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Original Article

A Comprehensive Comparative Analysis of Passenger Demand Prediction for Improving the Urban Bus Transportation System (UBTS)

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Abstract - *Cities play a vital role in promoting commercial growth and wealth. The development of cities is mainly based on their social, physical, and institutional infrastructure. In this situation, the significance of urban transportation is dominant. Urban area transportation is a common public bus service and is mostly used to transport many people in urban areas. In this paper, a survey on important parameters for improving the UBTS is reviewed. At first, the article reviewed the flow of passenger prediction based on the UBTS. Here, the UBTS issues like the prediction of passenger flow, fleet size, passenger comfort perception, delay, driver's behaviour, sound level, vehicle breakdowns, and so on are reviewed. To overcome these issues, the authors have presented some techniques and solutions for urban transportation, which are reviewed. A systematic literature review is conducted for the urban transportation system from 2011 until 2021. This survey provides a technical direction for researchers' work, and the potential future aspects have been discussed.*

Keywords - *UBTS, Passenger Flow, Passenger Comfort Perception, Drivers Behaviours.*

1. Introduction

Road transportation is the transport of travellers and accomplishes a passenger demands like service quality, fleet size, and so on. It includes various industries, suppliers to infrastructure builders, public authorities, insurances, energy providers, and vehicle manufacturers' services [1]. Road transport gives indispensable mobility for all goods and citizens, supporting a nation's social prosperity and economy. More efficient and prospective bus operation management is needed in major cities to give reliable bus services [2]. As a fundamental part of public transportation, short-term bus passenger demands play a significant job in network planning and resource allocation. The growth of dynamic planning and control was promoted by real-time passengers [3]. Short-term bus passenger algorithm enhances the reliability and service quality and reduces the operation cost.

Nowadays, for public transportation, buses are mostly utilized in many cities. In urban areas, urban buses play a vital role [4-6]. A continuous method to predict and monitor passenger flow enhances the bus service quality. The utilization of automated data collection methods increases the process, and to track the bus, GPS-embedded units are widely utilized [7-8]. An urban-wide bus transit system (BTS) have the opportunity to predict and estimate the flow of passenger on every bus [9]. In urban-wide BTS, the passenger flow of each bus can be predicted with the developed big data systems. Bus rapid transit (BRT) design needs to enhance the reliability and capability of a conventional bus method [10].

The buses are given high priority at the intersections, and at the same time, to minimize the delay, the design features of BRT are utilized. The main objective of BRT is to consolidate the speed and size of the bus at a reduced price [11-13]. Due to the cost-effectiveness, the Bus Rapid Transit (BRT) systems are improved worldwide [14]. The bottleneck BRT is a powerful method in rush hour to release pressure on passengers. The flow of passenger forecasts is the origin of the alteration and BRT operation system. It is measurable for upgrading the vehicle facilities, providing a quick warning to the intermittent event of urban traffic, and making the urban communities more secure and smarter.

The most popular term for the integrated use of ICTs in transportation is "intelligent transport systems" (ITS). It is applicable for all forms of transportation, which includes road, rail, ship and air, as well as every component of a transportation system, which includes infrastructure, vehicle and the driver or user, all of which relate vigorously. Based on the vehicle information and accurate real-time traffic, the transportation network controllers and other users (businesses, people, and local governments) making decisions is the main goal of ITS. Thus, the transportation system's overall performance was increased [65], resulting in developed resource use and more logical physical flow coordination. The transportation process may assist by ITS in different ways. There are numerous fragmented contributions in the present literature, each focusing on a distinct issue (e.g. public transport location and management, parking spot availability, smart traffic lights, tracking and tracing of dangerous goods). A full picture of the existing knowledge body should be gathered to suggest future research areas. [66].

The review paper is planned as a survey: some analysis of the literature review along with the contribution of our work is explained in the next section. The third section explains passenger prediction flow, passengers' comfort perception, CO_2 emission, and maximum profits. The final section provides the review conclusion.

2. Related Work

For the development of the bus passenger flow prediction model, Gummadi et al. [15] presented an artificial neural network model. Their design was intended to provide the particular bus passenger flow over some undefined time frame to build the proactive method for transit agencies. At a given time (t), the quantity of passengers has been taken as input for developing the ANN model. To compare and develop the flow of passenger prediction was their main objective. Thus, they developed ANN and ARIMA methods.

Luo et al. [16] designed a method to configure a constrained stop transit administration with an existing accessible fleet size from the current normal service. At first, a technique for restricted stop service was presented to limit the user's cost through the fixed fleet size. A heuristic algorithm was introduced from the predefined set for constrained stop administration instead of choosing lines to look through the transit line structure. At last, to represent the presentation of constrained stop service, the various extents of commuter flow and distinctive travel behaviours are explained for various scenarios.

Identifying quality factors was the main aim of Calvoa et al. [17], which helped improve the existing transportation services such as Colombia. For urban bus riders, Handte et al. [18] give how their method may have been used for the public transport system. Crowd-aware route recommendations and micro navigation were used by urban bus navigators (UBN) for bus users.

Depending upon the revealed preference data, the crowding evaluation for bus travelling and the urban tram was examined by Yap et al. [19]. Depending upon the Dutch case network, the bus crowding and urban tram valuation were estimated in a European context. Their study supports the decision-making process to reduce crowding levels.

Using the XGBoost algorithm, Lv et al. [72] addressed the bus passenger flow prediction. With the point of interest data, the big data of the bus card can be merged through the XGBoost algorithm. At first, based on the Amap web service application interface, the point of interest data around bus stops were collected.

Yu et al. [73] designed a bus controller design method based on data collection and edge computing requirements. According to the current scheduling requirement, intelligent bus control scheduling was developed. Through efficient bus scheduling, intelligent traffic control can be realized; thus, the robustness of the bus network operation could be enhanced.

The passenger satisfaction towards service of public transportation was presented by Bhattarai [74]. By using 11 parameters, the satisfaction level of services was evaluated like speed, driver and passenger, the behaviour of conductor, fare, seating arrangement and space for standing, availability of timetable and route information, access for children and old age people, access for various disabled people, cleanliness and comfort.

First, our work is based on passenger demand prediction for improving urban bus transportation. For improving urban bus transportation, the arrival time of the bus, fleet size (i.e., bus size), seat availability, crowding, service quality, passenger satisfaction, and comfort perception had to know. It helps the passenger travel on the bus because the passengers know the details about the bus. If passengers want to go anywhere, they choose a bus, so the urban bus transportation system also increases. If a higher amount of passenger will travel means, revenue will increase. If high revenue occurs, the bus with a higher amount of seats, bus size and quality will increase. So all of this will improve the urban bus transportation system.

3. Important Parameters to Improve Urban Bus Transportation System (UBTS)

3.1. Flow of Passenger Demand Prediction

Escolano et al. [20] presented the computer vision method using optical flow for onboard bus passenger counting. The method gives the demand forecast in the EDSA route for the bus dispatch scheduling system. On the bus, the cameras are installed, which capture images of alighting passengers and boarding. For passenger tracking and motion detection, the optical flow is utilized. The passenger count is relayed to a central dispatch scheduling system for every bus.

The hybrid model Wavelet-SVM was presented by Sun et al. [21]. It consolidates the integral advantages of SVM and Wavelet. Three important stages are in the wavelet-SVM forecasting method. Initially, using a wavelet, it decomposes the passenger flow data into various low and high-frequency series. The SVM method was applied during the prediction stage to predict and learn the related high and low order series of frequency. The SVM strategy was applied during the expectation to learn and anticipate the related low and high recurrence arrangement.

3.1.1. Bus Arrival Time

Yap et al. [22] investigated the passenger impact of planned disturbances using smart card data. Bus travelling time prediction was done by Amita et al. [23] to apply ANN. The prediction time of a bus for applying proactive methods to give bus arrival real-time information to the passenger and transit agencies. The separation between the bus stations, delays, and dwell time input for developing the ANN model. The average speed between the bus stop, delays, a separation between the bus stations, and arrivals/departure times were collected in Delhi for two urban routes. By using GPS, the model was tested, validated, and developed.

Based on the Kalman filtering algorithm and support vector machines (SVMs), a dynamic prediction of the travel time model, which includes multiple bus routes, was presented by Bai et al. [24]. The dynamic model performance was validated in Shenzhen, China. For bus prediction's travel time, the outcome of the proposed dynamic model is feasible. In [62], the LSTM model was introduced for predicting the arrival time of each bus. A hybrid BAT factor that considers real-time and historic data was introduced to maximise the overall prediction rate efficiency.

3.1.2. Seat Availability in Bus

Bauera et al. [25] assessed the black carbon concentrations in four seating locations: average exposures, non-rush hour periods, rush hour periods, and priority seating locations. In the means of black carbon concentrations, they found no statistically significant difference between other locations and priority seating locations. For priority seating areas, work might be important to refine the most suitable area for bus stops and buses.

Crump et al. [26] tested the passenger seat belts in four US cities. Only 1% (2 out of 156) of passengers had seat belts when provided. Most bus passengers are not put on seat belts even when provided.

To depict seat-searching through the procedure of a passenger, Ji et al. [27] built a model of Markov. An algorithm consolidating the Markov method was exhibited to plan the short-turning system. Their method minimizes the cost, which includes the passenger's operational cost and the time of waiting for cost. The procedure was established to generate optimum decision variables values. Additionally, the optimal plan for the short-turning method was sensitivity to seat capacity.

Sam et al. [28] recognized the association between the independent and dependent variables via Pearson Chi-Square and cross-tabulations. On a public bus, they observed perceived safe seats, trip duration, and occupational status, which determine the preferred seating. Schmöckera et al. [29] presented a frequency-based assignment model to find seats in their perceptions. Their model required many nodes, and the user equilibrium assignment issue was presented. The Markov-type network loading process found an equilibrium solution.

3.1.3. Crowding

To demonstrate the dynamic development of the passenger flow network, du et al. [30] introduced a flow rate-based method. An integer linear programming method was presented based on the basic model to solve the bus transit issue. In Singapore, they validate their model against a real scenario.

The bus arrival time issues faced by the people were solved by Mukundan et al. [31]. The IOT is utilized to give the passengers waiting for real-time information at the bus stop. The information like crowd density, traffic information, and arrival time of the incoming buses are prearranged. The passenger's waiting time and anxiety were reduced by using the smart bus navigation method. The positive impact is created by this method and the people who desire to utilize the public mode of transportation.

Yang et al. [75] designed a bi-level method during the bus route to plan the short-turning method. The main objectives of the upper-level method were to diminish the travel time and the cost of operation. To catch the passenger administration decisions, the lesser level method was utilized. To determine the different service frequencies, a bi-level algorithm was developed.

3.1.4. Service Quality

In Dhaka, the main method of mass travel available is the bus. On an average working day, the bus carries about 1.9 million passengers. The bus has improved from 10% to 30% for all types of trips. There are 8,583 minibuses and 11,060 buses plying on the road. The bus routes are limited to about 200 kilometres in the north-south direction. Currently, the bus services lack the door to door services and standard services Mustaqeem et al. [33]. The introduction of MRT and BRT and lane separation for NMVs and MV are some of the significant events to be started in their method.

To distinguish the key influential factors of transport service quality and to estimate the passenger assessment of bus service quality, Wu et al. [34] applied the Bayesian network. Mutual information analysis and an evidence sensitivity analysis were utilized to derive the degree of influence. To obtain passenger satisfaction, improving quality to manage these aspects are basic procedures. Chakrabarti et al. [35] used the data to analyze the variations in boarding across lines. Reliability improvements for transit agencies may lead to productivity gains.

3.1.5. Passenger Satisfaction

For urban rail transit to set up a traveller satisfaction assessment model in China, Shen et al. [36] utilized the ACSI model. The parameter estimation strategy and structural equation modelling (SEM) strategy were utilized, i.e., Partial Least Squares (PLS), to estimate their model. An evaluation indicator method, including three indicators, was established to measure passenger service satisfaction. To quantize the level of traveller agreement, the satisfaction index is obtained. The IPA matrix is utilised to show the merits and demerits of the services.

From the passenger perception perspective, a set of satisfaction evaluation indicator methods was constructed by Weng et al. [37]. It was composed of 6 to 21-level indexes. A satisfaction evaluation model was presented after testing the validity and reliability of the indicator scheme. The multivariate Analysis of variance methods was deployed to evaluate the satisfaction influencing factors. The time, travel purpose, and passenger age are the three factors of satisfaction score. For public transportation, they provide positive contributions toward normalizing performance evaluation.

Cheng et al. [38] proposed an SEM model to evaluate the current bus traffic transfer service. Depending on the passenger's perceptions at HSR stations during the bus transfer process, the factors that affect passenger satisfaction are analyzed by the economy, service, safety, comfort and convenience. To investigate the correlations of passenger satisfaction, an SEM was implemented. To guide the planning of new ones and to enhance the service of existing HSRs, the finding can give helpful data for managers and planners.

In Dhaka, the relationship between the quality of bus service and its influencing factor was examined by Quddus et al. [39]. The discrete choice model was developed with a sample size of 955. Vehicle condition, waiting times, exit and entry processes, safety and punctuality are the main factors the passenger's demand. Findings from their studies can be utilized to improve bus transport and to develop the regulations and policies in Dhaka.

Jiao et al. [67] designed an enhanced STL-LSTM model which combined three LSTM neural networks, multiple features, and a seasonal trend decomposition procedure depending on locally weighted regression. Beijing's daily bus passenger flow prediction was selected as a research objective during the pandemic.

To predict the passenger flow of Karnataka State Road Transport Corporation, Nagaraj et al. [68] used a deep learning approach with a greedy layer-wise algorithm, recurrent neural network and long short-term memory algorithm. For prediction, some parameters were measured, such as revenue, slot number, passenger count, destination, source, bus type and bus id. These parameters were processed using a greedy layer-wise algorithm to cluster data into regions.

3.1.6 Re-routing

Kalra et al. [69] proposed an innovative method with the help of re-routing the bus on the go based on public demand. A central server enabled the interaction of public demand with routing. A dynamic routing algorithm was proposed to facilitate the on-demand nature, preparing new routes for buses in real-time. New and more efficient routes were suggested based on the aggregated data collected.

Bulak and Elkharaz [70] presented to alter a traditional transportation service behaviour to facilitate system effectiveness and diminish traffic congestion through a modelling-based routing approach. A dual objective goal programming optimization was developed to select the best alternative routes for university shuttle bus services.

In the context of bus-based VANET, an algorithm for the Internet of Energy, i.e. street centric routing scheme, was proposed by Khan et al. [71]. At first, a multipath routing scheme was proposed using path and street consistency probability. Then, a relay bus selection mechanism was introduced to enhance the packet forwarding by using ant colony optimization clustering.

3.1.7. Fleet Size

Liang et al. [40] explained a set of best control formulations to diminish the costs for the passenger. To acquire the transport activity, many conditions were communicated with plan-based control schemes and headway-based holding control. For the passengers to diminish, the total cost was the main goal. Under different operational settings, the effect of this optimization scheme was tested. The total cost was directed between the schedule and headway. The optimization model minimized the number of buses.

The numerous buses in the transport courses and the presentation of control bus schemes were explored by Liang et al. [41]. With the expanding number of buses, an adaptive control model was presented to search for suitable transport. A lot of numerical tests were led furtherly. Rogge et al. [42]

provided a genetic algorithm to optimise the bus fleet's cost. The defined issues cover fleet composition, the development of battery buses, and charging infrastructural optimization.

To resolve the mixed bus fleet management (MBFM) issues, Li et al. [43] proposed an NLABC method. Due to the operating cost of electric buses and range limitations in MBFM, the routing issues were the major problem. To solve the recharging issues, two routing schemes are presented. Diesel buses, hybrid-diesel buses, electric buses and compressed natural gas buses are considered while counting various purchase costs, external emission costs and operating costs. They apply the formulation to illustrate the method. For managing the bus fleet, the outcomes give the vehicle routing with mixed fleet optimization, and bus service coordination is an important consideration.

3.2. Comfort Perception of Passenger

A passenger safety perception model for buses was studied by Khoo et al. [44] using the Bayesian network. The bus driver's behaviour was perceived through the bus motion profile. Using GPS, the road geometry was recorded and computed by the passenger with the help of Google Maps. The following section discusses the parameters that significantly enhance the comfort perception of each passenger on the bus.

3.2.1. Air Conditioning

In a model predictive control method, Hea et al. [45] aimed to increase energy efficiency. In real-time, three approaches are proposed to understand the traveller amount variation: Markov-chain and stochastic prediction based on Monte Carlo.

For different HVAC methods, Göhlich et al. [46] studied to conduct the cost analysis. The economic assessment depends upon comprehensive energy consumption.

To enhance the intercity bus air-conditioning scheme design, an exergy analysis was implemented by Tosun et al. [47]. Exergy destructions ($\dot{E}$xdest) and Energy Efficiency (ψ) of the whole method and its subunit were assessed.

The thermos physical blend R-445A properties were evaluated by Schulze et al. [48]. An R-134a air conditioning method data were employed in a transient simulation to estimate the blend below transient boundary settings. Using R-445A, the maximum cooling capacity was reduced, and the cumulated COP was lower.

3.2.2. Seat Comfort

The ergonomic suitability of the passenger seats was determined by AJAYEOBA et al. [76], which was used in Lagos in the molue buses. The variables from the relevant design measured seat height, seat depth, backrest length, backrest depth and backrest frame height and were measured with a standiometer. The anthropometric dataset contains 612 males and 327 females, and design variables of 40 small molue and 52 big buses were measured. For Nigerians, the molue buses will be very ergonomically suitable when the important modification could be affected on the design variables of the seats by the automobile industry. In a mass transport vehicle, Quatmann et al. [50] provided a seat modification assembly with a passenger seat, mainly an aircraft.

3.2.3. Level of Noise

Annoyance and the noise effects on bus drivers' health were evaluated by Bruno et al. [51]. 200 bus drivers participated in a cross-sectional study from a public transport company. Annoyance and health effects were measured with passengers, traffic, irritations, headache and sleep quality. The data on bus drivers working time and age were also obtained. LA_{eq} was evaluated for noise exposure in 80 buses. Statistical Analysis consisted of spearman's correlation coefficient, mean, one-way ANOVA, minimum and maximum. The three outcomes from bus drivers are highly annoyed, little annoyed, and not annoyed. The equivalent sound pressure level was the bus's limit for occupational comfort.

3.2.4. Bus Delay

A bus may be blocked by traffic lights and other buses from entering and exiting the stop. To model, each type of delay was the main goal of Huo et al. [52]. When modelling delay occurs, the traffic lights, berth number, bus service rate and bus arrival rate are considered. In Queueing theory, the occupy-based delay is modelled. The two stops in Canada and Vancouver are selected for model validation and parameter estimation. For the selected stops, the model validation shows the average accuracy rate.

Nagatani et al. [53] studied a bus schedule controlled by capacity in a shuttle BTS. The dynamic bus motion is related to the bus schedule. On the arrival of buses, it increases the bus lateness, which significantly affects the inflow rate. In unstable states, the shuttle bus arrival oscillates different periods.

The InterQuartile Range (IQR) was introduced in [63] to estimate the travel time variation. The performance achieved by this approach effectively maximizes the efficiency of the public transport system. Finally, the travel time was predicted using the LSTM (Long short-term memory) approach. Furthermore, the fleet management process also managed the bus adequacy for various times on a particular day.

An improved form of deep belief network (DBN) architecture for travel time prediction was introduced in [64]. The Gaussian-Bernoulli was used with RBM (restricted Boltzmann machines) to enhance the DBN performance. This technique was validated using the real-time traffic data collected from Shenyang, China.

3.2.5. Driving Style and Drivers Behaviour

Based on personalized driver modelling, driving styles were evaluated by Shi et al. [54]. Initially, they established a personalized driver design by neural networks. Then, an aggressiveness index was proposed to quantitatively calculate driving classes based on Energy spectral density (ESD) analysis. At last, to detect abnormal driving behaviour this index was applied.

From four trunk lines based on automatic vehicle location (AVL) data, Cats et al. [55] analyze the main causes of bus riding times deviations. A bus-riding time deviation method was assessed with trip attributes, link characteristics, performance indicators, and auto-regressive effects. The relation between self-report crashes and driving behaviours questionnaire was investigated by Varmazyar [56]. To select drivers, a proportional method was utilized from nine areas. The questionnaire collected data, including demographic information and driver behaviour. In SPSS software 16, the data was analyzed by regression logistic and Pearson correlation.

3.3 Maximum Operating Profit

Armaselu et al. [57] have introduced an interactive framework to maximise the total profit for public transportation route planning. Two approximation algorithms are the main contribution of the method. On a real-world dataset, the algorithms were tested.

Maximizing the revenue: For electric tour bus systems, revenue management and sustainable service design were described by Ko et al. [58]. The two mathematical methods were established for designing the method and controlling the revenue executive's logical method.

3.4. CO_2 Emission

In Beijing, using PEMS on-road emissions was tested by Zhang et al. [59]. Fuel and CO_2 rates are first related to driving conditions and based on BJBC, CO_2 and fuel were estimated. Furthermore, they explored the impacts of operating conditions like air conditioning, load mass, average speed, and traffic patterns. Lajunen et al. [60] evaluated the CO_2 emission and cost of various buses. In the autonomous vehicle simulation software, the simulation models of various power trains were developed. For both fuel and energy pathways and bus operations, the CO_2 emission was calculated. For the primary energy sources, two various working environment circumstances were utilized. Tarulescu et al. [61] have reduced the transportation sector's greenhouse gas emissions and energy usage. From the Brasov Metropolitan area, they analyzed the road transportation system.

Table 1. Survey for Urban Bus Transportation

Author Name	Urban Bus Transportation	Objective	Methods	Evaluation Measures	Results	Future Scope
Amita [29]	Bus Arrival Time	Travel time prediction	ANN	RMSE and mean absolute error	Their model attains good accuracy	Moreover, deep learning algorithms also included increasing the prediction accuracy.
Ji et al. [34]	Seat Availability	Optimum scheme of short tuning method allowing for seat availability	Markov Model	The cost function of the vehicle	The total amount of cost is reduced	The metaheuristic Algorithm is created to deliver ideal estimations of the decision variables.
Yang et al. [40]	Crowding	To design a short turning method for bus crowding	Bi-Level model	Bus load profile, cost, empirical cumulative density function	Cost reduction, the method is sensitive to seat capacity	An improved metaheuristic algorithm is introduced to get a good strategy for the short-turning method.

Liang et al. [51]	Fleet size	The multi-objective optimal formulation was the design	Monte Carlo scheme	The cost function, percentage of average arrival passenger	A cost function is reduced	Using a hybrid metaheuristic algorithm reduces the overall function and minimises the number of buses on routes.
Hea et al. [56]	Air conditioning	Forecast and Analysis of passenger amount changes are used to enhance AC energy efficiency.	RBF-NN, predictio n of stochastic and Markov-chain based on Monte Carlo.	Energy consumption and temperature performance	To achieve increasingly stable temperature execution	Self-learning model for driving conditions
Huo et al. [64]	Bus delay	To model each type of bus delay at the bus stop.	Block-based and transfer block-based delay	The impact of arrival rate and service time on the bus.	Accuracy is high	-
Shi et al. [67]	Driving style and drivers behaviours	Based on personalized driver modelling, evaluate the driving style by normalizing driving behaviour.	Using neural network	ESD, throttle position and radial base function	Scheme effectiveness is checked.	To establish the personalized driver model by deep learning algorithms.

4. Discussion

The growing usage of Automatic Vehicle Location (AVL) systems for traffic data gathering has come from fast improvements in sensor technology. GPS sensors are the most widely used AVL system because they are a tried-and-true, reasonably inexpensive technology. In addition, several transportation providers have GPS sensors installed in their cars. One of the most intriguing issues in the field of Intelligent Transportation Systems (ITS) is extracting relevant data from such a huge database collected over time.

As predicted, the writers' research techniques are influenced by their studies' goals. Analytical models, for example, were primarily employed to give quantitative tools that could be utilized in various situations: a problem's solution is achieved through a well-defined, analytical and scientific calculation procedure. Similarly, other authors constructed simulation models for analyzing and forecasting the dynamic unfolding related to events or processes after fixing the analysts' specific parameters. In most situations, both analytical models and simulations may be applied in settings other than those for which they were originally intended (for example, changing certain input variables, such as the size of the city, the kind of vehicles, and so on) and calculating how the results change. On the other hand, case studies and surveys related to analyzed cases were typically less generalizable due to the distinctiveness of the subjects.

The findings revealed that the influence of ITS on both people and freight transportation has yet to be thoroughly explored using an integrated approach. However, some writers attempted to summarise the beneficial impacts on residents as a result of the deployment of ITS for freight transportation in a qualitative manner. Indeed, freight trucks contribute significantly to city congestion and environmental nuisances such as pollution and noise, which negatively influence the urban quality of life.

5. Conclusion

This paper discusses a survey on important parameters for urban transportation systems. Here, the prediction of passenger flow, fleet size, passenger comfort perception, delay, drivers behaviour, sound level, vehicle breakdowns, and so on are reviewed. A systematic literature review is conducted for urban transportation systems from 2011 until 2018. The advantage of bus prediction in UBTSis that it advances improved learning achievement. Some prominent difficulties forced by UBTSare usability issues and frequent technical issues. A few difficulties and various points of interest in UBTS usage were found, which were discussed briefly in the above sections. Prediction of public transportation passenger flow by a data-driven method based on big data is the scope of the research. This survey provides a technical direction for researchers' work, and the potential future aspects have been discussed. The whole higher order transit system's merits of BRT are indicated in this review. It can clarify the state of the art and identify the needs in research to create consensus where none existed before.

In the future, to study and analyze the challenges of earlier passenger demand prediction models and propose new dynamic clustering, route scheduling and demand forecast prediction techniques. Also, in the future, passengers' comfort perception must be needed. The following factor affects passenger comfort level: driver's behaviour, driving style, seat comfort, level of noise, delays and air conditioning. To predict the flow of passengers is to plan their trips and reduce the waiting time, and passenger flow estimation will help to determine the bus progress and predict the appropriate fleet size. After that, delay prediction is discussed in public transportation for awareness of the situation. Thus, the passengers know the trip time in advance. The CO_2 emission reduction method is utilized because of global warming and its effects. Researchers have started focusing on the Hazards of gases that are emitted by vehicles. So efforts are made to calculate the emission and minimize it. So in the future, the passenger flow prediction, travelling time and waiting time of passengers, passenger comfort perception, delay prediction for the situation, maximizing the operating profit, and CO_2 emission will be discussed.

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