A SYSTEMATIC REVIEW ON FORECASTING PASSENGER FLOWS OF MAULTIMODAL TRANSPORTATION SYSTEM INTEGRATING METRO

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ABSTRACT

Metro Rail Transit (MRT) is widely acknowledged as one of the most efficient options within urban transportation networks. It's undeniable that integrating a metro system into a multi-modal transportation network holds immense significance. However, it remains pivotal to gauge its effectiveness in fostering urban travel development. This underscores the essentiality of not only predicting passenger flows within the metro system, but also assessing potential shifts in modes of transportation, alterations in passenger travel times, route congestion dynamics, and the associated travel costs. While numerous research papers concentrate on predicting passenger flow within individual modes of transportation, there is a noticeable lack of emphasis on the intricacies of multimodal systems. However, a multimodal transportation system comprises multiple modes, with each mode exerting an influence on the demand for other modes, particularly in terms of passenger flow and various other aspects. Therefore, it's imperative to approach the transportation system holistically rather than viewing it as disparate components. This study focuses on forecasting passenger flows within a multimodal system that includes the integration of a metro system as public transit. Given that Metro Rail Transit (MRT) is recently introduced in Bangladesh, this research offers a comprehensive understanding of predicting passenger flow within the context of a multimodal transportation system. The insights gained from this study are expected to be of great value to planners and policymakers, aiding them in making well-informed decisions regarding transportation planning and management.

Keywords: *Metro Rail Transit, Passenger Flow, Multimodal System.*

1. INTRODUCTION

In our increasingly interconnected world, the movement within urban environments has become an unavoidable concern. The efficient management of passenger flows, especially within multimodal transportation systems, determines overall effectiveness and sustainability of urban mobility. Among the diverse transportation modes of complex systems, the Mass Rapid Transit (MRT) or metro systems have emerged as pivotal components with unparalleled capacity, environmental benefits, and alleviate traffic congestion and promote accessibility. The matter needs urgent approach as the sustained urbanisation trend is giving rise to ever-expanding cities, each grappling with the daunting challenge of accommodating and facilitating the movement of its residents. Meeting the mobility needs of these growing urban populations is a multifaceted endeavour that necessitates a comprehensive understanding of the dynamics involved. Accurate forecasting of passenger flows within multimodal transportation systems, particularly when MRT systems are integrated, is crucial for several compelling reasons. Firstly, precise forecasting assists urban planners, transportation authorities, and policymakers to make informed decisions regarding resource allocation, service enhancements and infrastructure development. It efficiently allocates resources, such as trains and staff, by matching them with expected passenger demand, in turn, reduces operational costs, enhances service quality, and ultimately, improves urban mobility experience. Moreover, precise forecasting is indispensable for emergency preparedness and response within urban transportation systems. In times of unforeseen events, having an accurate understanding of expected passenger flows effectively manages emergency and evacuation procedures, ensuring the safety of commuters. Beyond immediate operational benefits, accurate forecasting is integral to the long-term sustainability and development of urban transportation networks. It guides capacity expansion planning and promotes the efficient utilisation of infrastructure and resources. By predicting passenger flows, congestion can be reduced in cities, environmental burdens can be alleviated, and greenhouse gas emissions can be decreased, thereby contributing to a greener and more sustainable urban environment. Furthermore, in an era of digital innovation and smart cities, precise forecasting underpins the development of data-driven, responsive transportation networks that adapt to real-time demands. This adaptive approach enhances the overall quality of urban life, reduces commuter stress, and supports economic growth by facilitating convenient and reliable public transit. Therefore, a systematic review that scrutinises forecasting methods within multimodal transportation systems, with a specific emphasis on MRT integration, is not only timely but essential. By doing so, it equips stakeholders with a comprehensive understanding of how to harness the full potential of MRT systems and drive innovation in urban transportation. The result is not merely an improvement in mobility but the creation of more livable, sustainable, and resilient cities. In the realm of forecasting passenger flows within multimodal transportation systems that integrate metro services, existing studies have been limited in their scope, lacking comprehensive case studies and thorough method comparisons, including the exploration of method limitations. This study aims to address these gaps by focusing on the following key aspects:

1. Analysis of the employed methodology, variables, and resultant outcomes, offering nuanced insights into the research framework.
2. Identifying challenges in current research, this study aims to propose solutions tailored for the context of a developing country such as Bangladesh.

2. STATE-OF-THE-ART FORECASTING PASSENGER FLOW METHODS

Many forecasting techniques can be used to forecast the trends of Multimodal Transportation Systems. The common methods include Machine Learning, Deep Learning, Statistical Modelling, Simulation etc.

2.1. Machine Learning

Machine Learning techniques are also quite effective at handling the nonlinear features of passenger flow forecasting. AlKhereibi et al. (2023) developed several machine learning models including ridge regression, lasso regression, elastic net, k-nearest neighbor, support vector regression, decision tree, random forest, extremely randomized trees, adaptive boosting, gradient boosting, extreme gradient boosting, and stacking ensemble learner to predict metro ridership based on the built environment around the stations using a ridership database collected from 38 different metro stations in the state of Qatar. Furthermore, they evaluated the models for their predictive performance and found that the decision tree showed the highest performance among the base learners.

Park et al. (2022) developed a two-step procedure for predicting subway passenger transport flow using geographical information by clustering method, a type of unsupervised machine learning technique. Supervised machine learning was used in (Huang et al., 2020) and (Toque et al., 2017). Huang et al. (2020) used machine learning for only short-term passenger flow prediction by using the historical data of Beijing rail transit whereas (Toque et al., 2017) used widely popular machine learning technique Random Forest as well as Long-Short Term Memory (LSTM) neural networks for both long and short-term forecasting of passenger flow in multimodal transport, aiming to predict the number of passengers entering and boarding at each train station or bus and tram stop using smart card dataset. However, Huang et al. (2020) showed that their proposed method is more stable and accurate than the LSTMNN and it has good applicability for different locations in terms of some performance metrics like absolute relative error (ARE), mean absolute error (MRE), mean absolute error (MAE), and root mean square error (RMSE). A significant reduction in all the performance metrics were noticed when using their proposed model instead of the LSTMNN prediction models.

2.2. Deep Learning

Deep Learning models are also gaining attention in the field of forecasting due to their ability to capture the nonlinearity and latent correlation features (Liu et al., 2019).

X. Yang et al. (2021) proposed a spatiotemporal long short-term memory model (Sp-LSTM) model which predicts the volume of outbound passengers at urban rail transit. Liu et al. (2019) proposed an end-to-end deep learning architecture called Deep Passenger Flow (DeepPF) for forecasting the metro inbound/outbound passenger flow. J. Zhang et al. (2021) developed a deep learning architecture combining the residual network (ResNet), graph convolutional network (GCN), and long short-term memory (LSTM) (called "ResLSTM") to forecast short-term passenger flow in urban rail transit on a network scale.

It is noticeable that Deep Learning is primarily used to forecast short-term passenger flow. Although most studies neglect spatial features of travel data, the spatiotemporal characteristics was taken into account by (X. Yang et al., 2021). Furthermore, they also showed that the proposed Sp-LSTM outperforms some of other prediction models in terms of mean absolute error (MAE) and root mean square error (RMSE). As it is addressed by (X. Yang et al., 2021) that the passenger volume in one station is closely related to the passenger volume of the adjacent stations', Liu et al. (2019) used average travel time instead of the geographical distance to capture the spatial characteristics of travel data because the correlation between the stations should not be measured by geographical distance.

2.3. Artificial Neural Network

Artificial Neural Networks have been attractive alternatives for forecasting due to their ability to learn from experience (data-driven approach), infer the unseen part of the population containing noisy information, be more flexible and generalized functional forms than traditional statistical methods, and finally, being nonlinear (G. Zhang et al., 1998).

J. Yang et al. (2020) introduced a novel attention mechanism based end-to-end neural network is presented to predict the inbound and outbound passenger flow which explores the latent dependency between flow of forecast target station and historical flows from surrounding stations. But, they mainly addressed the temporal extent of data whereas the spatial extent was not explored. The spatial extent of data was explored by (Lin et al., 2020) who used neural networks to predict passenger flow based on land use considering both the spatial correlations of metro stations within the metro line and the temporal correlation of time series in passenger flow prediction.

2.4. Hybrid Models

The flow of passengers is rarely pure linear or nonlinear. As a result, it is crucial to capture both attributes of the flow. Therefore, a hybrid model is useful in this case as neither linear models nor nonlinear models can adequately model and fit passenger flow datasets (Li et al., 2018). Li et al., (2018) proposed a hybrid model that combines both the symbolic regression and Autoregressive Integrated Moving Average Model (ARIMA) and compared it with the performance of the ARIMA model and the Back Propagation Neural Network model which showed that the hybrid model outperformed the other two models. Glišović et al. (2016) integrated genetic algorithm (GA) and Artificial Neural Network (ANN) to forecast the monthly passenger volume on Serbian railways and showed that the developed hybrid model performs better than the traditional SARIMA model.

2.5. Autoregressive Integrated Moving Average (ARIMA)

Autoregressive Integrated Moving Average (ARIMA) is one of the popular statistical analysis approaches involving time series data. It can be used to better understand the dataset and predict future trends. Feng & Cai (2016) built-up ARIMA model for forecasting the passenger flow of the next day by using the detailed historical data of passenger flow in a typical metro station. Yan et al. (2018) used ARIMA for short-term traffic flow prediction and passenger flow prediction of five subway stations of Guangzhou Metro using data from online passenger ticket records. Subsequently, they showed that the ARIMA model performs better than SVM (Support Vector Machine), AIC (Akaike Information Criterion), or SACF ((Sample Auto-Correlation Function) and SPACF (Sample partial Auto-Correlation Function) in short-term traffic flow prediction. Zhu (2010) developed the ARIMA model to forecast the passenger flow of the Shanghai metro and analyze the change rate of daily passenger volume against the ‘7-day’ average before and during the main holidays. Milenković et al. (2016) used a Seasonal ARIMA model to address the strong correlation between time series and seasonal characteristics of monthly passenger counts by using historical data of the Serbian railway network.

It is important to make the time series data stationary before using ARIMA for prediction purposes otherwise the prediction will be closer and closer to infinity (Yan et al., 2018). However, the aforementioned techniques cannot capture the nonlinear nature of passenger flow forecasting due to their assumptions of linearity (G. Zhang et al., 1998). Although linear assumption can be convenient in some cases to understand the relationships in detail, it fails in the areas where relationships are non-linear (Granger, 1993). To address this issue, various techniques like Deep Learning, Machine Learning, and Artificial Neural Networks (ANN) have been developed in recent papers.

3. CHALLENGES AND THE WAY FORWARD

3.1 Strengths and Weaknesses of Forecasting Methods

The Autoregressive Integrated Moving Average (ARIMA) model is widely recognized for its efficacy in the analysis and prediction of time series data, particularly in the context of short-term forecasting. The model possesses the ability to incorporate temporal dependencies, rendering it well-suited for comprehending and forecasting patterns within datasets. Nevertheless, the ARIMA model is predicated on the assumption of linearity and necessitates the time series data to exhibit stationarity, thus posing a constraint when confronted with nonlinear associations. The attainment of stationarity might pose significant challenges.
On the other hand, Artificial Neural Networks (ANN) provide a high degree of adaptability and the capacity to comprehend intricate nonlinear associations. The system exhibits adaptability, as it possesses the capability to acquire knowledge from experience using a data-centric methodology, while also demonstrating proficiency in managing substantial volumes of data and variables. However, the inherent complexity of artificial neural networks (ANNs) presents a significant obstacle to the task of interpretation. Artificial neural network (ANN) models have a tendency to exhibit overfitting, particularly when confronted with limited datasets, and the process of training these models can be computationally demanding.

Machine Learning approaches, including regression, decision trees, and ensemble algorithms, have demonstrated efficacy in managing nonlinear characteristics and big datasets. These approaches provide a range of options in terms of algorithms, hence offering flexibility and adaptability. Conversely, the issue of interpretability can provide a barrier for certain machine learning models, and the efficacy of these models may be compromised if the selected method is not appropriately aligned with the unique attributes of the data.

Deep Learning models, such as Long Short-Term Memory (LSTM) and Residual Networks (ResNet), have exceptional proficiency in capturing intricate patterns and nonlinearity within datasets. Large-scale, high-dimensional datasets facilitate the automatic learning of hierarchical features. Despite their remarkable efficiency, these models exhibit a substantial computational burden and necessitate considerable computational resources. The extent of interpretability may be constrained, and the issue of overfitting becomes more salient in situations where the available data is scarce.

Hybrid models integrate linear and nonlinear components in order to effectively capture the intricate nature of passenger flow information. The integration of many models allows for a comprehensive approach to forecasting, encompassing multiple perspectives and factors. However, it is important to acknowledge that these models do have certain limitations, namely the potential for increased complexity and the associated difficulties in interpreting the models. The process of selecting and integrating many models necessitates a high level of skill.

3.2 Method-to-Method Comparison

While examining the various forecasting methodologies, the resulting summary of the comparisons can be outlined as follows:

- The comparison between ARIMA and ANN reveals that ARIMA offers a simpler and more interpretable approach, however it may encounter difficulties in capturing nonlinear interactions. On the other hand, Artificial Neural Networks (ANN) exhibit greater flexibility, nonlinearity, and proficiency in processing intricate patterns. However, they are deficient in terms of interpretability.

- Artificial Neural Networks (ANNs) and Machine Learning (ML) are two distinct approaches in the field of data analysis. ANNs, characterized by their data-driven methodology, have the ability to effectively capture intricate nonlinear interactions. In contrast, Machine Learning exhibits versatility by providing a range of algorithms that possess distinct trade-offs in terms of interpretability and performance.

- When comparing Deep Learning to Machine Learning, it is evident that Deep Learning possesses a notable advantage in its ability to automatically capture detailed patterns and features. Machine Learning exhibits greater interpretability and demonstrates enhanced performance when applied to smaller datasets.

- The comparison between Deep Learning and Hybrid Models reveals that Deep Learning possesses significant capabilities in capturing nonlinearity, whereas Hybrid Models amalgamate both linear and nonlinear elements. Hybrid models have the potential to enhance performance by capitalizing on the respective advantages of symbolic and data-driven methodologies.
- The comparison between ARIMA and Hybrid Models reveals that ARIMA primarily relies on linear modeling techniques, whereas Hybrid Models incorporate a combination of linear and nonlinear features. Hybrid models have the potential to exhibit superior performance compared to ARIMA models in effectively capturing the intricate nature of interactions present within datasets pertaining to passenger flow.

In brief, the selection of a forecasting technique is contingent upon the distinct attributes of the data, the inherent nature of the associations, and the objectives of the forecasting methods. When choosing a suitable forecasting methodology, it is imperative to thoroughly evaluate the strengths and drawbacks of each method.

4. CONCLUSIONS AND POLICY RECOMMENDATIONS

While analyzing several forecasting techniques for multimodal transportation systems, it is observed that the Autoregressive Integrated Moving Average (ARIMA) method proves to be efficient in short-term forecasting due to its capability to incorporate temporal relationships. Nevertheless, there are several issues that occur as a result of the assumption of linearity and the requirement for data stationarity. Artificial Neural Networks (ANN) provide the capability to effectively handle nonlinear relationships, hence providing flexibility and efficiency. However, ANN models face issues due to their limited interpretability and vulnerability to overfitting. Machine Learning approaches have demonstrated effectiveness in handling nonlinear information; nonetheless, concerns regarding interpretability can potentially hinder the comprehension of the models. Deep Learning, characterized by the utilization of advanced models such as Long Short-Term Memory (LSTM) and Residual Networks (ResNet), has exceptional proficiency in capturing complex patterns. However, it encounters challenges in terms of processing demands and limitations in interpretability. Hybrid models, which incorporate both linear and nonlinear components, offer a comprehensive methodology for forecasting. However, their intricate nature necessitates meticulous deliberation. The challenges encompass the need to strike a balance between interpretability and adaptability, mitigating the issue of overfitting, and assessing the availability of computational resources. The policy recommendations can be formulated as follows:

4.1 Consideration of Variables for Researchers Conducting Research

- Analyzing the consequences of precise prediction of passenger movement on urban planning, distribution of resources, and the construction of infrastructure.
- It is imperative for researchers to possess a comprehensive understanding of the temporal and spatial properties of the data.
- Analyzing the spatial correlations between metro stations along a metro line and their influence on passenger flow is crucial and for that Average Travel Time can be used considering that as correlations between the stations can not always be reflected by the geographical distance.
- It is of importance to give due consideration to the extent of effort, cost, and time entailed in the process of data preprocessing.

- The selection of a forecasting methodology should be congruent with the distinct characteristics and goals of the undertaking.
- Capturing both the linear and non-linear attributes of passenger flow therefore, adequately model and fit passenger flow datasets.

4.2 Five C's for Decision-Makers in Developing Countries such as Bangladesh

Comprehensive Planning: Decision-makers should give priority to thorough planning that considers the complexities of multimodal transportation systems, especially when incorporating MRT. This entails analyzing not only the current movement of passengers inside the MRT system, but also comprehending possible changes in other transportation modes, variations in journey durations, route congestion patterns, and related travel expenses.

Capacity Building: Decision-makers should organize training programs to ensure that professionals are adequately prepared to make knowledgeable judgments on the allocation of resources, improvements in services, and development of infrastructure.

Collaborative Governance: Decision-makers should build collaborative governance structures in order to allow the exchange of information, coordinated decision-making, and combined efforts in tackling difficulties pertaining to predicting passenger flows and improving multimodal transportation networks.

Customized Methodologies for Context: Policy makers should actively promote the development and application of forecasting techniques that take into account the unique temporal and spatial characteristics of the data. This will ensure that the methodologies used are in line with the objectives and difficulties of the local situation.

Communication and Public Awareness: It is imperative for decision-makers to proactively involve the public, by addressing their concerns and seeking their support for sustainable and efficient solutions for urban mobility.

In conclusion, it is imperative to align the capabilities of individual forecasting methods with the particular requirements of the forecasting task and the attributes of the accessible data. It is imperative for policymakers and academics to consistently assess and modify their methodologies in order to ascertain the efficacy and dependability of multimodal transportation system predictions, particularly within the framework of emerging nations such as Bangladesh.

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