Jurnal Ilmiah Ilmu Terapan Universitas Jambi
ISSN (Print) 2580-2240 (Online) 2580-2259
Volume 6, Nomor 2, Desember 2022

Estimation of Queue Length at Signalized Intersections Using Artificial Neural Network

Sara Respati*[1], Mohamad Isram[1], Fatmawati[1], Sri Kusrini[2]
[1]Department of Civil Engineering, Politeknik Negeri Balikpapan, Indonesia
[2]Dinas Perhubungan Balikpapan, Balikpapan, Indonesia
Email korespondensi: sara.wibawaning@poltekba.ac.id

ABSTRACT

Signalized intersections are points in the transportation network where vehicles from various directions meet. They are critical points for traffic jams, and this is an application of applied science in the technology field. The vehicle queue length is one of the performance parameters of a signalized intersection. Long queues of vehicles pose a high risk of accidents involving many vehicles. Feedback signal control (actuated signal control) can improve intersection performance. One variable that can be used as feedback input is the vehicle queue length. Traffic in Indonesia is mixed traffic where various vehicles use the same road lane and with low lane discipline. This causes the traffic system to become complex stochastic, and non-linear. Modeling queue length using a static linear algorithm cannot capture the phenomenon of this complex traffic system. Therefore, this research aims to build a machine learning-based queue length model using artificial neural networks (ANN). This model studies the traffic system with historical data so that it can model queue lengths with reasonable accuracy through the training process. The estimation model was built and applied to the Muara Rapak signalized intersection, Balikpapan. Data on queue length for 10 days, 2 hours/day, was obtained using CCTV and direct field surveys. The model testing results show that ANN has a good level of accuracy with MAE, RMSE, and MAPE of 3.8 m, 4.9 m, and 6%, respectively.

Keywords: Artificial Neural Network; Queue Length; Signalized Intersection

INTRODUCTION

Signalized intersections are critical points in the transportation network and are a source of congestion. One of the key factors that influences the performance of signalized intersections is the length of the vehicle queue. Vehicle queue length is the longitudinal space occupied by vehicles stopping at signalized intersections. During high traffic flows, such as during rush hour, road users experience poor driving conditions comfortable. To increase the level of driver comfort and improve intersection performance, intersections with feedback signal control or actuated signal control designs can be used. This control uses the latest intersection condition data as feedback to regulate the signalized intersection cycle time. With appropriate arrangements for intersection conditions, vehicle queues at intersections can be reduced. In addition, this optimally utilizes existing infrastructure, such as CCTV installed at signalized intersections. One component that can be used for a feedback system is the length of the vehicle queue. The queue length factor has been widely used for developed queue-based feedback control systems. Thus, queue length estimation is a fundamental component in adaptive traffic control systems (Comert and Cetin, 2011; Heshami, & Kattan, 2021; Tawfeek, 2022; Reyad, & Sayed, 2023; Xu et al., 2023). Various studies have been carried out on this matter, but most of the estimation models apply homogeneous traffic conditions with disciplined vehicle user conditions.

The characteristics of traffic flow in non-lane based mixed traffic (without lane discipline) are significantly different from homogeneous traffic with lane discipline (Asaithambi et al., 2016; Qi et al., 2021; Graves, Nelson, & Chakraborty, 2023; Mohammad et al., 2023). Driving habits, lateral and longitudinal vehicle movements have a significant impact on the formation of queue lengths in mixed traffic. Therefore, the queue length estimation model used for traffic conditions with lane discipline is not suitable for use in mixed traffic conditions without lane discipline. Jithender and Mehar (2022) built a multivariate regression model for queue length in mixed traffic conditions with the variables approach volume, minimum number of vehicles in the queue, approach width, red time, and proportion of cars and two-wheeled vehicles. Based on correlation analysis, these variables determine their influence on the regression model. Thus, the regression model must be calibrated for each location. This study also shows that field queue lengths cannot be estimated well by the M/M/1 queuing model and HCM queue-based estimation (Transportation Research Board, 2010). These two queuing models are models developed for homogeneous traffic with lane discipline. Harahap, Darmawan, Fajar, Ceha, and Rachmiatie (2019) used modeling and simulation to estimate the length of waiting time for vehicles at intersections. The model developed is based on the theory of M/M/1 random arrival and departure patterns. Vehicle composition factors were not taken into account in the mentioned studies. Anusha, Vanajakshi, and Subramanian (2022) used the Kalman-Filter approach to estimate queues and delays in mixed traffic conditions. In the study, the queue is defined as the number of vehicles in the queue. In this research, the output of the estimation model is the queue length in length units.

In homogeneous traffic conditions with lane discipline, the length of the vehicle queue is controlled by the length of the vehicle. In mixed traffic without lane discipline, vehicle length cannot be a reference for the length of the vehicle queue. On the other hand, vehicle composition is one of the main factors in determining queue length. Compared to two-wheeled vehicles (MC), passenger cars have wider longitudinal and lateral gaps between vehicles. Due to the smaller lateral and longitudinal gaps in motorbikes, road density is higher when the proportion of motorbikes is high. Due to the many combinations of types of vehicles in front (leader) and those behind (follower) in mixed traffic, the longitudinal space between vehicles varies in value (Gowri & Sivanandan, 2015; Sahraei, & Akbari, 2020; Tan et al., 2020; Lanzaro, Sayed, & Alsaleh, 2022). The width of a passenger car is smaller than the width of the road lane, causing motorbikes to fill the empty space. Motorbikes are able to perform zigzag maneuvers slowly and move close to the front of the intersection (Gowri & Sivanandan, 2015; Li, Xu, & Wu, 2022; Tang et al., 2022; Shabab et al., 2023).

Based on the explanation above, in mixed traffic conditions without lane discipline, the queue length is complex and nonlinear. This causes the queue length to not be estimated properly using parametric models. In parametric models, estimates are carried out based on data distribution and using initial assumptions regarding the initial relationship between input and output. Thus, the parametric model has the disadvantage of being applied to a complex and nonlinear system that does not have uniform variations in its variables. On the other hand, non-parametric models do not require assumptions regarding data distribution and have high flexibility for modeling complex systems. Machine learning is a non-parametric model with a data driven concept, that is, the model is built based on historical data, so it is flexible and no initial assumptions are needed regarding the distribution of the data.

Machine learning models have been applied to estimate queue lengths. Artificial neural networks (ANN) and Support Vector Machine (SVM) have been applied to estimate queue lengths at ferry terminals (Zhang, Zou, Tang, Ash, & Wang, 2016; Chen et al., 2021; Tambe, Pawar, & Yadav, 2021; Du et al., 2022; Ashqer et al., 2023). In addition, Random Forest (RF) has been used to estimate queue lengths using data from GPS and license plate recognition (LPR) (Wang et al., 2020; Qi et al., 2021; Liu et al., 2022; Sivam et al., 2022). Based on the explanation above, this research aims to determine the characteristics of vehicle queues in mixed traffic conditions and to estimate the length of vehicle queues using a machine learning model in the form of ANN. This machine learning algorithm was applied to the signalized intersection of Muara Rapak, Balikpapan.

METHODOLOGY

Machine learning is a data driven method, namely building models based on data. The more data that is studied, the model or algorithm is able to recognize the system well and has high accuracy. This application of artificial intelligence can also be used in various industries and continues to be used by researchers, one of which is in calculating the length of queues at signalized intersections.

ANN or artificial neural network is an algorithm whose working process resembles the neural network of the human brain and is a machine learning model that is often used for modeling complex systems. ANN produces a non-linear model with many layers (except in the case of a single perceptron). The basic concept of ANN can be seen in Figure 1. ANN consists of an input layer, hidden layer(s), and an output layer. The input layer can consist of one or more neurons. Hidden layers are layers between the input layer and the output layer. Connections in this layer's neurons are given a weight which is updated in the learning process until the stop criterion is met. The output layer is the last layer of the system. In general, the working concept is as follows: the input layer receives input to each of its nodes, after each node in the input layer has obtained the required data it will be multiplied by its weight to produce the sum (amount) or what is better known with an accumulator, then the accumulator will be entered into the Activation Function which is used with the equation $Y = F(NET)$. For example, in Figure 1, the value $x1{:}1$ is obtained from the addition of Layer 0 multiplied by each weight, the formulation of which can be seen in Equation 1.

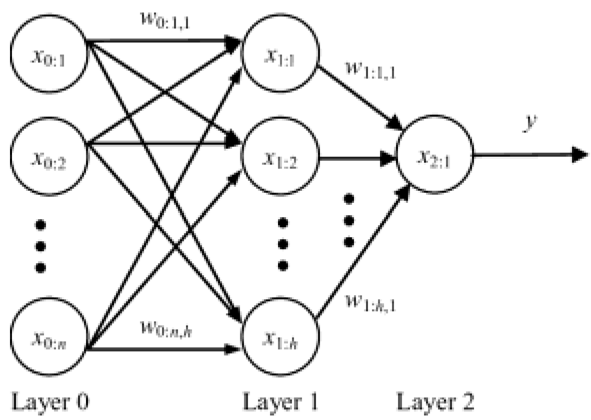


Figure 1. Basic Concept of ANN

$$x_{1:1} = \sum_{i=1}^{I} x_{0:i} w_{0:i} \tag{1}$$

The relationship between nodes is associated with a value called weight. Each node has its own output, error and weight. Output is the output of a node. Error is the level of error contained in a node of the process being carried out. Weight is the weight of that node to other nodes in different layers. The initial weight can be chosen randomly and initialized with a relatively small value, ranging from -0.1 to 0.1. At the training stage, the weight will be adjusted through a mathematical calculation process to achieve the appropriate weight value. The training process of a neural network consists of forward, backward and weight update processes. In the training process, learning functions are used, including gradient descent and the Lavenberg-Marquardt learning function. The more data used, the better the training process of the ANN model and the smaller the error level produced in the output layer, thus the smaller the system error.

Gao et al. (2020) developed a model using Deep ANN to estimate queue lengths at signalized intersections using CCTV data. The Deep ANN model is able to read the number of vehicles at the intersection and use it as input for the next process. Previously Dheeban et al (2021) had built a queue length prediction model using ANN and showed that ANN could predict queue length with high accuracy. Chen et al (2022) used Deep ANN to predict vehicles passing through intersections when the light is green in mixedtraffic conditions.

Apart from queue length, ANN has also been used to model other parameters. For example, in mixed traffic conditions, Jammula, Bera, and Ravishankar (2018) developed a model to predict travel time using ANN. The results show that ANN has better accuracy than simple regression models. ANN is built with several input scenarios, so it can be seen what parameters influence the results and what inputs can provide estimates with high accuracy. Studies regarding queue length in mixed traffic conditions using ANN still have minimal application. Therefore, this research aims to build an ANN model to estimate the length of vehicle queues at signalized intersections with mixed traffic conditions without lane discipline.

Location and Research Data

This research uses vehicle queue data at signalized intersections in the city of Balikpapan, East Kalimantan. There are many traffic jam points in Balikpapan at protocol road intersections, one of which is at the Muara Rapak intersection. During peak hours, there are quite long queues of vehicles on several arms of the intersection, including on the arms of the road coming down from Rapak. This intersection arm is of concern to both the city government and Balikpapan residents, because fatal accidents have occurred several times on this arm. The geometry of the road at this intersection has a fairly high slope, which often puts heavy vehicles at risk if they are not in prime condition so they can sweep away the vehicles in front of them that are queuing at the intersection.

Traffic engineering can be used as a solution to reduce queue lengths at critical intersections, such as in the case of the Muara Rapak intersection. With CCTV data that has been installed at 51 points in the city of Balikpapan, vehicle queue data can be obtained and can be used to build a model that can estimate the length of vehicle queues. The research location is shown in Figure 2. Data collection was carried out for 10 days on weekdays and peak hours.

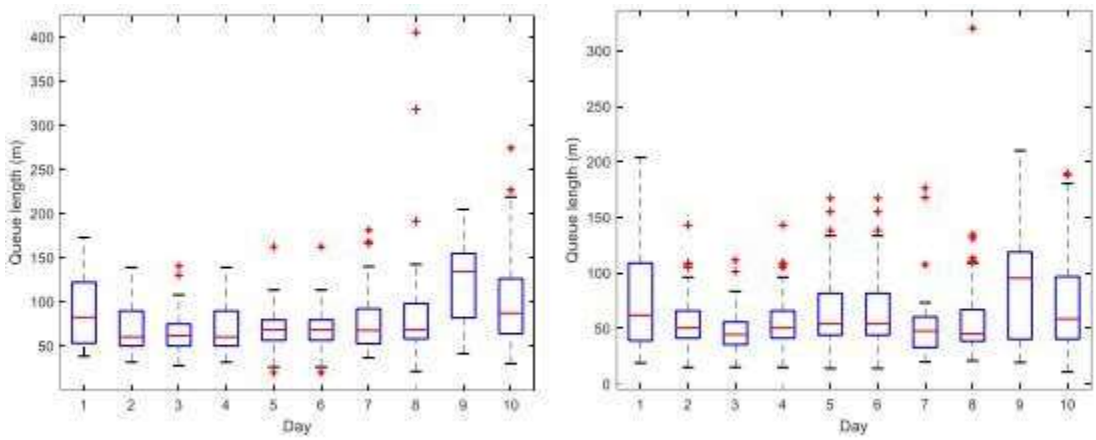
Figure 2. Research location map

Vehicle Queue Characteristics

Figure 3 shows a boxplot or distribution of vehicle queue length data for 10 days, which consists of 47 cycles per day. It can be seen that the average queue length (red line in the middle of the boxplot) for all days varies from around 50 m to 130 m. Apart from that, it can also be seen that the data distribution for queue length data per day also has high variations as indicated by the width of the upper and lower borders of the boxplot;

Jurnal Ilmiah Ilmu Terapan Universitas Jambi
ISSN (Print) 2580-2240 (Online) 2580-2259
Volume 6, Nomor 2, Desember 2022

There are also outliers in the queue data which are indicated by red plus signs. From Figure 3, it can be seen that the queue for Lane 1 is higher than for Lane 2.



(a) (b)

Figure 3. Boxplot of queue length data (a) Lane 1 and (b) Lane 2 each cycle for 10 survey days

Characteristics of Vehicle Composition in Queues

The composition of vehicles by lane (lane 1 and lane 2) per vehicle type can be seen in the graph below. Figure 4 shows that the number of MCs in the queue in Lane 2 is higher compared to the MCs in Lane 1. While in the LV case, more LVs stop in Lane 1 compared to Lane 2 (Figure 5), the same thing happens in the HV case (Figure 6).

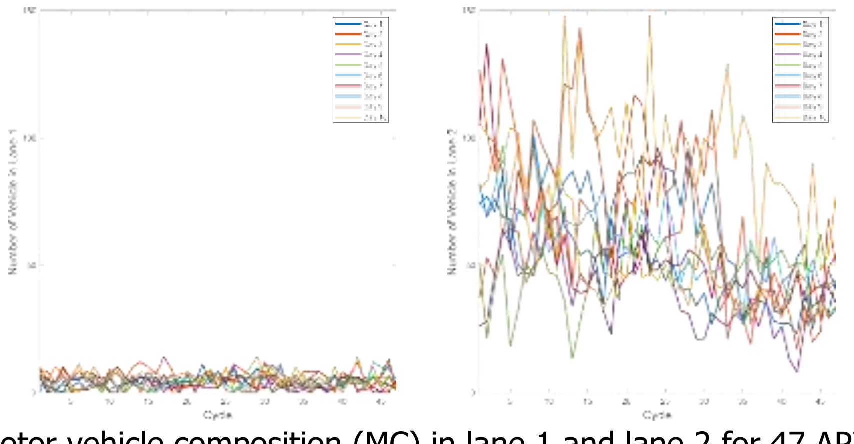


Figure 4. Motor vehicle composition (MC) in lane 1 and lane 2 for 47 APIL cycles and 10 survey days

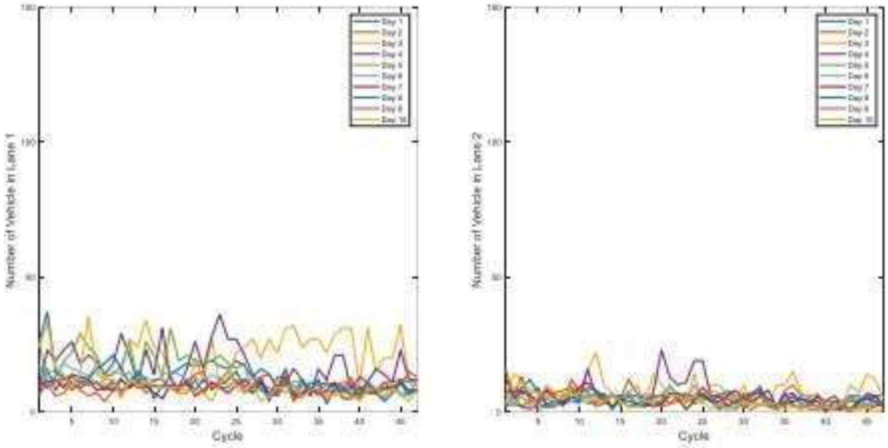


Figure 5. Composition of light vehicles (LV) in lane 1 and lane 2 for 47 APIL cycles and 10 survey days

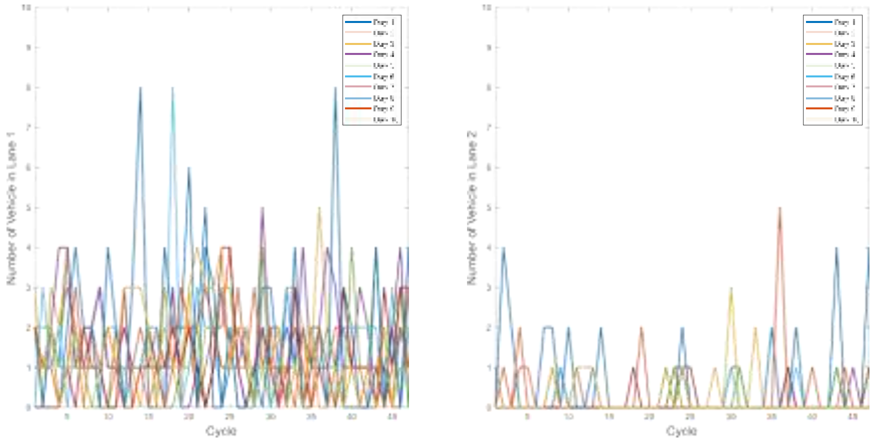


Figure 6. Composition of light vehicles (LV) in lane 1 and lane 2 for 47 APIL cycles and 10 survey days

Estimated Vehicle Queue Length Using Ann

Estimation of vehicle queue length in mixed traffic at the study location using ANN, using three inputs consisting of the number of MC, LV and HV queuing. The output of the estimation is the queue length. This study uses 70% of the data for the training process and 30% for testing.

In the estimation process, it is necessary to select a training algorithm that is used to update the weight of each node so that the resulting error is smaller. In this research, three training algorithms were used consisting of Levenberg-Marquardt backpropagation, Bayesian regularization and scaled conjugate gradient backpropagation. The algorithm that gives the smallest error will be selected to further determine the ANN architecture in the form of the number of neurons in the hidden layers.

The level of accuracy of the estimation is seen from the mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE). 10 neurons were used in the hidden layer to test the accuracy level of the training algorithm, where the estimated performance can be seen in Table 1.

Table 1. Queue length estimation performance

Training Algorithm	MAE (m)	RMSE (m)	MAPE (%)
Bayesian regularization	6.2	7.8	9.6
Levenberg-Marquardt backpropagation	4.9	6.3	8.4
Scaled conjugate gradient backpropagation	7.7	8.5	11.9

Levenberg-Marquardt backpropagation provides the highest level of estimation accuracy. This is indicated by the smaller MAE, RMSE and MAPE values compared to the other two algorithms. So, the Levenberg-Marquardt backpropagation algorithm was chosen as the training algorithm and used to determine the number of neurons in the hidden layer. The influence of the number of neurons, between 1 and 20, on the level of estimation accuracy is then sought to determine the number of neurons in the ANN architecture. Below shows the MAE, MAPE and RMSE values for various numbers of neurons.

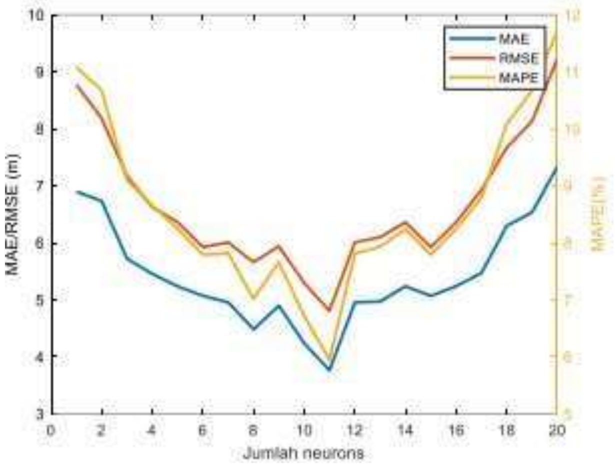


Figure 7. ANN performance using various numbers of neurons

The image above shows an increase in accuracy when the number of neurons increases from one neuron to 11 neurons. However, the error increases when the number of neurons is more than 11. So in this study 3 inputs were used, 11 neurons in the hidden layer and 1 output with Levenberg-Marquardt backpropagation as the training algorithm. This model can estimate the length of the vehicle queue with an MAE of 3.8 m, RMSE of around 4.9 m and MAPE of 6%. With this small error value, it can be said that the model can estimate vehicle length with a good level of accuracy.

CONCLUSIONS

The conclusions that can be obtained from the results of the research and discussion described are as follows. The length of vehicle queues in mixed traffic varies. Vehicle composition is an important factor in forming the length of vehicle queues. One of the critical sections at the Muara Rapak signalized intersection, Balikpapan, was taken as a case study in this research. This section has 2 lanes. Lane 1 generally has a longer queue than Lane 2. When compared with the number of vehicles, Lane 2 is filled with a high composition of motorbikes. It can be said that although the composition of motorbikes is high in Lane 2, the queue length is smaller than in Lane 1 - this shows that the pile of motorbikes is queuing with a very small gap. LV, including cars and pick-ups, dominates Lane 1 and a small portion occupies Lane 2. Heavy vehicles have the smallest composition and generally occupy Lane 1.

Mixed traffic is a complex nonlinear system, so in this research, queue lengths are estimated using a machine learning approach, namely by applying ANN. The ANN architecture consists of 3 inputs, namely the number of MC, LV and HV vehicles, 11 neurons in the hidden layer and 1 output in the form of queue length. The training algorithm that gives the best results is Levenberg-Marquardt backpropagation. The ANN model has good accuracy in estimating queue length, namely with a MAPE of 6%.

Acknowledgments
We express our gratitude for funding from the Balikpapan State Polytechnic under the DIPA Collaboration scheme (31/PL32.13/SPK-LT/2022) with the Balikpapan City Transportation Service as a research collaboration partner.

REFERENCES

Anusha, S., Vanajakshi, L., & Subramanian, S. C. (2022). Dynamical systems approach for queue and delay estimation at signalized intersections under mixed traffic conditions. *Transportation letters, 14*(6), 578-590.

Ashqer, M. I., Ashqar, H. I., Elhenawy, M., Almannaa, M., Aljamal, M. A., Rakha, H. A., & Bikdash, M. (2023). Evaluating a signalized intersection performance using unmanned aerial Data. *Transportation Letters*, 1-9. https://doi.org/10.1080/19427867.2023.2204249

Chen, H.-H., Lin, Y.-B., Yeh, I.-H., Cho, H.-J., & Wu, Y.-J. (2022). Prediction of Queue Dissipation Time for Mixed Traffic Flows With Deep Learning *IEEE Open Journal of Intelligent Transportation Systems, 3*, 267-277.

Chen, P., Wei, L., Meng, F., & Zheng, N. (2021). Vehicle trajectory reconstruction for signalized intersections: A hybrid approach integrating Kalman Filtering and variational theory. *Transportmetrica B: transport dynamics*, *9*(1), 22-41. https://doi.org/10.1080/21680566.2020.1781707

Dheeban, S. S., Muthu Selvan, N. B., & Umashankar, S. (2021). Artificial neural network based solar energy integrated unified power quality conditioner. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *43*(1), 1-25. https://doi.org/10.1080/15567036.2021.1919247

Du, J., Wu, F., Yin, J., Liu, C., & Gong, X. (2022). Polyline simplification based on the artificial neural network with constraints of generalization knowledge. *Cartography and Geographic Information Science*, *49*(4), 313-337. https://doi.org/10.1080/15230406.2021.2013944

Gao, K., Han, F., Dong, P., Xiong, N., & Du, R. (2019). Connected vehicle as a mobile sensor for real time queue length at signalized intersections. *Sensors, 19*(9), 2059.

Graves, R. T., Nelson, Z. E., & Chakraborty, S. (2023). A decentralized intersection management system through collaborative negotiation between smart signals. *Journal of Intelligent Transportation Systems*, *27*(2), 272-294. https://doi.org/10.1080/15472450.2021.2016405

Heshami, S., & Kattan, L. (2021). A queue length estimation and prediction model for long freeway off-ramps. *Journal of Intelligent Transportation Systems*, *25*(1), 122-134. https://doi.org/10.1080/15472450.2020.1846125

Gao, K., Huang, S., Han, F., Li, S., Wu, W., & Du, R. (2020). An integrated algorithm for intersection queue length estimation based on IoT in a mixed traffic scenario. *Applied Sciences, 10*(6), 2078.

Gowri, A., & Sivanandan, R. (2015). Evaluation of right-turn lanes at signalized intersection in non-lane-based heterogeneous traffic using microscopic simulation model. *Transportation letters, 7*(2), 61-72.

Harahap, E., Darmawan, D., Fajar, Y., Ceha, R., & Rachmiatie, A. (2019). Modeling and simulation of queue waiting time at traffic light intersection. In *Journal of Physics: Conference Series* (Vol. 1188, pp. 012001): IOP Publishing.

Jammula, J. K., Bera, R., & Ravishankar, K. V. R. (2018). Travel time prediction modelling in mixed traffic conditions. *International Journal for Traffic and Transport Engineering, 8*(1), 135-147.

Lanzaro, G., Sayed, T., & Alsaleh, R. (2022). Can motorcyclist behavior in traffic conflicts be modeled? A deep reinforcement learning approach for motorcycle-pedestrian interactions. *Transportmetrica B: transport dynamics*, *10*(1), 396-420. https://doi.org/10.1080/21680566.2021.2004954

Li, X., Xu, P., & Wu, Y. J. (2022). Pedestrian crossing volume estimation at signalized intersections using Bayesian additive regression trees. *Journal of Intelligent Transportation Systems*, *26*(5), 557-571. https://doi.org/10.1080/15472450.2021.1933471

Liu, D., An, C., Yasir, M., Lu, J., & Xia, J. (2022). A Machine Learning Based Method for Real-Time Queue Length Estimation Using License Plate Recognition and GPS Trajectory Data. *KSCE Journal of Civil Engineering, 26*(5), 2408-2419.

Mohammad, A. A., Al Nawaiseh, H. M., Alhajyaseen, W. K., Dias, C., & Mehran, B. (2023). Lane-based analysis of the saturation flow rate considering traffic composition. *Transportation Planning and Technology*, *46*(5), 1-19. https://doi.org/10.1080/03081060.2023.2214144

Qi, W., Wang, Y., Bie, Y., & Ren, J. (2021). Prediction model for bus inter-stop travel time considering the impacts of signalized intersections. *Transportmetrica A: Transport Science*, *17*(2), 171-189. https://doi.org/10.1080/23249935.2020.1726525

Reyad, P., & Sayed, T. (2023). Real-Time multi-objective optimization of safety and mobility at signalized intersections. *Transportmetrica B: Transport Dynamics*, *11*(1), 847-868. https://doi.org/10.1080/21680566.2022.2141911

Sahraei, A. M., & Akbari, E. (2020). Review and evaluation of methods for estimating delay at priority junctions. *Australian Journal of Civil Engineering*, *18*(2), 126-139. https://doi.org/10.1080/14488353.2020.1743591

Shabab, K. R., Mustavee, S., Agarwal, S., Zaki, M. H., & Das, S. K. (2023). Dynamic mode decomposition type algorithms for modeling and predicting queue lengths at signalized intersections with short lookback. *Journal of Intelligent Transportation Systems*, 1-15. https://doi.org/10.1080/15472450.2023.2205022

Sivam, S. S., Rajendran, R., & Harshavardhana, N. (2022). An investigation of hybrid models FEA coupled with AHP-ELECTRE, RSM-GA, and ANN-GA into the process parameter optimization of high-quality deep-drawn cylindrical copper cups. *Mechanics Based Design of Structures and Machines*, 1-25. https://doi.org/10.1080/15397734.2022.2120497

Tambe, S., Pawar, A., & Yadav, S. K. (2021). Deep fake videos identification using ANN and LSTM. *Journal of Discrete Mathematical Sciences and Cryptography*, *24*(8), 2353-2364. https://doi.org/10.1080/09720529.2021.2014140

Tan, C., Liu, L., Wu, H., Cao, Y., & Tang, K. (2020). Fuzing license plate recognition data and vehicle trajectory data for lane-based queue length estimation at signalized intersections. *Journal of Intelligent Transportation Systems*, *24*(5), 449-466. https://doi.org/10.1080/15472450.2020.1732217

Tang, K., Wu, H., Yao, J., Tan, C., & Ji, Y. (2022). Lane-based queue length estimation at signalized intersections using single-section license plate recognition data. *Transportmetrica B: transport dynamics*, *10*(1), 293-311. https://doi.org/10.1080/21680566.2021.1991504

Tawfeek, M. H. (2022). Perceptual-based driver behaviour modelling at the yellow onset of signalised intersections. *Journal of Transportation Safety & Security*, *14*(3), 404-429. https://doi.org/10.1080/19439962.2020.1783414

Transportation Research Board. (2010). *Highway Capacity Manual (HCM 2000)*:

National Research Council, Washington, DC, USA.

Xu, P., Li, X., Wu, Y. J., & Noh, H. (2023). Network-level turning movement counts estimation using traffic controller event-based data. *Journal of Intelligent Transportation Systems*, *27*(5), 677-691. https://doi.org/10.1080/15472450.2022.2075701

Wang, Y., Li, Z., Ye, Z., & Zhang, Y. (2020). Nighttime safety evaluation for signalized intersections at the signal cycle level based on rear-end conflict models considering lighting and traffic conditions. *Traffic injury prevention*, *21*(1), 87-92. https://doi.org/10.1080/15389588.2019.1701670

Zhang, W., Zou, Y., Tang, J., Ash, J., & Wang, Y. (2016). Short-term prediction of vehicle waiting queue at ferry terminal based on machine learning method. *Journal of Marine Science and Technology*, *21*(4), 729-741.