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A Review on Statistical Models for Street Level Travel Time Estimation Using GTFS Features

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ABSTRACT: The transition towards Intelligent Traffic Systems (ITS) is inevitable in future. Accurate travel time estimation is vital for the effectiveness of modern public transportation systems. It plays a central role in applications such as real-time passenger information, transit planning, and traffic management. With increasing urbanization and demand for efficient mobility, transit agencies are turning to data-driven models to improve service reliability. One valuable data source is the General Transit Feed Specification (GTFS), which standardizes public transportation schedules and associated geographic information. When integrated with statistical modeling techniques, GTFS features can significantly enhance the precision of street-level travel time estimations. This paper presents a comprehensive review of statistical models for forecasting street level travel time employing GTFS features, along with associated challenges that the sector faces.

Keywords: General Transit Feed Specification (GTFS), Intelligent Traffic Systems (ITS), Statistical Models, Regression, Forecasting Accuracy.

I. Introduction

In the era of smart cities and intelligent transportation systems, accurate estimation of street-level travel time has become increasingly important. It plays a key role in route planning, public transit scheduling, and providing real-time information to commuters. One of the most widely adopted data formats for transit systems is the General Transit Feed Specification (GTFS), which offers a standardized framework for sharing transit schedule and geographic information [1]. GTFS data, when combined with robust statistical models, can be a powerful tool for estimating travel time in urban transit networks. GTFS datasets include both static and real-time components. The static feed provides information about routes, trips, stops, stop times, calendars, and agencies [2]. Real-time extensions of GTFS (GTFS-RT) can offer vehicle positions, service alerts, and trip updates such as delays or early arrivals. These features make GTFS highly valuable for modeling travel time between stops, particularly at the street level where fine-grained predictions are necessary. GTFS features such as stop sequences, scheduled arrival times, distances, and headways between vehicles serve as the foundation for building statistical models [3].

Fig.1 Share of Modes of Transport in ITS

(Source: https://www.grandviewresearch.com/industry-analysis/intelligent-transportation-systems-industry

Figure 1 depicts the Global ITS market in which the Roadway has the maximum share [4]. A variety of statistical models have been used for travel time estimation. One of the most common is the linear regression model, which attempts to find a straight-line relationship between travel time and factors such as stop distance, scheduled time, and traffic conditions. While easy to implement and interpret, linear models can be overly simplistic and fail to capture the nonlinear relationships common in urban traffic dynamics. For this reason, more advanced techniques such as Generalized Linear Models (GLMs) have been adopted. GLMs allow for a wider range of distributions, making them better suited for skewed travel time data, such as using the Gamma distribution for continuous, positive-valued durations [5].

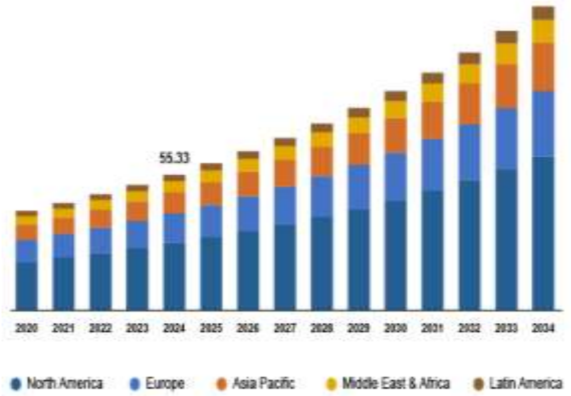

Fig.2 The ITS Global Market in Billion USD

Source: https://www.polarismarketresearch.com/industry-analysis/intelligent-transport-system-market

By region, the study provides the intelligent transportation system market insights into North America, Europe, Asia Pacific, Latin America, and the Middle East & Africa. North America held the largest market share in 2024 due to its advanced transportation infrastructure, high vehicle penetration, and significant investments in smart city projects. The region has been at the forefront of adopting advanced technologies such as real-time traffic management, vehicle-to-everything (V2X) communication, and predictive analytics [6]. The US dominated the market within the region, driven by robust government initiatives and funding for modernizing transportation systems. Programs such as the ITS deployment initiatives by the Federal Highway Administration's and the presence of key industry players further accelerated the growth of the market in the region. The growing adoption of electric and autonomous vehicles in the US, supported by a comprehensive network of charging stations and intelligent traffic systems, further contributes to the region's leadership [7].

The intelligent transportation system market in Asia Pacific is expected to witness a significant CAGR over the forecast period due to rapid urbanization, increasing population, and significant government investments in smart transportation infrastructure. Countries such as China and India are leading this growth due to their extensive focus on reducing traffic congestion, improving road safety, and lowering environmental impact. China stands out as a dominant country in the region, driven by its ambitious smart city initiatives, widespread deployment of advanced traffic management systems, and integration of AI-driven solutions. The region's focus on enhancing public transportation, including high-speed rail systems and intelligent bus networks, further drives demand for intelligent transportation systems [8].

Time series models, including AI & ML models, are also employed to model temporal patterns in travel times. These models are especially effective in capturing periodic trends and short-term variations, which are common in transit systems influenced by rush hours and day-of-week effects [9]. However, they often require large historical datasets and can be sensitive to missing or noisy data. Another statistical approach is the use of Mixed-Effects Models, which include both fixed effects (such as time of day or day of the week) and random effects (such as variations between different drivers or bus lines). These models are ideal for capturing hierarchical or nested structures in transit data [10].

II. Forecasting Street Level Traffic Time

To forecast future travel time trends, it is necessary to model it in terms of a time series model as [11]:

$$\boldsymbol{Travel\ Time} = \boldsymbol{f(time, other\ govering\ variables} \quad \textbf{(1)}$$

Based on type, the intelligent transportation system market is categorized into advanced traveler information system (ATIS), advanced traffic management system (ATMS), advanced transportation pricing system (ATPS), advanced public transportation system (APTS), and emergency medical system (EMS). The advanced traffic management system (ATMS) segment held the largest market share in 2024 due to its crucial role in optimizing traffic flow and mitigating congestion in increasingly urbanized environments. The growing adoption of ATMS solutions arises from their ability to leverage real-time data, predictive product analytics, and adaptive signal control to enhance road network efficiency and reduce travel times. Urban centers worldwide have prioritized ATMS technologies to address the escalating challenges of population growth, vehicle density, and environmental concerns. Governments and municipalities have invested heavily in these systems to improve traffic safety, minimize fuel consumption, and lower carbon emissions, aligning with goals of sustainability and smart city development [12].

III. Existing Statistical Models

The statistical machine learning models used for forecasting are presented in brevity in this section [13]-[14]:

Support Vector Machine (SVM):
Before the advent of deep learning, traditional machine learning models such as Support Vector Machines (SVM), Decision Trees, Random Forests, and K-Nearest Neighbors (KNN) were widely used for satellite object detection. These models typically relied on handcrafted features, such as texture, edges, and spectral indices, to distinguish between different objects.

The SVM classifies based on the hyperplane.
The selection of the hyperplane H is done on the basis of the maximum value or separation in the Euclidean distance d given by:

$$d = \sqrt{x_1^2 + \cdots \ldots \ldots . x_n^2} \quad (2)$$

Here,
x represents the separation of a sample space variables or features of the data vector,
n is the total number of such variables
d is the Euclidean distance

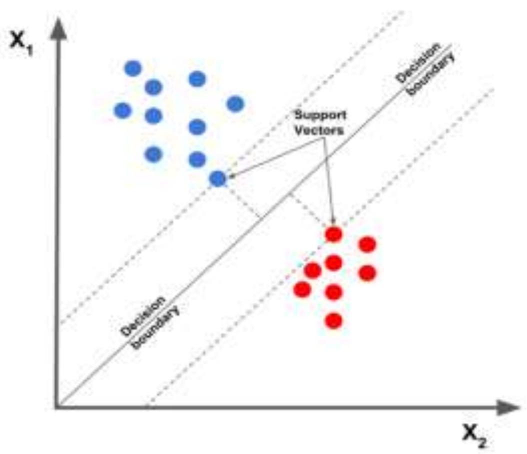

Fig.3 The SVM Model

Figure 3 depicts the SVM Model.

The (n-1) dimensional hyperplane classifies the data into categories based on the maximum separation. For a classification into one of **'m'** categories, the hyperplane lies at the maximum separation of the data vector **'X'.** The categorization of a new sample **'z'** is done based on the inequality:

$$d_x^z = Min(d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z) \quad (3)$$

Here,
d_x^z is the minimum separation of a new data sample from **'m'** separate categories
$d_{C1}^z, d_{C2}^z \ldots d_{C2=m}^z$ are the Euclidean distances of the new data sample **'z'** from m separate data categories.

For instance, SVMs are effective for binary classification tasks, such as distinguishing between urban and rural areas, while Random Forests are used for multi-class classification problems, such as land cover mapping. However, these models struggle with complex patterns in high-resolution imagery and require extensive feature engineering, which limits their scalability and accuracy

ARIMA:
In an autoregressive integrated moving average model commonly known as the ARIMA model assumes that the future value of a variable can be linearly modelled as a function previous samples of the variables and errors of prediction.

$$y_t = \theta_0 + \varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \varphi_p y_{t-p} + \cdots \ldots \ldots \ldots . \theta_q \varepsilon_{t-q} \quad (4)$$

Here,
y_t is the value of the output variable at time 't'
ε is the prediction error
θ *and* φ are called the model parameters
p *and* q are called the orders of the model

One of ARIMA's key strengths lies in its ability to handle both stationary and non-stationary data. While the ARIMA model assumes the input time series is stationary (i.e., its statistical properties like mean and variance remain constant over time), it incorporates differencing techniques to convert non-stationary data into a stationary format. This makes it highly adaptable for real-world datasets that often exhibit trends or seasonality.

Neural Networks:
Owing to the need of non-linearity in the separation of data classes, one of the most powerful classifiers which

have become popular is the artificial neural network (ANN). The neural networks are capable to implement non-linear classification along with steep learning rates. The neural network tries to emulate the human brain's functioning based on the fact that it can process parallel data streams and can learn and adapt as the data changes. This is done through the updates in the weights and activation functions.

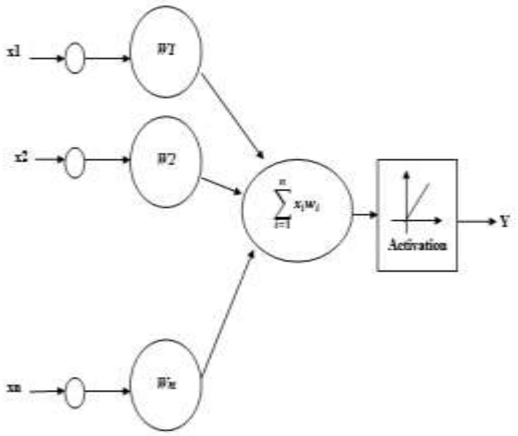

Fig.4 The ANN Model

Figure 4 depicts the ANN model.
The input-output relation of a CNN is given by:

$$y = f(\sum_{i=1}^{n} x_i w_i + b) \quad (5)$$

Here,
x denote the parallel inputs
y represents the output
w represents the bias
f represents the activation function

The neural network is a connection of such artificial neurons which are connected or stacked with each other as layers. The neural networks can be used for both regression and classification problems based on the type of data that is fed to them. Typically the neural networks have 3 major conceptual layers which are the input layer, hidden layer and output layer. The parallel inputs are fed to the input layer whose output is fed to the hidden layer. The hidden layer is responsible for analysing the data, and the output of the hidden layer goes to the output layer. The number of hidden layers depends on the nature of the dataset and problem under consideration. If the neural network has multiple hidden layers, then such a neural network is termed as a deep neural network. The training algorithm for such a deep neural network is often termed as deep learning which is a subset of machine learning. Typically, the multiple hidden layers are responsible for computation of different levels of features of the data.

Long Short Term Memory (LSTM):

The LSTM networks are a specialized type of recurrent neural network (RNN) designed to process and predict data sequences by learning long-term dependencies. Unlike traditional RNNs, which suffer from vanishing or exploding gradient problems during training, LSTMs incorporate a unique architecture with gates and memory cells that help retain important information over long periods.

The LSTM primarily has 3 gates:
1) Input gate: This gate collects the presents inputs and also considers the past outputs as the inputs.
2) Output gate: This gate combines all cell states and produces the output.
3) Forget gate: This is an extremely important feature of the LSTM which received a cell state value governing the amount of data to be remembered and forgotten.

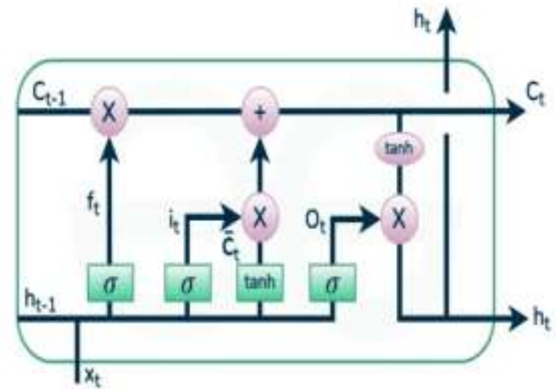

Fig.5 The LSTM Model

Figure 5 depicts the LSTM model.

The relation to forget by the forget gate is given by:

$$f = \sigma(W_f[h_{t-1}, x_t] + b_i) \quad (6)$$

Here,
f denotes forget gate activation
w_f are forget gate weights.
h_{t-1} Denotes Hidden state from the previous time step
x_t is present input.
b_i is the bias

The advantages of LSM are:

Capturing Long-Term Dependencies: LSTMs maintain long-term memory using the cell state, unlike traditional RNNs.
Mitigating Vanishing/Exploding Gradients: Gates help regulate gradient flow, enabling stable training over long sequences.
Versatility: Useful for several time series prediction problems.

However, the major challenge happens to be the problem of overfitting.

Convolutional Neural Networks (CNNs): The family of CNNs are the backbone of modern satellite object detection. CNNs automatically learn hierarchical features from raw images, eliminating the need for manual feature extraction. The Convolutional Neural Networks (CNNs) can automatically extract hierarchical characteristics from images, they have become the mainstay for image classification applications. These neural networks perform exceptionally well in applications like picture identification because they are specifically made for processing organised grid data. Convolutional, pooling, and fully linked layers are among the layers that make up a CNN's architecture. Convolutional layers identify patterns in the input image by applying filters, hence identifying local features. By reducing spatial dimensions, pooling layers preserve significant information. High-level features are integrated for categorization in fully connected layers.

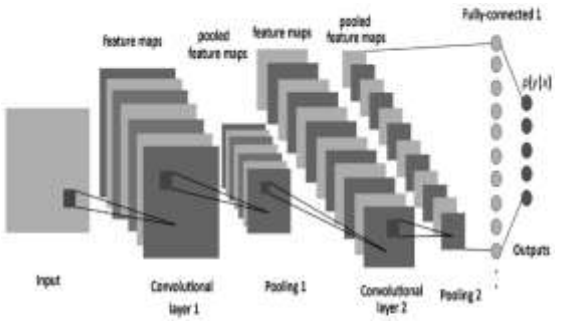

Fig.6 The CNN Model

Figure 6 depicts the CNN model.

The convolution operation is given by:

$$x(t) * h(t) = \int_{-\infty}^{\infty} x(\tau)h(t-\tau)d\tau \qquad (7)$$

Here,
x(t) is the input
h(t) is the system under consideration.
y is the output
*is the convolution operation in continuous domain

For a discrete or digital counterpart of the data sequence, the convolution is computed using:

$$y(n) = \sum_{-\infty}^{\infty} x(k)h(n-k) \qquad (8)$$

Here
x(n) is the input
h(n) is the system under consideration.
y is the output
*is the convolution operation in discrete domain

In this approach, the back propagation based neural network model has been used. A backpropagation neural network for traffic speed forecasting typically consists of an input layer, one or more hidden layers, and an output layer. The number of nodes in the input layer corresponds to the features used for prediction, The hidden layers contain nodes that learn and capture the intricate patterns within the data, while the output layer provides the predicted traffic speed. The training of a backpropagation neural network involves the iterative application of the backpropagation algorithm. During the training process, historical data is used to feed the network, and the algorithm calculates the error between the predicted and actual energy demands. This error is then propagated backward through the network, adjusting the weights and biases of the connections to minimize the prediction error. This iterative process continues until the network converges to a state where the error is minimized. Successful backpropagation neural network models for traffic speed forecasting can be integrated into energy management systems.

IV. Previous Work

A summary of noteworthy contribution in the domain is presented here:

Ukam et al. [16] proposed that the nature of paratransit services makes for increased uncertainty in trip time, leading to reported unreliability and dissatisfaction by the users. While providing travel information has proved helpful in formal bus services and has been recommended for paratransit setup, little is reported about efforts at providing information to paratransit users. This study focused on one strand of possible travel information that can be provided – Travel Time. An artificial neural network (ANN)-based model was developed to predict paratransit travel times, geared towards providing information to improve user experiences. The developed model was tested on a real-world paratransit bus route (minibus taxi) in Kumasi. A travel time survey that employed a mobile phone application was used to collect data onboard the vehicles on the study route. Two ANN models were trained. The first used only historical datasets, while the second incorporated real-time information. The results show that the model in which real-time information was included performed better than that trained with only historical data. The developed models were compared with a historical average model and a regression-based model, and the results showed that the ANN models outperformed the others. The study showed that the nature of paratransit services and the limitations of continuous data collection, notwithstanding, travel times of paratransit trips can be predicted to a reasonable level of accuracy, as can be relied upon in providing information to the users.

Maass et al. [17] proposed that estimating temporal patterns in travel times along road segments in urban settings is of central importance to traffic engineers and city planners. In this work, authors propose a methodology to leverage coarse-grained and aggregated travel time data to estimate the street-level travel times of a given metropolitan area. The main focus is to estimate travel times along the arterial road segments where relevant data are often unavailable. The central idea of our approach is to leverage easy-to-obtain, aggregated data sets with broad spatial coverage, such as the data published by travel analysis, as the fabric over which other expensive, fine-grained datasets, such as loop counter and probe data, can be overlaid. The proposed methodology uses a graph representation of the road network and combines several techniques such as graph-based routing, trip sampling, graph sparsification, and least-squares optimization to estimate the street-level travel times. Using sampled trips and weighted shortest-path routing, we iteratively solve constrained least-squares problems to obtain the travel time estimates.

Akhtar et al. [18] proposed that traffic congestion prediction has led to a growing research area, especially of machine learning of artificial intelligence (AI). With the introduction of big data by stationary sensors or probe vehicle data and the development of new AI models in the last few decades, this research area has expanded extensively. Traffic congestion prediction, especially short-term traffic congestion prediction is made by evaluating different traffic parameters. Most of the researches focus on historical data in forecasting traffic congestion. However, a few articles made real-time traffic congestion prediction. This paper systematically summarises the existing research conducted by applying the various methodologies of AI, notably different machine learning models. The paper accumulates the models under respective branches of AI, and the strength and weaknesses of the models are summarised.

Chen et al. [19] proposed that the estimation of urban arterial travel time distribution (TTD) is critical to help implement Intelligent Transportation Systems (ITS) and provide travelers with timely and reliable route guidance. The state-of-practice procedure for arterial TTD estimation commonly assumes that the path travel time follows a certain distribution without considering link correlations. However, this approach appears inappropriate since travel times on successive links are essentially dependent along signalized arterials. In this study, a copula-based approach is proposed to model arterial TTD by accounting for spatial link correlations. First, TTDs on consecutive links along one arterial in Hangzhou, China are investigated. Link TTDs are estimated through the nonparametric kernel smoothing method. Link correlations are analyzed in both unfavorable and favorable coordination cases. Then, Gaussian copula models are introduced to model the dependent structure between link TTDs. The parameters of Gaussian copula are obtained by Maximum-Likelihood Estimation (MLE). Next, path TTDs covering consecutive links are estimated based on the estimated copula models. The results demonstrate the advantage of the proposed copula-based approach, compared with the convolution without capturing link correlations and the empirical distribution fitting methods in both unfavorable and favorable coordination cases.

Sun et al. [20] proposed the design and implement a door-to-door travel time estimation framework, which aims to analyze the potential competitiveness of on-demand air taxis in Europe when competing with existing transportation modes: car, railway and traditional air transportation. The grid cell-based framework, opposed to previous studies, allows for fine-grained, high-resolution estimation of travel time lower-bounds between any points in the region of interest. Region-specific results on domination points and competition transitions of all modes are obtained and reported. The work helps to understand the

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competitiveness of on-demand air taxis through the lens of door-to-door travel time estimation. keyword: On-demand air mobility; Competition range; Grid-based framework.

The accuracy of prediction is computed as:

$$Ac = 100 - \frac{100}{M}\sum_{i=1}^{N}\frac{E-E_i|}{i}\,\% \qquad (9)$$

Here,
n is the number of errors
i is the iteration number
E is the actual value
E_i is the predicted value

V Challenges with Statistical Modelling for Predicting Street Level Travel Time:

Accurate traffic time prediction at the street level is vital for efficient urban mobility, traffic management, and real-time navigation systems. While statistical models such as linear regression, autoregressive models, and generalized linear models have been widely used for this purpose, they face several critical challenges. These limitations hinder their effectiveness in capturing the complexity and dynamics of real-world traffic, especially in dense urban environments with high variability [21] .

One of the primary challenges lies in the assumptions of linearity and stationarity inherent in many statistical models. Linear regression, for example, assumes a linear relationship between independent variables (like distance, time of day, or weather) and travel time, which often oversimplifies reality. Urban traffic is inherently nonlinear due to complex interactions among vehicles, signal systems, and unpredictable human behavior.

Another major issue is the inability to capture spatial dependencies effectively. Street-level travel time is influenced by the status of neighboring roads, intersections, and regional traffic flow. Traditional statistical models typically treat data points independently and struggle to incorporate spatial correlations unless explicitly modeled, which is both technically demanding and computationally expensive. As a result, these models often lack the granularity and sensitivity required for hyper-local predictions.

Data quality and availability also pose significant challenges. Street-level traffic prediction demands high-resolution data, such as timestamps, GPS locations, and vehicle trajectories, often supplemented by GTFS feeds or sensor networks. Statistical models are sensitive to missing, noisy, or inconsistent data, and imputation techniques may not always preserve the underlying temporal or spatial structure. Incomplete datasets lead to biased or inaccurate predictions, especially in areas with sparse sensor coverage or poor reporting infrastructure [22].

Moreover, statistical models struggle with incorporating dynamic and external factors such as accidents, weather changes, special events, or roadwork, which can cause abrupt deviations in travel time. While such events have a substantial impact on traffic flow, modeling them statistically requires complex feature engineering and often results in models that are rigid or overfitted. Unlike machine learning models, traditional statistical techniques are less adaptable to real-time anomalies or sudden changes in traffic patterns.

Scalability and computational complexity present additional limitations. Although statistical models are often praised for their simplicity, applying them to large-scale, high-dimensional datasets—especially in metropolitan areas with thousands of road segments—can become computationally intensive. Furthermore, updating these models in real-time or integrating them into live traffic management systems is often impractical without significant pre-processing and tuning [23].

VI. CONCLUSION

It can be concluded that data analysis for or Street Level Travel Time Estimation Using GTFS Features and model interpretability is critically essential. Model ineroperatibility versus performance trade-offs must be considered. While statistical models offer high interpretability, they often sacrifice predictive accuracy in favor of simplicity. For modern urban traffic systems where precision and responsiveness are crucial, this trade-off limits their application. Emerging alternatives like deep learning models can outperform statistical models in many scenarios but do so at the cost of transparency and explainability. This paper presents a comprehensive review on the need for statistical models, their pros and cons along with a summary of the most recent noteworthy contribution in the field of research.

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