Urban Arterial Traffic Volume and Travel Time Estimation with Use of Data Driven Models

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Abstract: In recent years, the development of technology and the availability of large amounts of data have transformed the way transport systems are managed, particularly through the forecasting of traffic conditions. This work aims to develop traffic prediction models, with a specific focus on traffic volume and travel time of an urban arterial. These models are based on Machine Learning algorithms, which find frequent application in the literature for various forecasting tasks. The traffic data that were utilized in the development process were sourced from a road section of Alexandras Av. in Athens. According to the results, the models are capable of accurate predictions with an acceptable fit to the data. Finally, a comparison is drawn between Machine Learning models, the BPR Volume-Delay function, and a BPR-ML hybrid approach. Ultimately, the findings reveal that Machine Learning methods exhibit superior forecasting capabilities.

Keywords: traffic forecasting, traffic volume, travel time, Gradient Boosting, BPR function.

1. INTRODUCTION

In the modern high congested urban environments, accommodating the growing traffic demand has proven to be a complex task on a short-term scale, as permanent interventions in transportation systems are time-consuming and involve significant costs. Therefore, optimal management and utilization of existing transportation networks are deemed necessary to address the challenge of rising demand.

Research has shown that predictive traffic models that can link the fundamental macroscopic traffic variables with travel times stand as pivotal tools for the optimal management of transportation systems, enhancing efficiency and also leading to safer, more viable network level traffic conditions (Vlahogianni et al. 2014). Volume-Delay functions, which are mathematical expressions correlating travel time and traffic volume within a road link, stand out as a typical example. In particular, the Bureau of Public Roads (BPR) function, has been consistently utilized as a tool for traffic modelling due to its straightforward mathematical formula and computational efficiency. In a complex spatiotemporal traffic environment, it provides a simple theoretical framework for the relationship of traffic volume and travel time without involving many variables and necessitating excessive amounts of input data (Mtoi & Moses, 2014). Additionally, one notable advantage of the BPR function lies in its ability to be adjusted to locally observed traffic volume-travel time data of specific road links, by tuning its parameters appropriately (Mehbub Anwar et al., 2011).

The question is raised whether contemporary methods, such as Machine Learning prediction models, may provide more accurate predictions compared to conventional approaches. The absence of a calibration framework for the BPR function is apparent in the pertinent literature. Originally designed for segments of highways in developed nations, the function encounters challenges when applied to diverse road infrastructures with varying characteristics such as illegal parking, road geometry, vehicle size and percentage of heavy transport (Mehbub Anwar et al., 2011; Pan et al., 2022; Saberi & Figliozzi, 2011).

The diverse characteristics of road infrastructures mentioned have a substantial influence on the intricate process of estimating the traffic variables necessary for applying the function (Mehbub Anwar et al., 2011). In particular, accurately determining the traffic capacity (C) of a road link is a complex undertaking, particularly when faced with a lack of appropriate data (Petrik et al., 2014; Saberi & Figliozzi, 2011). Lately, research has diverged from classical mathematical / analytical expressions to Machine Learning prediction models that appear less constrained by assumptions about data behaviour and are flexible and resilient to noise and missing data.

Specifically, Shallow Machine Learning models pose as viable candidates for tackling the traffic forecasting problem (Manibardo et al., 2022). Drawing again on the literature, it is also worth noting that traffic state data that are closely related to the predictor variable, are frequently utilized as input feature for these models. Common examples include the use of travel time data of previous time intervals when predicting travel time (Qiu & Fan, 2021; Zhang & Haghani, 2015, Cheng et al., 2019), or traffic volume of adjacent road links when forecasting traffic volume (Yang et al., 2017; Ying et al., 2017). Additionally, a lack of traffic prediction at network level is a common denominator among the literature (Manibardo et al.; 2022), further emphasizing the challenges of data collection pertaining to certain traffic parameters, such as traffic volume. The framework proposed in this work aims to address those issues by formulating Shallow Machine Learning models that rely solely on easily accessible data.

Also, a deliberate decision was made to explore the predictive capabilities of the models without incorporating data of temporal and spatial correlation like the ones mentioned above.

The primary objective of this study is to develop Machine Learning models that can predict traffic volume in an urban road segment, by utilizing travel time data as the only traffic parameter related feature. This approach is justified by the ease of access and abundance of travel time data, which can be collected via GPS devices, mobile apps, or other location-tracking services at a minimal cost. On the other hand, the collection of traffic volume data is more complex. It requires the installation of infrastructure such as traffic cameras and loop detectors, which involves logistical challenges and higher costs (Bae et al., 2017). Moreover, these data are usually managed by public authorities, making access more complicated. For the prediction tasks, Decision Trees (DT) and Gradient Boosting Decision Trees (GBDT) were used, two tree-based supervised Machine Learning algorithms. The models were trained on actual travel time data from Google Maps and traffic volume data from loop detectors installed on Alexandras Avenue in Athens.

Aside from its apparent utility, the task of travel time forecasting also assists in accomplishing the supplementary goal of this study, which is the comparison of contemporary Machine Learning methods with conventional approaches of correlating traffic variables, such as Volume-Delay Functions. This comparative analysis between historical and contemporary methodologies elucidates whether and to what extent predictive capabilities have advanced in the digital era. The Bureau of Public Roads (BPR) function is one of the most widely used Volume-Delay Functions and was employed as a tool for travel time prediction in this study. The assumptions inherent in the BPR function present an opportunity for comparison with the non-parametric, Machine Learning models. Lastly, a hybrid BPR-ML approach was explored in order to evaluate potential benefits of the integration of the functions modelling capabilities to previously mentioned Machine Learning models. The same traffic data were used in all of the mentioned approaches.

A distinction among data-driven methods involves categorizing them into parametric and non-parametric models. A considerable portion of the initial literature, particularly concerning traffic prediction, has explored the utilization of parametric models. These models necessitate the determination of specific parameters based on available data to yield predictions. Notable examples include Autoregressive Integrated Moving Average (ARIMA) models, Linear Regression models, Bayesian Networks, and the aforementioned Volume-Delay Functions. While these models are known for their interpretability and computational simplicity, the research community is distancing itself from traditional statistical methods due to their limitations in addressing the dynamic and non-linear nature of traffic flow. (Manibardo et al., 2022).

Non-parametric models provide a solution to the aforementioned drawbacks of statistical methods. In this context, both the structure and parameters of the models are shaped by the data itself through an automated learning process. This results in enhanced accuracy when modelling intricate and non-linear phenomena, such as traffic flow. To achieve a detailed decoding of patterns among variables through the learning process, a larger volume of data is typically required compared to statistical models. Notable models within this category encompass Neural Networks, k-Nearest Neighbours Regression, and Decision Trees. Tree-based Machine Learning models are frequently employed in the literature for predicting traffic volume and travel time due to their notable predictive accuracy, simplicity, and minimal data requirements (Janković et al., 2021; Zhang & Haghani, 2015; Cheng et al., 2019). The assessment of feature importance is another advantage of these models, offering valuable insights into the relationships of traffic variables (Yang et al., 2017 and Qiu & Fan, 2021).

The subsequent sections unfold as follows: Section 2 elucidates the theoretical framework of the chosen methodology, while Section 3 delves into the application of the method, alongside the presentation of the outcomes. Lastly, Section 4 encapsulates the primary findings and prospects for future endeavours.

2. METHOLOGICAL APPROACH

Lately, Machine Learning models have also been successfully used in combination with several analytical equations from traffic flow theory, e.g., Microscopic traffic flow models (Lighthill – Whitham – Richards - LWR model) and car following models (Lu et al. 2023). In this paper, one of the first attempts to model the volume-delay function is proposed. Other attempts include (Madadi & Homem de Almeida Correia, 2024; Bae et al., 2017). In the first example, a combination of a Graph Neural Network and a Genetic Algorithm is employed to address the User-Equilibrium Traffic Assignment Problem in road networks. The BPR function serves as the readout function for calculating total travel times, similar to performing a graph regression task. In the latter case, a Multilayer Perceptron Neural Network is used to achieve long-term traffic volume and truck percentage estimates. Consequently, adjusted volume-to-capacity ratios are proposed, by incorporating the aforementioned predictions, and alongside a transformation of the BPR function into various curve-fitting models, travel time estimates in hypothetical traffic conditions of construction zones are achieved.

Decision Trees stand as a fundamental algorithm in Shallow Machine Learning, adept at both classification and regression tasks. While Decision Trees boast advantages, such as high interpretability, ease of visualization, and effectiveness in handling complex, non-linear problems, they encounter limitations. Decision Trees can be prone to overfitting the data, especially in complex scenarios. The top-down approach used by the algorithm may not always lead to the optimal decision tree structure, potentially affecting its performance.

To overcome some of the aforementioned limitations, a pairing of the Decision Trees algorithm with ensemble learning methods, such as boosting, proves beneficial. One such application of this synergy is seen in the Gradient Boosting Decision Trees (GBDT) algorithm. At its core, this algorithm revolves around Decision Trees. The utilization of the Gradient Boosting technique enhances predictive accuracy by progressively introducing Decision Trees into the model. The final prediction is obtained by aggregating the predictions of all weak learners.

An alternative approach for the prediction of travel time proposed by the modelling framework of this study is the BPR function. Travel time stands as a fundamental consideration when determining a commute within a road system, intricately tied to the traffic flow of a road segment. To describe this phenomenon, Volume-Delay Functions (VDFs) have been developed. One widely known function is the Bureau of Public Roads Function (BPR), developed by the Bureau of Public Road in the 1960s as part of the Highway Capacity Manual.

$$T = T_{ff}\left(1 + \alpha\left(\frac{V}{C}\right)^{\beta}\right) \quad (1)$$

Parameter α of the BPR function expresses the ratio of travel time under free-flow conditions to the corresponding time under maximum traffic capacity conditions. Meanwhile, parameter β expresses the rate of change from free-flow conditions to congested conditions. Higher values of the β parameter imply shorter time delays under low traffic volume (Mahdi et al., 2022; Pan et al., 2022). This results in the delayed recognition of traffic congestion. Typically, the parameters α and β are assigned values of 0.15 and 4, respectively. However, practical applications of the function, as indicated by Mahdi et al. (2022), involve a diverse set of parameter values

As mentioned in earlier sections, BPR function requires a calibration process for parameters α and β. For this purpose, the least squares method is proposed, a widely used technique for fitting functions. Pythons SciPy library employs the Levenberg-Marquardt algorithm to adjust function parameters and minimize the sum of squared residuals. This process ensures a best-case scenario for the prediction outcome of the BPR function, particularly beneficial when uncertainty exists regarding specific function variables. For instance, in this study, only an approximate estimate of road traffic capacity (C) could be derived from the available data.

3. IMPLEMENTATION AND RESULTS

3.1 Data collection and pre-processing

The models were developed using traffic volume and travel time data obtained from two selected locations on Alexandras Avenue in central Athens. These locations are equipped with loop detectors, spaced at an approximate distance of 2.3 km. The first sensor, labelled MS423, is situated at geographical coordinates: (37.98706952, 23.75875395), while the second sensor, MS407, at: (37.9914926, 23.73333264).

Hourly traffic volume data for 80 days were collected from the databases of the National Technical University of Athens (NTUA) for the specified loop detectors. For each month from December 2022 to March 2023, 20-day intervals were selected, during which the detectors recorded data without any malfunctions. For the examined road segment of Alexandras Av. between the two detectors, travel time data (duration) were

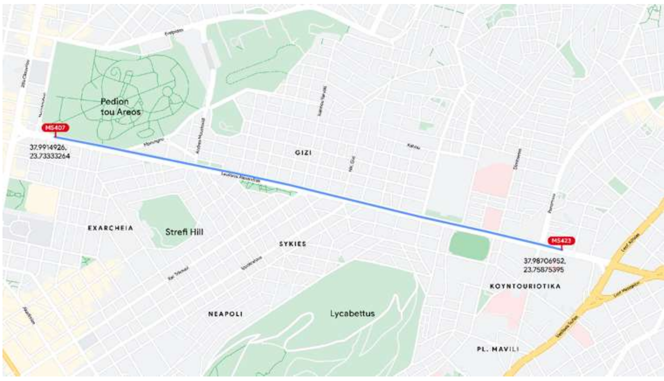

Figure 1. Geographical representation of Alexandras Avenue road segment.

sourced from Google Maps databases. The data were retrieved from https://outscraper.com for the same hourly intervals mentioned earlier. In addition to actual hourly travel time data, the dataset included the estimated range of travel time, represented by two duration values: a minimum estimate (duration_min) and a maximum estimate (duration_max). All travel time data were recorded in minutes.

Next, to facilitate the identification of patterns in the data, a subset of relevant input features was selected based on which the algorithms categorized the data. In Table 2 the features that were utilized in the models are presented.

Table 1
Input features of ML models.

Weekday	The value of 1 is assigned for weekday and 0 for weekends
Rush_hour	The value of 1 is assigned for morning peak hours (8:00 - 11:00), 2 for afternoon peak hours (15:00 - 19:00), and 0 for all other hours of the day.
W+R2	Combination of the two features above. For weekdays, values of 1 or 2 are assigned depending on the peak hour. For the weekend, it takes the value 0 regardless of the observation time.
min_max	The difference between the maximum and minimum travel time estimates from Google Maps database (duration_max - duration_min).
diff	The difference of two consecutive travel time data points.

As mentioned earlier, the goal of this study is to forecast travel time and traffic volume using Machine Learning algorithms, specifically Decision Trees and GBDT. The development process of the algorithms was largely identical across both prediction scenarios. Traffic volume and travel time were not only the target variables for the models, but were also utilized as features to predict one another. The exact features that were used in each model will be presented subsequently.

Travel time prediction models exhibited acceptable prediction errors and demonstrated good fit to the data with minimal experimentation. In the context of traffic volume prediction, all tested feature combinations failed to yield the desired outcome. Notably, the normalization of traffic volume data in the database significantly contributed to reducing prediction errors. Using the logarithm of traffic volume data resulted in decreased variance in the database. This normalization technique is commonly applied in Machine Learning models, particularly when certain algorithms are sensitive to the scale of the data points. In order to evaluate the models prediction accuracy, the predicted traffic volume values were converted back to their original scale. To further mitigate the error, a statistical analysis of the database was conducted. The nearly identical traffic volume values of loop detectors MS407 and MS423 were averaged and grouped according to their corresponding travel time values found in the database. Next, the statistical measures for traffic volume values, specified in Table 2, were calculated.

Table 2
Traffic volume statistics per travel time class.

Travel Time (minutes)	Count	Median	Mean	Standard Deviation
4	496	280.75	334.17	213.05
5	295	737.50	780.12	263.85
6	279	1031.00	1000.73	153.00
7	249	1063.00	1054.40	82.15
8	220	1057.75	1036.74	96.47
9	177	1041.50	1032.03	83.24
10	96	1040.00	1042.26	69.13
12	36	1045.25	1034.42	119.58

During the preparation process, a random split of the samples was performed, allocating 80% for model training (train set) and 20% for testing (test set).

Next, using the same database, the prediction of travel time values for the same road segment was carried out using the BPR function. Given that the BPR function pertains to a specific road link, the approach adopted involved using the average traffic volume of both detectors. An algorithm was developed, utilizing the least squares method, to fit the function to the existing data. The initial values of α and β were set at the common values of 0.15 and 4 respectively.

Subsequently, free-flow travel time (T_{ff}) and road traffic capacity (C) were approximately estimated based on the existing data. The minimum observed travel time value in the data (Tff = 4 minutes) was designated as the free-flow travel time. Practical factors, such as traffic signals, the presence of a dedicated bus lane, and illegal parking in the right lane, significantly influence the actual road capacity. The exact calculation of this variable was deemed infeasible with the available data. It was also assumed that, for certain time intervals, demand exceeded the actual traffic capacity of the road (V/C > 1). Various traffic capacity values between the mean and maximum traffic volume values observed in the database were tested for the function. The actual road traffic capacity value was selected as 1050 vehicles, corresponding roughly to an average travel time of 10 minutes in the database.

The optimization logic of the algorithm is to generate the smallest possible error, irrespective of whether the parameter values fall within "logical" bounds. With each new initial traffic capacity value, the algorithm provided different values for the parameters α and β, yet the final prediction result remained consistent. After establishing the aforementioned terms of the BPR function, the final values of parameters α and β were devised by minimizing the error between the predicted values of the function and the actual travel time values. For the evaluation of the model, the same error and goodness-of-fit metrics were applied. Finally, a hybrid approach was carried out by combining the predictions of BPR and Machine Learning models. The travel time predictions generated by these models were averaged and evaluated for accuracy.

3.3 Results

Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) were utilized to evaluate the prediction accuracy, while R^2 was employed to evaluate the models fit to the data. Table 3 showcases performance metrics and the importance level of each feature in the Machine Learning models designed for predicting traffic volume. Subsequent to these tables, diagrams depicting predicted versus actual values (Fig. 2) are provided for both loop detectors, initially with the GBDT model.

Table 3
Performance metrics of ML models for traffic volume prediction.

Metric	Decision Trees	GBDT
R^2	0.79	0.80
MAE	95.88	95.88
MAPE	14.55%	14.55%
Feature importance		
duration (min)	0.8056	0.8092
min_max	0.0960	0.0889
Weekday	0.0733	0.0796
Rush hour	0.0129	0.0059
W+R2	0.0017	0.0037
diff	0.0105	0.0127

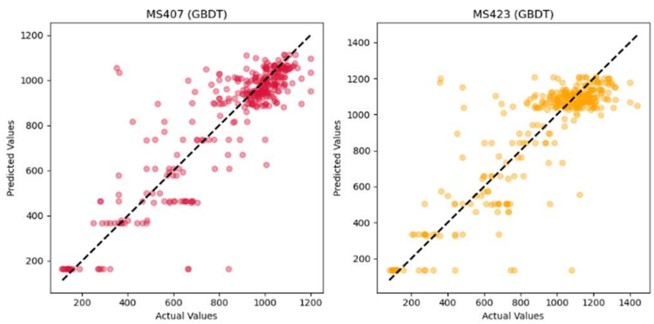

Figure 2. Predicted versus actual traffic volume values for both detector loops (GBDT).

Table 4 presents the results for predicting travel time using both ML and BPR-based models. These are visually complemented by Figures 3 providing a graphical representation of the findings, similar to the approach utilized for traffic volume.

Table 4
Performance metrics of trained models for travel time prediction.

Metric	Decision Trees	GBDT	BPR	BPR-DT	BPR-GBDT
R^2	0.82	0.76	0.48	0.68	0.66
MAE	0.69	0.69	1.08	0.86	0.89
MAPE	9.75%	9.75%	16.78%	12.87%	13.42%
Feature importance					
MS423	0.1021	0.0942			
MS407	0.6768	0.6865			
Weekday	0.1299	0.1018			
W+R2	0.0912	0.1175			

The two Machine Learning models appear to exhibit similar performance, both in terms of prediction accuracy and fit to the data, regardless of the prediction variable. Finally, as expected, travel time proved to be the feature with the greatest importance on traffic volume prediction. Conversely, in the

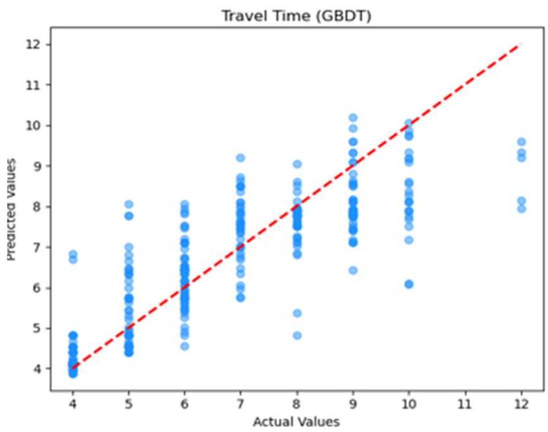

Figure 3. Predicted versus actual travel time values (GBDT)

case of travel time, the volume data of loop detector MS407 emerged as the most influential variable.

The BPR function also demonstrated an acceptable MAPE in predicting travel time, albeit higher compared to Machine Learning methods. The R^2 metric indicates that the BPR function struggles to accurately capture the patterns observed in the data. This is further confirmed by Fig. 15. Particularly noticeable is the functions inability to predict travel time accurately at the maximum values of the database (9-12 minutes). By combining the travel time predictions of ML and BPR models, a small improvement is attained, although Machine Learning models still exhibit superior accuracy.

4. CONCLUSIONS

After summarizing the findings of this work, several key conclusions emerge. The Machine Learning models developed, consistently demonstrated impressive predictive capabilities for the targeted traffic variables in every scenario, despite their straightforward and simplistic design. Conversely, the BPR function-based prediction methods proved to be less effective, exhibiting lower accuracy in predictions and struggling to fit to the available data. Even with the application of the least squares optimization method, the travel time predictions using the BPR function still incurred greater errors compared to the Machine Learning approaches.

In light of the above, it can be deduced that employing comparable methods might prove effective in estimating traffic volume data, which is often more difficult to collect. In the specific case of this study, forecasting traffic volume values for a road link was achieved solely with knowledge of easily accessible travel time data. This underscores the notion that simple models with a concise set of variables can serve as valuable tools, though they may not universally represent the optimal strategy for every traffic prediction scenario.

It remains unclear whether the models employed in this study can replicate a similar predictive performance in different road segments. The application of analogous methodologies and models to different road sections could provide clarity on this matter. Expanding the scope of traffic forecasting by introducing additional variables could be a fruitful endeavour. Integrating weather data, accident statistics, impact of traffic signals, and other factors into Machine Learning models, coupled with established traffic parameters, holds the potential to enhance predictive capabilities. The models developed in this work could be refined by incorporating more extensive and diverse datasets, enabling additional feature combinations. In conjunction with the above, exploring the application of Deep Learning approaches also stands as a promising direction.

Lastly, the establishment of a comprehensive calibration framework for the BPR function, coupled with a rigorous definition of its terms and underlying assumptions, would significantly amplify its effectiveness as tools for traffic analysis. Only through this process could the capabilities of Volume-Delay Functions be integrated for the generation of Physics-Informed Machine Learning models. With technology advancing swiftly, it is evident that capitalizing on the ever-expanding wealth of information for the development of innovative traffic engineering applications should be central to both research endeavours and the management of transportation systems.

REFERENCES

R. E., & Politis, I. (2021). Fitting Volume Delay Functions under interrupted and uninterrupted flow conditions at Greek urban roads. *European Transport - Trasporti Europei*, *83*. https://doi.org/10.48295/ET.2021.83.7

Barros, J., Araujo, M., & Rossetti, R. J. F. (2015). Short-term real-time traffic prediction methods: A survey. *2015 International Conference on Models and Technologies for Intelligent Transportation Systems, MT-ITS 2015*, 132–139. https://doi.org/10.1109/MTITS.2015.7223248

Behrooz, H., & Hayeri, Y. M. (2022). Machine Learning Applications in Surface Transportation Systems: A Literature Review. *Applied Sciences (Switzerland)*, *12*(18). https://doi.org/10.3390/app12189156

Cheng, J., Li, G., & Chen, X. (2019). Research on travel time prediction model of freeway based on gradient boosting decision tree. *IEEE Access*, *7*, 7466–7480. https://doi.org/10.1109/ACCESS.2018.2886549

IEEE Staff. (2018). *2018 International Conference on Information, Communication, Engineering and Technology (ICICET)*. IEEE.

Janković, S., Uzelac, A., Zdravković, S., Mladenović, D., Mladenović, S., & Andrijanić, I. (n.d.). TRAFFIC VOLUMES PREDICTION USING BIG DATA ANALYTICS METHODS. *International Journal for Traffic and Transport Engineering*, *2021*(2), 184–198. https://doi.org/10.7708/ijtte2021.11(2).01

Laña, I., Sanchez-Medina, J. J., Vlahogianni, E. I., & Ser, J. Del. (2021). From data to actions in intelligent transportation systems: A prescription of functional requirements for model actionability. *Sensors (Switzerland)*, *21*(4), 1–34. https://doi.org/10.3390/s21041121

Liu, Y., Zhang, N., Luo, X., & Yang, M. (2021). Traffic Flow Forecasting Analysis based on Two Methods. *Journal of Physics: Conference Series*, *1861*(1). https://doi.org/10.1088/1742-6596/1861/1/012042

Liu, Z., Li, Z., Wu, K., & Li, M. (2018). Urban Traffic Prediction from Mobility Data Using Deep Learning. *IEEE Network*, *32*(4), 40–46. https://doi.org/10.1109/MNET.2018.1700411

Maerivoet, S., & De Moor, B. (2005). *Transportation Planning and Traffic Flow Models*.

Mahdi, M. B., Alrawi, A. K., & Leong, L. V. (2022). Compatibility between delay functions and highway capacity manual on Iraqi highways. *Open Engineering*, *12*(1), 359–372. https://doi.org/10.1515/eng-2022-0022

Manibardo, E. L., Lana, I., & Ser, J. Del. (2022). Deep Learning for Road Traffic Forecasting: Does it Make a Difference? *IEEE Transactions on Intelligent Transportation Systems*, *23*(7), 6164–6188. https://doi.org/10.1109/TITS.2021.3083957

Marshall, N. L. (2018). Forecasting the impossible: The status quo of estimating traffic flows with static traffic assignment and the future of dynamic traffic assignment. *Research in Transportation Business and Management*, *29*, 85–92. https://doi.org/10.1016/j.rtbm.2018.06.002

Mehbub Anwar, A. H. M., Fujiwara, A., & Zhang, J. (n.d.). *Estimation of BPR Function for Dhaka City by Incorporating the Influence of Illegal On-Street Parking and Street-Occupancy*.

Pan, Y., Guo, J., Chen, Y., Abbasi, M., List, G., & Zhou, X. (n.d.). *A review of volume-delay functions: Connecting theoretical fundamental, practical deployment and emerging applications A review of volume-delay functions: Connecting theoretical*. https://ssrn.com/abstract=4143355

Petrik, O., Moura, F., & De Abreu E Silva, J. (2014). The influence of the volume-delay function on uncertainty assessment for a four-step model. *Advances in Intelligent Systems and Computing*, *262*, 293–306. https://doi.org/10.1007/978-3-319-04630-3_22

Qiu, B., & Fan, W. (2021). Machine learning based short-term travel time prediction: Numerical results and comparative analyses. *Sustainability (Switzerland)*, *13*(13). https://doi.org/10.3390/su13137454

Saberi, M., & Student, G. (n.d.). *A Study of Freeway Volume-to-Capacity Ratio Based Travel Time Approximations Using Archived 1 Loop Detector Data 2 3*.

Suh, S., & John Kim, T. (1990). A HIGHWAY CAPACITY FUNCTION IN KOREA: MEASUREMENT AND CALIBRATION. In *Tmnspn. Res.-A* (Vol. 3).

TRB. (2011). *Dynamic Traffic Assignment: A Primer*. www.TRB.org

Vlahogianni, E. I., Karlaftis, M. G., & Golias, J. C. (2014). Short-term traffic forecasting: Where we are and where we're going. *Transportation Research Part C: Emerging Technologies*, *43*, 3–19. https://doi.org/10.1016/j.trc.2014.01.005

Wang, Y., Zhang, D., Liu, Y., Dai, B., & Lee, L. H. (2019). Enhancing transportation systems via deep learning: A survey. In *Transportation Research Part C: Emerging Technologies* (Vol. 99, pp. 144–163). Elsevier Ltd. https://doi.org/10.1016/j.trc.2018.12.004

Wu, X. B. (n.d.). *Characterization and calibration of volume-to-capacity ratio in volume-delay functions on freeways based on a queue analysis approach Food supply chain management View project DTALite 2.0 strategic and semi-dynamic transportation flow assignment and simulation View project*. https://www.researchgate.net/publication/347967287

Yang, S., Wu, J., Du, Y., He, Y., & Chen, X. (2017). Ensemble Learning for Short-Term Traffic Prediction Based on Gradient Boosting Machine. *Journal of Sensors*, *2017*. https://doi.org/10.1155/2017/7074143

Yuan, T., Da Rocha Neto, W., Rothenberg, C. E., Obraczka, K., Barakat, C., & Turletti, T. (2022). Machine learning for next-generation intelligent transportation systems: A survey. *Transactions on Emerging Telecommunications Technologies*, *33*(4). https://doi.org/10.1002/ett.4427

Zhang, Y., & Haghani, A. (2015). A gradient boosting method to improve travel time prediction. *Transportation Research Part C: Emerging Technologies*, *58*, 308–324. https://doi.org/10.1016/j.trc.2015.02.019