Traffic Estimation of Various Connected Vehicle Penetration Rates: Temporal Convolutional Network Approach

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***Abstract*— Traffic estimation using probe vehicle data is a crucial aspect of traffic management as it provides real-time information about traffic conditions. This study introduced a novel framework for traffic density estimation using Temporal Convolutional Network (TCN) for time series data. The study used two datasets collected from a three-leg intersection in Greece and a four-leg intersection in Germany. The model was built to predict the density in an approach of the signalized intersection using features extracted from the other approaches. The results showed that the highest accuracy was achieved when only probe vehicle data was used. This implies that relying solely on probe vehicle data from two approaches can effectively predict traffic density in the third approach, even when the Market Penetration Rate (MPR) is low. The results also indicated that having Signal Phase and Timing (SPaT) information may not be necessary for high accuracy in traffic estimation and that as the MPR increases, the model becomes more predictable.**

***Index Terms*— Deep learning, probe vehicles, traffic density, congestion, temporal convolutional network.**

I. INTRODUCTION

THE continuous progress in communications, computing, Connected and Automated Vehicles (CAVs), and the Internet of Things (IoT) has expanded the possibilities for intelligent transportation systems. As a result of these technological advancements, the need for various types of data, such as traffic, travel times, congestion times, traffic monitoring, and movement trends, has become increasingly diverse. Consequently, there is an urgent need to explore and implement new methods for collecting data on traffic volume on roads [1], [2].

Traffic density estimation is a crucial aspect of transportation planning and traffic management. Accurate traffic density estimation is essential for the efficient use of road infrastructure, reducing congestion, and improving traffic safety [3], [4]. There are various methods for estimating traffic density, including traditional methods such as loop detector data and video-based methods, as well as newer methods such as GPS-based data and floating car data [5], [6].

Traffic density estimation plays an important role in advancing CAVs for several reasons [7], [8]. First, it can improve traffic management by optimizing traffic density and reducing congestion, which can improve the performance of CAVs. Second, CAVs rely on real-time traffic information to make safe and efficient driving decisions. Accurate traffic density estimation can help ensure that CAVs have access to the most up-to-date traffic information, improving safety for all road users. Third, it can improve energy efficiency and optimize energy usage by adapting to real-time traffic conditions. Accurate traffic density estimation can help CAVs make more efficient driving decisions, leading to improved fuel efficiency and reduced emissions. Fourth, it can improve mobility as accurate traffic density estimation can help improve the mobility of CAVs by allowing them to navigate the road network more efficiently. This can help reduce travel times and improve travel reliability for CAVs. Last, accurate traffic density estimation can help plan and model the traffic density in urban areas and highways. This can help in better understanding the traffic dynamics and by this, improve the planning of the transportation infrastructure.

The MPR for Connected Vehicles (CVs) can impact traffic density estimation [9], [10]. As the number of CVs on the road increases, more real-time data will be available to traffic management systems, which can help improve traffic density estimation accuracy. Additionally, as more CVs communicate with each other and traffic management systems, they can help reduce congestion and improve traffic density, further increasing the demand for CVs and increasing the market penetration rate. In addition, the accuracy of traffic density estimation can also affect the demand for CVs. Poor traffic density estimation can lead to CVs being less efficient and unsafe, decreasing the demand for these vehicles and, thus, decreasing the market penetration rate.

Road network complexity and traffic congestion depend on time, location, and heterogeneous traffic patterns. As a result, different parts of the road often have unique, time-varying traffic patterns, making it challenging to process and model

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traffic data [6], [11]. Therefore, various deep learning and machine learning techniques, which can handle large amounts of historical and real-time stochastic data, are utilized to predict traffic density at various road infrastructures.

Collecting traffic data is an important step in understanding and managing the density of vehicles on roads and highways [12], [13], [14]. Various methods for collecting this data include manual counts, automated sensors, and GPS tracking. Manual counts involve physically counting vehicles at a specific location and can provide detailed information about traffic density and patterns. Automated sensors, such as loop detectors and video cameras, can continuously monitor traffic density and provide real-time data. GPS tracking, through mobile devices or dedicated tracking devices, can provide information on the movement of vehicles and can be used to infer traffic patterns and congestion. Each method has its own advantages and disadvantages, and the choice of method will depend on the specific needs and resources of the project. Understanding the methods of data collection is crucial for the accurate measurement and analysis of traffic density, which in turn is essential for the effective planning and management of transportation infrastructure [12], [13], [14].

Collecting traffic data using drones, also known as unmanned aerial vehicles (UAVs), is an innovative and increasingly popular method for monitoring and analyzing traffic density [14], [15]. Drones equipped with cameras and other sensors can capture detailed images and video of traffic, including the number and types of vehicles and the speed and direction of travel. This data can be used to generate real-time traffic maps, identify bottlenecks, and measure the effectiveness of traffic management strategies. Additionally, drones can provide a unique perspective on traffic density, allowing for the analysis of traffic patterns in hard-to-reach areas such as bridges, tunnels, and highways.

This study introduced a novel framework for traffic density estimation using Temporal Convolutional Network (TCN) for sequential time series data. One of the main advantages of TCNs is their ability to handle long-term dependencies in sequential data [16], [17], [18]. This study used two datasets collected from a three-leg intersection in Greece and a four-leg intersection from Germany. The model was built to predict the density in an approach of the signalized intersection using features extracted from the other approaches.

II. Related Work

Various studies have been conducted to estimate traffic flow and density using different data collection methods. It is important to note that the choice of method for traffic flow and density estimation depends on the specific needs and constraints of the project, as well as the availability of data. Therefore, it is important to carefully evaluate the suitability of different methods and to properly utilize the available sources. One widely used method for traffic density estimation is the Kalman filter, which is a mathematical tool for estimating the state of a system based on noisy measurements. The Kalman filter has been applied to traffic density estimation in various studies, including [8], [19]. Another method for traffic flow estimation is the Macroscopic Fundamental Diagram (MFD), which describes the relationship between traffic flow and density on a network level. The MFD has been used in various studies, including [7], [20], [21].

Various studies have been conducted to estimate traffic density and congestion using different data modalities, such as Bluetooth travel time sensors, anonymous call data, GPS trajectories, license plate recognition, mobile sensors, and social media data [22], [23], [24]. In [25], authors presented case studies measuring the sampling rate of Bluetooth sensors on highway segments in Maryland and Delaware, with results showing an average hourly Bluetooth sampling rate of 2% to 8% of vehicles. Caceres et al. [3] proposed models for inferring the number of vehicles moving from one cell to another using phone call data and tested them on intercell boundaries with different traffic backgrounds and features. Zhan et al. [26] developed various frameworks using machine learning and license plate recognition data for citywide traffic volume prediction, link-based traffic state estimation, and lane-based real-time queue length estimation, respectively. Experimental results demonstrated that the proposed framework could significantly improve citywide traffic volume prediction. Liu and Ma [27] described a real-time arterial data collection and archival system and an innovative algorithm for time-dependent arterial travel time estimation. Mo et al. [28] proposed a new vehicle speed profile estimation model using license plate recognition data. Genser et al. [29] proposed a simple yet efficient multiple linear regression model that fuses information from thermal cameras, video data, and travel times from the Google Distance Matrix API for arterial traffic state representation. Mei et al. [30] used enhanced semi-supervised clustering algorithms to identify probe vehicle trajectories in a mixed traffic corridor. Hiribarren and Herrera [31] proposed a method to estimate traffic states on arterials based on trajectory data, and Wang et al. [4] proposed a traffic congestion estimation framework using Twitter data. Aslam et al. [32] demonstrated that vehicular GPS taxi network data can be used to infer general traffic patterns in urban areas.

Using advanced techniques, Zheng et al. [33] applied a gradient-enhanced regression tree (DSTO-GBRT) for short-term traffic density prediction. They used electronic registration identification (ERI) to gather vehicle information, and their results showed promising insights in rush hour. Zhang et al. [34] combined Generative Adversarial Net (GAN) with graph CNN to address the blurry prediction issue and simultaneously predict traffic conditions in multiple future time intervals.

However, to the best of our knowledge, this is the first paper that uses TCNs model to infer traffic density in an intersection's approach using various MPRs of probe vehicle data from other intersection's approaches. The second crucial contribution of this study is investigating the effect of various scenarios on the accuracy of real-time traffic estimation. The problem was divided into three scenarios labelled as Scenario 1, 2, and 3. In Scenario 1, the model was given access to both probe vehicle data (from CVs) and SPaT information from the controller. In Scenario 2, the model was only given access to the probe vehicle data. Lastly, in Scenario 3, the model was given access to the probe vehicle data, SPaT information, and memory that saved five previous observations from the probe vehicle data. The study also tested the framework in two cases: three- and four-leg signalized intersection.

The practical significance of estimating traffic on one leg of an intersection based on information gathered from the other legs is underscored by its potential to enhance both traffic management and overall road safety. While traffic observations through CAVs in one leg offer valuable real-time data, relying solely on this source could result in blind spots and incomplete coverage, particularly in complex urban settings where communication disruptions can occur. By leveraging data from neighbouring legs of the intersection, the estimation process gains robustness and reliability. This approach becomes vital for accurately identifying congestion patterns, fine-tuning signal timings, and promptly responding to emergencies. Furthermore, the incorporation of data from multiple legs ensures a holistic representation of traffic conditions, accounting for a diverse array of road users, such as pedestrians and cyclists, and varying vehicle types. Consequently, this multi-leg approach transcends the limitations of single-source reliance, mitigating the risks of data gaps and fostering a more effective and dependable traffic estimation system that is crucial for optimizing intersection management and safety protocols. As this analysis lacks literature, this study will fill these gaps.

III. Methodology

A. Overview

This study aims to develop a real-time model for traffic density estimation using probe data. Figure I shows our proposed methodology as a framework. In general, we sampled a dataset of vehicles at a signalized intersection to create various rates of CVs market penetration. For each sample, we extracted ten different features that only depends on one sensor data (i.e., drones in our case). Consequently, we divided each sample into training and testing datasets to train and validate a TCN model that can be used for real-time prediction.

B. pNEUMA Dataset (T-Intersection)

The rise of sharing information and big data has led to a desire for more predictable and manageable mobility through better data utilization and resource use. This requires new methods of collecting traffic data, as the traditional methods of using fixed sensors or GPS devices are not effective enough in congested urban areas due to low coverage and high measurement errors. *pNEUMA* is an experiment that creates a comprehensive dataset of congestion by using ten drones to record traffic in a congested 1.3 km^2 area with 100 km of road network, 100 busy intersections, and half a million trajectories [14]. The use of UAVs in this multi-modal urban environment allows for deep examination of crucial traffic issues. This open-science project creates a unique and unprecedented observation of traffic congestion, offering numerous opportunities for researchers worldwide to use and test their models [14].

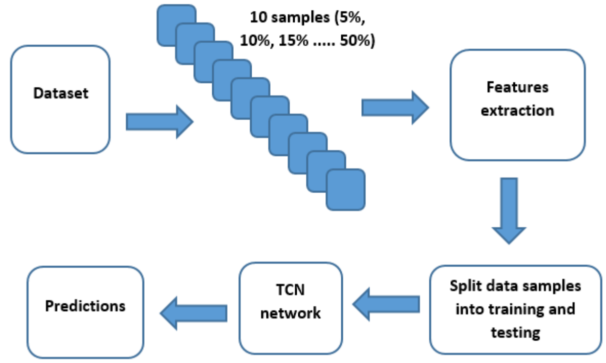

Fig. 1. Proposed framework for traffic density estimation.

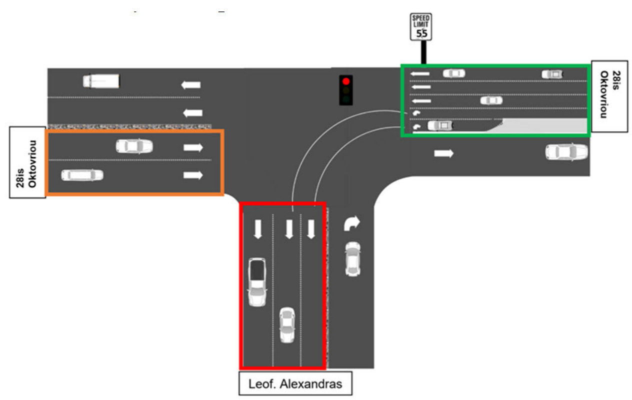

Fig. 2. Study area of a 3-way signalized intersection in athens, greece.

TABLE I
The Total Number of Vehicles in Each Polygon

Vehicle Type	Green	Orange	Red
Light- & medium-duty	491	233	448
Motorcycle	237	120	168
Heavy-duty	8	5	9
Bus	14	8	11
Total	750	366	636

In this study, a 14-minute video was recorded by a drone at a 3-way signalized intersection in Athens, Greece, as shown in Figure 2. The video showed the approach of three roads: Leof. Alexandras Road (west-bound to 28is Oktovriou Road) represented by a 300m red polygon, 28is Oktovriou Road (north-bound to Leof. Alexandras Road) represented by a 100m yellow polygon, and 28is Oktovriou Road (south-bound to 28is Oktovriou Road) represented by a 100m green polygon. The intersection was filmed from a high point in sunny weather. The intersection design has 5 lanes for the green polygon (including a left-turn pocket), 3 for the red one, and 2 for the yellow one. The red polygon has two extra traffic signals and the speed limit for all polygons is 55 km/h. The total number of vehicles in each polygon divided by the vehicle class during the monitoring period is shown in TABLE I. For simplicity, we used this dataset of three-leg intersection as a pilot case study to extensively develop the framework.

C. InD Dataset (Four-Leg Intersection)

We used this dataset to test our proposed framework on a four-leg intersection and with data with longer period. The inD dataset [15] includes trajectories of more than 11,500 road users, which are beside cars, trucks, and busses: more than 5000 VRUs such as pedestrians and bicyclists. The trajectories are extracted from drone video recordings made at German intersections in Aachen from 2017 to 2019. At four different locations, recordings were taken with a typical duration of around 20 minutes covering intersection areas of 80×40 meters to 140×70 meters. The speed limit is at 50 km/h and walkways exist. Apart from that, the measurement locations differ in terms of intersection shape, the number and types of lanes, right-of-way rules, traffic composition and kind of interaction.

In this study, we used data from the intersection at the *Frankenburg* near the city centre, which has four legs. Directly next to the crossing is a zebra crossing and many parking lots. At the intersection the right before left rule applies [15]. Due to the location in a residential area and at a park, there is a high number of cyclists and pedestrians. While the vehicles and cyclists interact with each other mainly at the intersection, the interaction with pedestrians takes place primarily at the zebra crossing. In addition, traffic is affected by vehicles moving in or out of parking spaces. We ignored the pedestrian crossing the road and included all other modes of transportation on the road. Figure 3 shows Frankenburg intersection in Aachen [15].

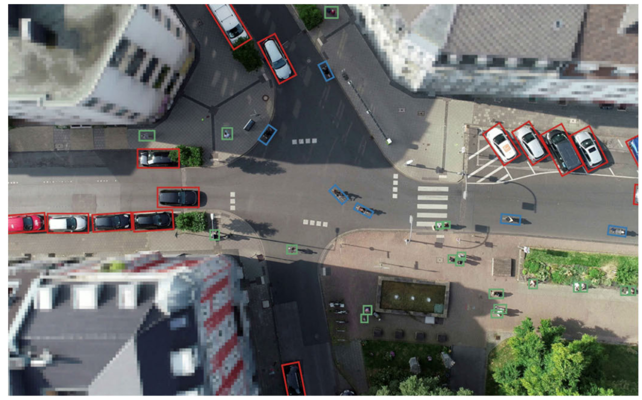

Fig. 3. Frankenburg intersection, Aachen.

D. Feature Extraction

The model uses various sample percentages as inputs starting from 5% to 50% with 5% increment. The data sample taken from the drones and can be considered as probe-vehicle data (e.g., CVs). The data is obtained by randomly selecting the sample from the actual measurements, which were acquired in the experimental campaign described in Dataset section. For each sample, we extracted the following features:

- **Target:** The total number of vehicles from the orange polygon plus the green polygon for each second, which was used as the output in the model.
- **Feature 1:** The number of sample vehicles in the orange and green polygon for each second.
- **Feature 2:** The number of sample vehicles in the orange polygon for each second.
- **Feature 3:** The number of sample vehicles in the green polygon for each second.
- **Feature 4:** Passed green time for the orange polygon, where 0 is not green and once the signal turns green, the feature starts counting from 1.
- **Feature 5:** Passed green time for the green polygon, where 0 is not green and once the signal turns green, the feature starts counting from 1.
- **Feature 6 to Feature 10:**Historical number of sample vehicles in the orange and green polygon at each time observation (t_i) (i.e., $t_{i-1}, t_{i-2}, t_{i-3}, t_{i-4}$, and t_{i-5}).

The passed green time is the longest time the vehicles would ever sit at a red light, which means the time it takes for the traffic light to change from red to green. In this study, the data was divided into a training and testing dataset. About 70% of the data was utilized for training the model and the remaining 30% was used for validation.

E. Temporal Convolutional Network (TCN)

A temporal convolutional network (TCN) is a type of deep learning architecture that is specifically designed to process sequential data, such as time series data [16], [17], [18]. TCNs are built on the same principles as convolutional neural networks (CNNs) but are modified to handle sequential data. In a TCN, the input data is passed through a series of layers, each of which applies a convolution operation to the data. The convolution operation is a mathematical operation that allows the network to extract features from the input data. The output of each layer is then passed through a non-linear activation function, such as a rectified linear unit (ReLU), before being passed to the next layer [16], [17], [18].

One of the main advantages of TCNs is their ability to handle long-term dependencies in sequential data. In traditional recurrent neural networks (RNNs), such as the long short-term memory (LSTM) network, the hidden state is passed through multiple time steps, which can lead to vanishing gradients and make it difficult for the network to learn long-term dependencies [16], [17], [18]. Although RNN is a typical model that can be used for sequence series data, however training the model might be relatively more difficult because of vanishing gradients, in which TCN does not suffer from. In contrast, TCNs use dilated convolutions, which allow the network to look at the input data over a much larger temporal context, effectively enabling it to learn long-term dependencies. TCNs have been applied to a variety of tasks such as time series forecasting, natural language processing and speech recognition [16], [17], [18]. Some studies that have shown the effectiveness of TCNs include [35], [36], [37], [38], [39], [40].

This study utilized TCN as a convolutional network that convolves over the time domain. TCN consists of dilated, causal 1D convolutional layers with the same input and output sizes [16], [17], [18]. Causal convolution is used to confident the model will not catch information from the future. Dilated convolutions were implemented where the filter is applied over an area larger than Its size by skipping input values with a specific step. The TCN contained a stack of causal

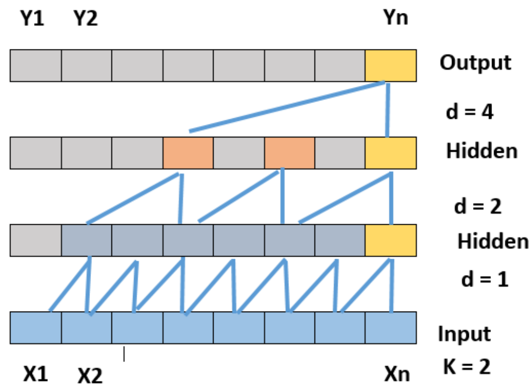

Fig. 4. Dilated causal convolution structure of TCN.

dilated convolutional layers with increasing dilation to increase the receptive field size rampantly [16], [17], [18]. Figure 4 represents dilated causal convolution structure of TCN.

We used Root-mean-square error (RMSE) (shown in Equation (1)) to evaluate the model and to compare between the predicted and actual number of vehicles on the road. RMSE has a value of 0 if the predicted values fit the referenced values perfectly and a positive value if the fit is less than perfect [41].

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{\left(Y_{pred} - Y_{ref}\right)^2}{n}} \tag{1}$$

where Y_{pred} is the predicted target value, Y_{ref} is the actual target value, and n is the number of testing observations i.

IV. Analysis and Results

A. pNEUMA Dataset (T-Intersection) Results

The developing of the framework in this study was based on the *pNEUMA* open data initiative, which is a unique collection of data acquired through an experiment using drones in the densely populated city centre of Athens. The dataset consists of over half a million detailed vehicle trajectories and covers a wide area in the central district of Athens, including both major and minor roads, bus stops, and signalized intersections. The dataset includes data from various types of vehicles, such as cars, taxis, motorcycles, buses, and heavy vehicles. In the study, part of the *pNEUMA* dataset was used to build a model that can estimate the traffic density in an approach using probe vehicle data and other features of the other approaches at a signalized intersection.

We divided the problem into three scenarios: Scenarios 1, 2, and 3. In Scenario 1, we assumed that the model has access to the probe vehicle data (i.e., information from CVs) and the signal phase and timing messages (sPaT) from the controller, which describes the current phase at a signalized intersection, together with the residual time of the phase, for every lane (hence every approach and movement) of the intersection sPaT. This means that features from 1 to 5 are used as inputs. In Scenario 2, we assumed that the model has only access to the probe vehicle data and has no access to the sPaT messages. This means that in this scenario, only features from 1 to 3 will be used as inputs. Lastly, in Scenario 3, we assumed that the

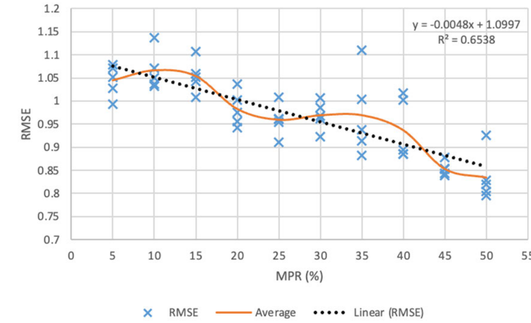

Fig. 5. Results for scenario 1.

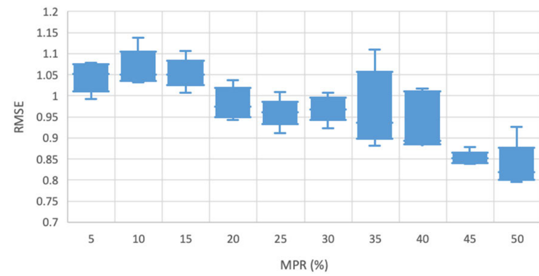

Fig. 6. Box plot for scenario 1.

model has access to the probe vehicle data, sPaT information, and has a memory that can save five previous observations from Feature 1, which is the number of sample vehicles in the orange and green polygon.

We executed the model for each sample using 5-fold cross validation then we took the average RMSE for each sample. Before applying the model, we hyper-parametrized the TCN model using Scenario 1 as a baseline and found that the optimal parameters for the number of filters, filter size, and the number of stacked residuals blocks are 32, 2, and 2, respectively.

For each scenario, we created two figures. The first one shows the results of running the 5-fold cross validation for each sample, the line average of the results, and the linear regression line that describes the mode"s relationship between MPR and RMSE. This is shown in Figure 5, Figure 7, and Figure 9 for Scenario 1, 2, and 3, respectively. The second figure shows the box plots of each scenario. The goal of constructing box plots is to determine if the values in the results for each sample are significantly different by comparing the distributions of the data sets. This is shown in Figure 6, Figure 8, and Figure 10 for Scenario 1, 2, and 3, respectively. Results show that as the MPR increases, RMSE decreases in all scenarios, which means the model becomes more predictable. Results also show that R^2 for Scenario 2 was the highest with about 0.78, followed by R^2 for Scenario 1 (about 0.65), where Scenario 3 achieved the lowest R^2 with about 0.44. Results from the box plots for the three scenarios show that there is a significant difference of RMSE for different values of MPR.

B. InD Dataset (Four-Leg Intersection) Results

We used this dataset to investigate the ability of the proposed framework to be applied on a four-leg intersection

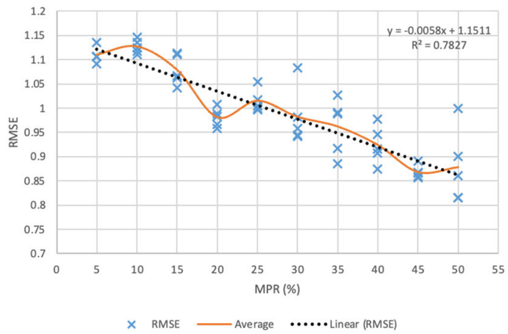

Fig. 7. Results for scenario 2.

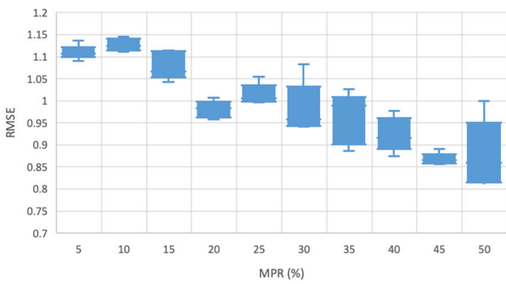

Fig. 8. Box plot for scenario 2.

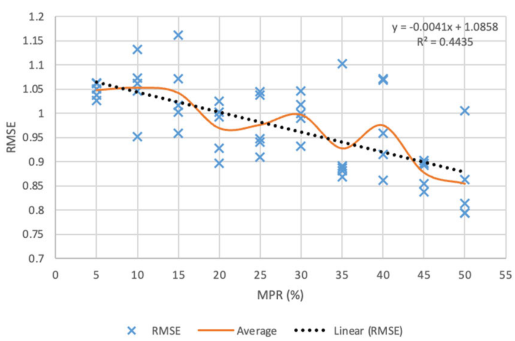

Fig. 9. Results for scenario 3.

and for longer monitoring period of 10 hours. As Scenario 1, in which we only used the probe vehicle data feature, outperformed the other two scenarios, Scenario 1 was used to test the framework. We used increment samples of CVs data from three approaches of the intersection to estimate the traffic density of the fourth approach. We applied a 5-fold cross-validation on each sample to implement the model, subsequently calculating the mean RMSE for every sample. We used the optimal parameter values for essential factors such as the quantity of filters (set at 32), filter dimensions (fixed at 2), and the count of stacked residual blocks (established at 2).

Figure 11 depicts the results of the RMSE across the different MPRs. The results confirmed that as MPR increased, the accuracy of the estimation increased. Results showed that when the number of approaches in the intersection (i.e., data sources) increased, the performance of the model improved. We can also argue that the confidence level on the model has also enhanced as the number of approaches increased and to some extent, the monitoring period was also relatively higher.

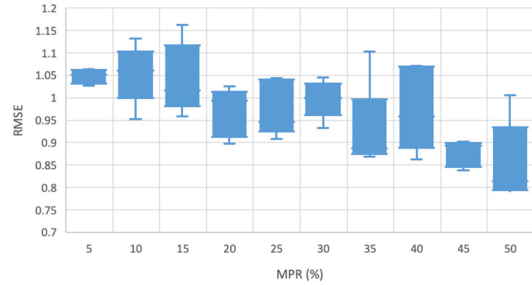

Fig. 10. Box plot for scenario 3.

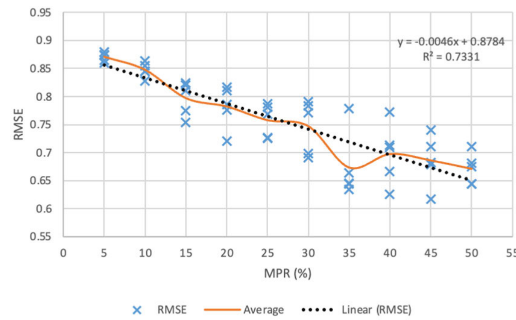

Fig. 11. RMSE results for the inD dataset.

V. Discussion

Probe vehicle data, which was used in all three scenarios, is important in traffic estimation because it provides real-time information about traffic conditions and movements. By collecting data from CVs, traffic analysis systems can accurately predict traffic density and make more informed decisions about traffic management, such as adjusting traffic signal timings or redirecting traffic. This data can also help to identify congestion, bottlenecks, and other traffic issues, leading to more efficient and effective solutions for reducing congestion [3], [42], improving traffic flow [43], and the study of driving behavior [44], [45]. In addition, probe vehicle data can provide valuable information for transportation planning and can support the development of new technologies for improved traffic management. SPaT data, which was used in Scenario 1 and 3, provides information about the current state of a traffic signal [9]. This information is critical for improving the efficiency and safety of traffic flow at intersections. By analyzing SPaT data, traffic analysis systems can make more informed decisions about traffic management, such as adjusting signal timings or redirecting traffic to alleviate congestion.

Additionally, SPaT data can optimize traffic signal timings for different traffic conditions and improve the coordination of signals at multiple intersections, leading to reduced delay, improved travel time, and enhanced safety. The availability of SPaT data also enables CAVs to make more informed decisions about route selection and speed control, leading to a more efficient and safer transportation system. However, results of this study (shown in Figure 12) found that Scenario 2, where only probe vehicle data was used, has achieved the highest accuracy if compared with Scenario 1 and 3, where SPaT information and previous probe data were used

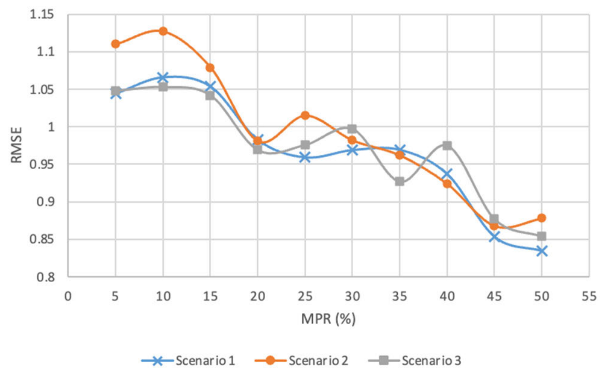

Fig. 12. Average RMSE for the three scenarios.

as additional inputs. This means that using only probe vehicle data from two approaches at a signalized intersection can be relatively sufficient to predict traffic density in the third approach, even when MPR is low. This also means that the availability of SPaT information might not be necessary to achieve high accuracy for traffic estimation. We also found that as the MPR increases, the difference of RMSE between the three scenarios decreases. In a mixed traffic, this method can be very beneficial to estimate traffic conditions in the presence of both traditional and CVs but also different vehicle classes including private and commercial vehicles, such as cars, trucks, and buses. However, the accuracy of the traffic estimation may vary depending on the heterogeneity and distribution of the mixed traffic and the quality of the probe data as shown in Figure 12.

Estimating traffic on one leg of a three-way intersection based on data from the other two legs holds practical significance for enhancing traffic management and safety. While CAVs on the same leg provide valuable real-time data, relying solely on them can lead to blind spots due to potential communication issues or incomplete coverage, especially in complex urban environments and low MPR. By cross-referencing observations from neighboring legs, the estimation becomes more robust, allowing for accurate detection of congestion, optimal signal timing adjustments, and prompt response to emergencies. This approach also accounts for a diverse range of road users and vehicle types, ensuring a comprehensive traffic picture. Therefore, while CAVs on the same leg offer valuable insights, a multi-leg approach mitigates risks associated with data gaps and ensures a more reliable traffic estimation system for better intersection management.

We also tested the framework using on four-leg intersection and for a relatively longer monitoring period. Based on the results, we can argue that our framework can be generalized into other cases. The success of employing TCNs within our framework and obtaining promising results in two distinct case studies underscores the potential for broader transferability. TCNs' ability to capture intricate temporal patterns and relationships, while minimizing vanishing gradient issues, makes them a robust choice across various cases. The underlying principles that made TCNs effective in the initial case studies can likely be leveraged in other scenarios as well. With proper adaptation and fine-tuning of hyperparameters, architecture, and input data preprocessing, TCNs hold promise for generalization to different case studies, providing a strong foundation to tackle new challenges in domains beyond those in which they were initially tested.

VI. Conclusion and Future Work

Traffic estimation using probe vehicle data is important because it provides real-time information about traffic conditions, which can be used for various purposes such as traffic management, navigation, and incident detection. This method can also provide more accurate and timely traffic information than traditional methods such as loop detectors or road-side cameras. By continuously monitoring the traffic, traffic estimation using probe vehicle data helps make better informed decisions and improve traffic efficiency and safety. This study introduced a novel framework for traffic density estimation using TCN network for sequential time series data. TCN was used as it was built on the same principles as CNN, but they are modified to handle sequential data and handle long-term dependencies by using dilated convolutions. We used two datasets of vehicles collected by drones from a three-leg intersection in Greece, and a four-leg intersection in Germany. We built the model to predict the density in an approach of the signalized intersection using features extracted from the other approaches. We extracted ten features including probe vehicle data with various MPRs, SPaT information, and previous probe vehicle data to create three scenarios. We computed the RMSE for each scenario to evaluate the proposed model, which in general showed promising real-time prediction results. We also discussed that estimating traffic on one leg of a signalized intersection based on data from the other legs holds practical significance for enhancing traffic management and safety. While CAVs on the same leg offer valuable insights, a multi-leg approach mitigates risks associated with data gaps and ensures a more reliable traffic estimation system for better intersection management.

In general, as the MPR increases, RMSE decreases, which means the model becomes more predictable. This can be applied to the three scenarios. The study's findings showed that the highest accuracy was achieved in Scenario 2, which used only probe vehicle data, compared to Scenario 1 and 3, which used additional inputs of SPaT information and previous probe data. This suggests that relying solely on probe vehicle data from two approaches at a signalized intersection can effectively predict traffic density in the third approach, even when the MPR is low. Additionally, the results indicate that having SPaT information may not be crucial for achieving high accuracy in traffic estimation. Moreover, as the MPR increases, the difference in RMSE between the three scenarios becomes smaller, making the proposed method suitable for estimating traffic density in the presence of both traditional and CVs at the intersection.

Applying TCNs directly to traffic density estimation presents both potential and challenges. While TCNs are adept at capturing temporal dependencies, challenges arise from data preprocessing, model architecture, and domain-specific nuances. Addressing varying data granularities and missing values requires careful preprocessing, and adapting input sequences to TCN's demands consideration. Tuning hyperparameters and network architecture, such as kernel sizes and dilation factors, is crucial for optimal performance. Complex traffic patterns may necessitate additional mechanisms like attention layers or Transformer-based components. Handling overfitting, ensuring real-time inference, and selecting appropriate evaluation metrics are further hurdles. Incorporating domain expertise and possibly transferring learning to specific road networks can enhance TCN's applicability. Ultimately, successful deployment hinges on iterative experimentation, aligning TCN's capabilities with the intricacies of traffic behavior and infrastructure.

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