is evaluated using the Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Symmetric Mean Absolute Percentage Error (SMAPE) metrics. Based on empirical analysis, it has been observed that the selected machine learning models outperform statistical models. However, there are differences in performance with respect to the different prediction horizon, such as, errors increase as the horizon becomes longer. The study will help PTS authorities to improve operational planning using daily ridership forecasts generated from the proposed forecasting methods.

Keywords
Public Bus Transportation, Ridership Forecasting, Urban Transit Planning

1. Introduction
With the increase in urbanization, the demand for transportation services is also increasing. It is leading to the increase in number of vehicles on the road, road congestion, travel duration, and environmental pollution (Halyal et al., 2022).Public transport systems (PTS) are widely recognized as way to sustainable urban mobility. It helps reduce congestion, energy consumption, and environmental impacts in urban mobility (Horváth, 2012). However, managing PTS is a challenging task ((Rajsman et al., 2013) and accurate ridership forecasting can help in effective strategic, tactical and operational planning in PTS (Banerjee et al., 2020).

Passenger demand influences the service frequency optimization, vehicle allocation, timetable scheduling, fleet optimization, routing decisions, etc. in PTS. Thus, demand forecasting required as an important input for operational planning and service scheduling in urban public transport systems (Banerjee et al., 2020).However, passenger demand patterns exhibit complex patterns in urban transport systems and often influenced by temporal variation, operational and external factors.

In past, research on passenger demand forecasting, exhibit three key limitations. Most of the studies focused on a single forecasting horizon, either short-term operational forecasting or long-term planning, without evaluating model performance across multiple horizons. Also, many machine learning-based approaches were tested on high frequency datasets only, without testing their applicability in real-world transit systems where data availability is constrained. The forecasting at daily time series level is addressed in only limited studies. Therefore, to evaluate the performance of statistical and machine learning models for passenger demand forecasting under limited daily data conditions, this study has been proposed. In which, forecasting accuracy across multiple prediction horizons (1-day, 7-day, and 28-day) would be done to identify suitable forecasting approaches.

Previous research on ridership forecasting in public bus transportation has applied various forecasting methods, including time-series models, statistical demand models, and machine learning methods. However, as mentioned earlier, the existing studies primarily focused either on (very) short or long-term forecasting. The empirical evaluation of forecasting methods, particularly, machine learning methods at daily ridership levels remains limited. To address this gap, in this study, a daily ridership forecasting problem has been studied using statistical and machine-learning forecasting approaches across different prediction horizons. Several statistical and machine learning based forecasting models are selected and their performance are evaluated using error metrics, Mean Error (ME), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Symmetric Mean Absolute Percentage Error (SMAPE).

The proposed study contributes to the literature on public bus transport by providing an evaluation of statistical and machine learning models for daily passenger demand forecasting using real-life data from 110 routes of an urban public bus network. For the prediction of passenger demand, this study derived several calendar-related and operations-related variables to help model the travel patterns. These variables include the day of the week, week of the year, month, weekend indicator, holiday indicator, long weekend indicator, and route direction indicator. It also examines forecasting performance across multiple prediction horizons, which are critical for operational planning decisions in PTS. Finally, it provides practical insights to the decision maker based on forecasting studied for effectively managing transit planning in urban areas.

The remainder of this paper is organized as follows. Section 2 presents the literature review related to passenger demand forecasting in public bus transportation systems. Section 3 describes the research methodology, including the forecasting models and performance evaluation metrics used in the study. Section 4 presents the empirical results and discussion of the forecasting performance. Section 5 discusses the managerial implications derived from the findings. Finally, Section 6 concludes the paper and outlines potential directions for future research.

2. Literature Review

1.1 Passenger Demand Forecasting in Public Bus Transportation

Passenger demand forecasting is a key component of planning and operating public transportation systems because transit agencies depend on demand estimates to allocate vehicle and design routes. Accurate forecasting of passenger demand helps transit agencies to match service supply with expected ridership demand levels and improve operational decision-making in urban transport systems (Banerjee et al., 2020). Urban public bus transportation systems operate in the real world, which are dynamic in nature, where travel demand is affected by population growth, land-use changes, and changing mobility patterns. These changes increase the complexity of transport planning decisions and require appropriate techniques to predict the future passenger demand. Ridership forecasting models support transit agencies by providing valuable insights into operational planning and service improvements on passenger demand (Deepa et al., 2022). Passenger demand in public transport systems is also affected by several things, such as travel time, fare levels, service reliability, and service quality. These factors that affect passenger travel behaviour are essential for developing forecasting models (García-Ferrer et al., 2006).

Passenger demand in public transportation systems is influenced by several external factors such as weather conditions, special events, and service disruptions. These factors include uncertainty in passenger demand patterns and increase the complexity of forecasting models (Rahmani et al., 2025). Research has also examined how disruptions and service disturbances influence passenger travel behaviour using smart card transaction data and transit records (Yap et al., 2018). In addition, studies have investigated how congestion influences travel demand patterns in urban public transport systems (Nguyen et al., 2020).

1.2 Forecasting Models Used for Passenger Demand Forecasting

In public transportation systems, passenger demand is being predicted by using statistical and time-series forecasting methods, which are widely used methods. These models are used to analyse the historical ridership data for identifying the patterns that vary with time, such as trends and seasonal variations. Thus, the future demand levels can be estimated. Time-series forecasting methods are very useful in transportation research because they can effectively capture fluctuations of passenger demand, which vary with time. Time-series forecasting methods are widely used for predicting transportation demand because they capture temporal patterns in historical data while providing interpretable forecasting results for planners (Xue et al., 2015). As a result, statistical forecasting techniques remain an important analytical tool for transit planners because they can provide interpretable demand predictions even when only limited historical data are available (Banerjee et al., 2020).

To improve forecasting accuracy, several studies have proposed hybrid forecasting models that combine statistical techniques with pattern recognition approaches. Hybrid models aim to capture both linear and nonlinear demand patterns in passenger ridership data and therefore provide improved forecasting performance compared with single-method approaches (Ma et al., 2014). Forecasting models have also been developed to estimate passenger demand at the level of individual bus routes or transit corridors. These models can help transit agencies to analyse the demand patterns and support operational planning decisions such as vehicle allocation and route design (Deepa et al., 2022). Recent studies have also tested forecasting methods that support short-term operational decision-making in public transport systems. Such models help transit operators to predict the fluctuations in passenger demand and improve service through managing the operational adjustments (Egu & Bonnel, 2021).

There is an increasing interest in applying machine learning techniques to forecast the passenger demand in public transportation systems (Alexandre et al., 2023). Machine learning algorithms are useful for identifying complex relationships between passenger demand and explanatory variables such as traffic patterns and weather conditions More recent studies have used deep learning techniques to consider spatial and temporal information for improving the accuracy of passenger demand prediction in transit systems (Radfar et al., 2025).

The existing literature shows that forecasting approaches have been developed to predict passenger demand in public bus transportation systems. These approaches include traditional statistical forecasting models, hybrid models and advanced machine learning models. However, many data-driven forecasting models require large datasets for effective implementation. In many practical situations of transportation planning, only limited historical ridership data may be available. Under such conditions, statistical forecasting methods are highly relevant because they require fewer observations as well as provide interpretable forecasting results for transportation planners.

Therefore, further research is needed to investigate how effective the demand forecasting methods are with real-life data in public bus transportation systems for multi-horizon planning. The study contributes by providing a comparative multi-horizon evaluation of forecasting models using limited real-life data and offers practical insights to transit planners for integrating data-driven forecasting models into public bus transportation systems.

2. Methodology

3.1 Dataset Description

A dataset on daily passenger demand data from a city bus transport network has been used in this study. It consists of a total of 110 routes. For each route, 182 days of historical observations are available. To evaluate the performance of forecasting models, the dataset was divided into training and testing sets. The first 154 days were used to train the model, while the remaining 28 days were used for testing. The study adopts a multi-step prediction approach, where passenger demand is predicted at 1-day, 7-day, and 28-day horizons to assess short- and medium-term forecasting accuracy. For the prediction of passenger demand, this study derived several calendar-related and operations-related variables to help model the travel patterns. These variables include the day of the week, week of the year, month, weekend indicator, holiday, long weekend indicator, and route direction indicator. These variables will help model the weekly demand patterns, seasonal variations, and impact of special events on the passenger demand.

3.2 Forecasting Models and Performance Metrics

In this study, we have also selected time-series approaches, such as Naive, moving average, Autoregressive Moving Average with Exogenous Regressor (ARIMAX), multiple linear regression, Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX), Error-Trend-Seasonality model, and machine learning models, such as decision tree and extreme gradient boost (XGBoost) models. These methods were chosen after review of literature on forecasting methods, doing exploratory data analysis for understanding data characteristics of PTS demand data, and our experience of past forecasting studies in the same domain A brief description of the methods is given below.

Naive

The Naive model is used as a benchmark method in time-series forecasting. It assumes that the forecast for the next period is equal to the most recent observation. The forecast is generated: $\widehat{y_{t+1}} = y_t$, where $\widehat{y_{t+1}}$ is the forecasted value for the next period, and y_t is the observed value at the current period t. It a simple but serves as a good base forecasting methods against which advanced models can be compared (Hyndman & Khandakar, 2008).

7-Day Moving Average (7MA)

The 7-day moving average forecasting method works on the assumption that the forecasted value for the next period is the average of the observed over the previous seven periods. The forecast is generated as: $\widehat{y_{t+1}} = \frac{1}{7}\sum_{i=0}^{6} y_{t-i}$, where $\widehat{y_{t+1}}$ is the forecasted value for the next period, and y_t is the observed value at the current period t. This approach is commonly used to smoothen fluctuations in time-series data and model patterns such as trends or seasonal variations. Moving average methods are useful when the demand series exhibits stable patterns with limited irregular fluctuations (Hyndman et al., 2002).

Autoregressive Moving Average with Exogenous Regressor (ARIMAX)

The ARIMAX model extends the ARIMA framework by incorporating external explanatory variables. It combines regression on exogenous predictors with ARIMA model, which makes it useful when demand is affected not only by its own past values but also by exogenous variables like calendar or operational factors. (Fischer & Planas (2000) describe this family of models as regression models with ARIMA errors.

Mathematically, the ARIMAX model can be represented as:

$$\widehat{y_t} = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \beta X_t + \epsilon_t$$

Where, $\widehat{y_t}$ is the forecasted value at time t, y_t is observed value at time t, ϕ_i are autoregressive co-efficient, θ_j are the moving average co-efficient, $X_{t,}$ represents exogenous variables, β is the co-efficient vector associated to exogenous variables, and ϵ_t is the error term at period t.

Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors (SARIMAX)

The SARIMAX model further extends ARIMAX by modelling seasonality in addition to exogenous variables. When the time series exhibits recurring seasonal patterns and when external regressors are expected to improve forecast accuracy, then SARIMAX can be a useful method to apply (Banaś & Utnik-Banaś, 2021) In past, it has been observed that incorporating seasonal fluctuations and an exogenous variable into a conventional ARIMA framework can significantly improve forecast accuracy.

Mathematically, the SARIMAX model can be represented as:

$$\widehat{y_t} = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \epsilon_{t-j} + \sum_{k=1}^{P} \Phi_k y_{t-kS} + \sum_{l=1}^{Q} \Theta_l y_{t-lS} + \beta X_t + \epsilon_t$$

Where, $\widehat{y_t}$ is the forecasted value at time t, y_t is observed value at time t, ϕ_i and θ_j are non-seasonal autoregressive and moving average coefficients, Φ_k and Θ_l represent seasonal autoregressive and moving average coefficients, S is the seasonal period, $X_{t,}$ represents exogenous variables, β is the co-efficient vector associated to exogenous variables, and ϵ_t is the error term at period t.

Error Trend Seasonality (ETS) based methods

The ETS models are decompositions methods with exponential smoothing models and represents the time series through error, trend, and seasonal components. In this method, a time series is decomposed into three components: error (E_t), trend (T_t), and seasonality (S_t) at each time period. These components are then combined in different ways to forecast the time series. Mathematically, an ETS model can be represented as: $y_t = f(E_t, T_t, S_t)$. The ETS model becomes a family of time series models as it tests additive or multiplicative—errors, trends, and seasonality. For example, ETS(A,A,A) represents a model with additive error, additive trend, additive seasonality, ETS(A,A,N) will model additive error, additive trend, no seasonality, ETS(M,A,A) will have multiplicative error, additive trend, additive seasonality. In this manner, it becomes a set of 27 models (Hyndman et al., 2002).

Decision Tree

A decision tree is a machine learning method that partitions the predictor space into smaller and more homogeneous subsets using a sequence of decision rules. It allows the model to capture nonlinear relationships and interaction effects. It divides the dataset into smaller and more homogeneous subsets using a series of decision rules, allowing the model to capture nonlinear relationships and interactions between variables. This method is easy to interpret and does not require any prior assumptions about the data distribution. The forecast is generated as: $\widehat{y_t} = f(X_t)$, where $\widehat{y}_t$ is the forecasted value at time t, and X_t represents the set of input features such as time indicators, calendar variables, and other relevant factors, and $f(\cdot)$ represents the tree-based decision rules learned from the data.

Extreme Gradient Boost (XGBoost)

XGBoost is an ensemble learning algorithm built on decision trees and gradient boosting. It constructs trees sequentially so that each new tree corrects the residual errors of the previous ones, while regularization helps control model complexity and reduce overfitting. (Fang et al. (2022) describe XGBoost as a decision-tree-based machine learning algorithm in which multiple individual trees are combined to yield accurate predictions. This method is highly effective in capturing complex nonlinear relationships and interactions in the data. The forecast is generated as:

$$\widehat{y_t} = \sum_{m=1}^{M} f_m(X_t)$$

Where $\widehat{y_t}$ is the forecasted value at time t, and $f_m(\cdot)$ represents the m^{th} decision tree, M is the total number of decision trees, X_t represents input features set.

3.3 Performance Metric

The performance of the forecasting model is evaluated based on bias, accuracy, and variance. Bias is used to check the tendency to under- or over-forecast the actual values. Accuracy measures the closeness of forecasted and actual values. Whereas variance captures the dispersion of the forecast, it indicates the stability of the forecasting model.

To check bias, Mean Error (ME) is used as an evaluation error metric. Let the forecast error at time *t* be defined as, where $y_t$is the observed value and $\hat{y}_t$is the forecast value.

The forecasting accuracy is measured using Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Variance of the forecasting model is measured using Mean Squared Error (MSE). MSE measures the squared deviation between actual and predicted values and reflects the magnitude of forecasting error, rather than variance. Since MSE is sensitive to the scale of the data, we use their relative versions to ensure comparability across different routes and time periods. Similarly, Symmetric Mean Absolute Percentage Error (sMAPE) is also used to check the accuracy of the forecasting model. SMAPE is used instead of MAPE because it provides a symmetric percentage error and avoids bias when actual values are close to zero. SMAPE represents the forecast error in percentage terms and normalizes the error by the magnitude of both actual and predicted values, making it suitable for comparing forecasting performance across datasets with different scales. Relative sMAPE represents the ratio of the SMAPE value of a given model to that of the naive benchmark model. The formulation of the error metric is given as:

$$ME = \frac{1}{n}\sum_{t=1}^{n} e_t$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n} | e_t |$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$$

$$sMAPE = \frac{1}{n}\sum_{t=1}^{n} \frac{|y_t - \hat{y}_t|}{(y_t + \hat{y}_t)/2}$$

These metrics provide interpretable measures to evaluate the forecasting models. The lower values of the error metric indicate better forecasting performance. Alongside, we have also calculated the relative error with the benchmark model. For this study, the naive method is used as a benchmark (Table 1 and Table 2, Table 3).

Table 1. Relative performance error metrics of various models for the 1-day prediction horizon, keeping Naive as a baseline model (lower the better)

Model	**ME**	**MAE**	**RMSE**	**SMAPE**
XGBoost	-0.060	0.227	0.228	0.264
DT	-0.071	0.231	0.231	0.272
SARIMAX	0.095	0.254	0.254	0.283
7MA	0.400	0.556	0.556	0.605
LR	0.594	0.636	0.636	0.670
ETS	0.593	0.649	0.650	0.701
ARIMAX	0.920	0.918	0.918	0.916
Naive	1.000	1.000	1.000	1.000

Table 2. Relative performance error metrics of various models for the 7-day prediction horizon, keeping Naive as a baseline model (lower the better)

Model	**ME**	**MAE**	**RMSE**	**SMAPE**
XGBoost	0.085	0.319	0.302	0.360
DT	-0.115	0.346	0.334	0.380
SARIMAX	0.161	0.399	0.388	0.432

Linear Regression	-0.039	0.702	0.626	0.738
7MA	0.047	0.727	0.693	0.762
ARIMAX	0.146	0.777	0.728	0.802
ETS	0.382	0.816	0.783	0.849
Naive	1.000	1.000	1.000	1.000

Table 3. Relative performance error metrics of various models for the 28-day prediction horizon, keeping Naive as a baseline model (lower the better)

Model	**ME**	**MAE**	**RMSE**	**SMAPE**
XGBoost	0.081	0.333	0.345	0.381
Decision Tree	0.014	0.361	0.373	0.401
SARIMAX	0.135	0.403	0.426	0.444
7MA	0.033	0.604	0.609	0.645
Linear Regression	0.006	0.594	0.573	0.647
ARIMAX	0.087	0.665	0.645	0.708
ETS	0.579	0.791	0.801	0.823
Naive	1.000	1.000	1.000	1.000

2. Results and Discussions

The prediction of passengers was done for 1-day, 7-day, and 28-day planning horizons. The performance of various models was evaluated using ME, MAE, RMSE, and SMAPE metrics. The Naive model was considered the benchmark for comparing forecasting errors across all the methods. Table 1, Table 2, and Table 3 present the relative performance of the various machine learning and traditional models for 1-day, 7-day, and 28-day prediction horizons, respectively. The Naive model produced the highest forecasting errors across all horizons, with SMAPE values of 15.78, 10.24, and 12.49, respectively. So, this model is used as a baseline model. The Symmetric Mean Absolute Percentage Error (SMAPE) across all the prediction horizons is shown in Figure 1.

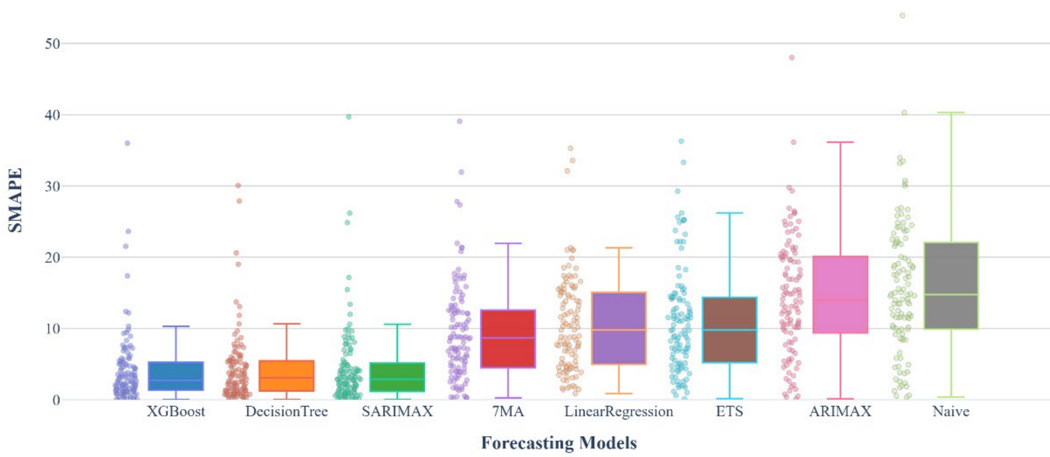
XGBoost consistently achieved the lowest error values with relative SMAPE values of 0.26 for 1-day, 0.36 for 7-day, and 0.38 for 28-day forecasting. This suggests that the XGBoost model can capture nonlinear patterns and seasonality present in the transportation demand data more effectively than other models. Unlike traditional statistical models, which rely on linear assumptions, XGBoost iteratively improves prediction accuracy by correcting residual errors, making it more effective in handling complex demand patterns in urban transport data.

Other machine learning model, the Decision Tree model, performs closer to the XGBoost across the three forecasting horizons. Its relative SMAPE values remain between 0.27 and 0.40, which also shows a substantial improvement over the baseline, Naïve method. Among time series models, SARIMAX performs relatively better across the prediction horizons, with relative SMAPE values between 0.28 and 0.44. This indicates that time-series models can still perform well when the data exhibits temporal structure, although machine learning models can capture additional patterns present in the dataset.

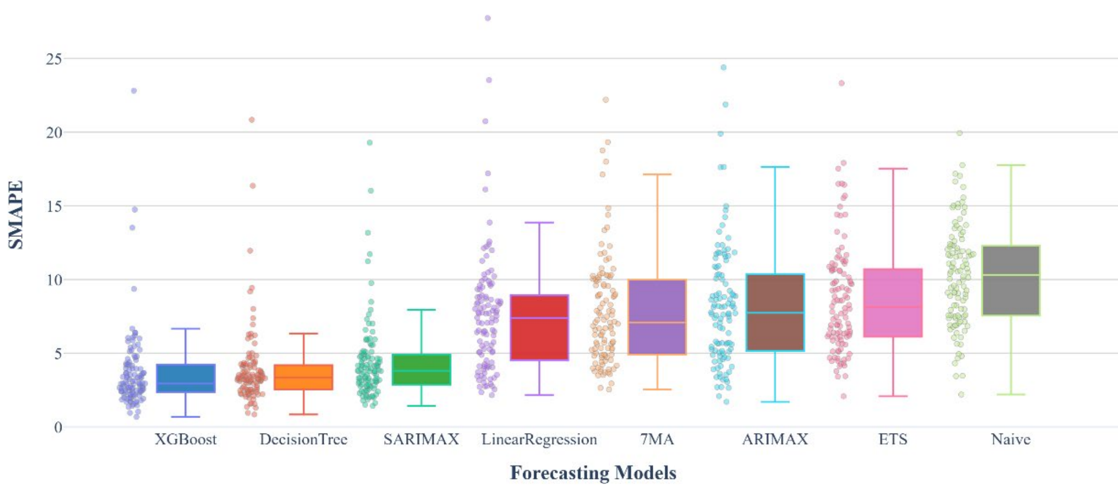
Beyond the top three models, the ranking of the remaining models varies across forecasting horizons. For example, 7-MA performs better for the longer forecasting horizon, while performance of models such as Linear Regression and ARIMAX differs depending on the forecast period. This variation is common in multi-step forecasting problems. Different models capture different characteristics of the data, such as short-term fluctuations, trend components, or smoothed patterns. As the forecasting horizon increases, the uncertainty of predictions also increases, and the accumulated forecast error may affect the performance of the models differently. As a result, while the top-performing models remain relatively stable, the variance of other models becomes sensitive to the forecasting horizon.

The distribution of errors for the XGBoost model is generally more concentrated with a lower median compared to other models across all horizons, indicating more stable forecasting performance. The models such as ARIMAX, ETS, and Naive show wider error distributions, suggesting greater variability in prediction accuracy. The spread of the MAE values also increases slightly as the forecasting horizon moves from 1-day to 28-day, reflecting the increased uncertainty associated with longer-term forecasts.

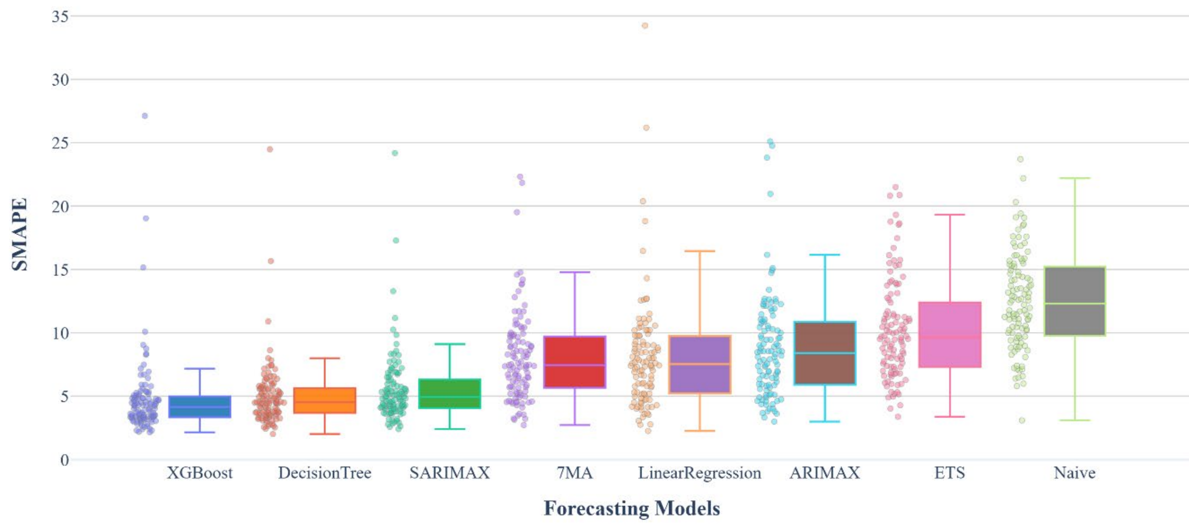
Overall, the results indicate that tree-based machine learning models provide better forecasting performance for passenger demand data, while traditional statistical models can provide good performance for certain forecasting horizons. However, the variation in model ranking beyond the top three models highlights the importance of evaluating forecasting methods across multiple horizons rather than on a single prediction period.



(a)



(b)



(c)

Figure 1. A visual representation of Symmetric Mean Absolute Percentage Error (SMAPE) across all the forecasting models (Lower SMAPE values indicate better performance)
(a) for the 1-day prediction horizon, (b) 7-day prediction horizon, (c) 28-day prediction horizon

3. Managerial Implications

The findings of this study provide several implications for public transport agencies involved in service planning and operations. Passenger demand forecasting can help to balance service supply and demand in urban bus systems, which is an important challenge in transit operations. By forecasting passenger demand in planning processes, transit agencies can make more informed decisions in fleet allocation, service frequency, and timetable design (Banerjee et al., 2020). Such demand-responsive planning helps improve the utilization of existing fleet resources while maintaining service availability across routes.

This study evaluated the performance of various models and suggests that machine learning models such as XGBoost and Decision Tree are able to handle complex temporal patterns in passenger demand data. Integrating such forecasting tools within operational planning systems may assist agencies in anticipating short-term fluctuations in ridership and adjusting vehicle deployment accordingly. This helps efficient service scheduling and reduces underutilized vehicle movements in urban bus networks. The transportation industry significantly contributes to environmental pollution. Demand-responsive service planning may also contribute to environmentally efficient public transport operations. When service frequency and vehicle deployment reflect observed demand patterns, unnecessary vehicle circulation can be reduced, which may lower fuel consumption and associated emissions in urban transport systems (Cats et al., 2016).

Transit agencies can integrate forecasting models such as XGBoost into existing decision-support systems to support daily vehicle allocation and scheduling. For example, short-term forecasts (1-day horizon) can be directly used for dispatch planning, while medium-term forecasts (7-day and 28-day) can support frequency adjustments and workforce planning. The observed reduction in forecasting error compared to the naive model indicates that data-driven forecasting can significantly improve planning efficiency and reduce underutilization of fleet resources. These improvements can lead to cost savings and better service reliability. Finally, the increase in forecasting errors across longer prediction horizons indicates that short-term demand forecasts are more helpful for operational decisions such as daily service scheduling and vehicle dispatching, while longer-term forecasts should be interpreted considering the uncertainty associated with extended prediction horizons.

4. Conclusion

The passenger demand forecasting in the urban public bus transit system is very crucial for effective operational planning. The forecasting of the passenger demand can be done using both traditional and machine learning forecasting models. The performance of several statistical and machine learning models for short-term and medium-term passenger demand forecasting in public bus transportation is evaluated in this study. The ridership time series data from 110 routes was used, and the models were evaluated for 1-day, 7-day, and 28-day prediction horizons using ME, MAE, RMSE and SMAPE error metrics. Among all the models, XGBoost performs well and produces the lowest forecasting errors for all three prediction horizons, followed by the Decision Tree model. This indicates that machine learning models are able to capture complex relationships present in the passenger demand data. SARIMAX performed best among all the statistical approaches. The analysis also shows that forecasting performance varies with the prediction horizon. Errors generally increase as the horizon becomes longer, which reflects the higher uncertainty associated with longer-term demand predictions.

This study contributes to the literature by providing a multi-horizon evaluation of statistical and machine learning models under limited data conditions, which is often the representation of the real-life public bus transit systems. However, the study has certain limitations. The dataset is limited to a single urban context, which may affect the generalizability of the findings. Future research may extend this analysis using datasets across multiple cities and incorporate additional explanatory variables such as weather and disruptions. Hybrid forecasting approaches with real-time data from multiple cities may provide additional insights into mobility systems in the context of the urban public bus transportation system.

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