Traffic Flow Optimization at Toll Plaza Using Pro-Active Deep Learning Strategies

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DEDICATION

"To My Inspirational, Caring and Beloved Parents and Siblings, Without Whom This Wouldn't be Possible"

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ABSTRACT

Global urbanization and increasing traffic volume have intensified traffic congestion on transportation infrastructure. This highlights the critical need to implement more intelligent and proactive transportation infrastructure solutions. Transportation infrastructure on freeway such as toll plazas are crucial for traffic flow and revenue, yet they often face congestion challenges, leading to longer queues, increased travel times, and environmental issues. To combat toll plazas congestion and optimize traffic management, this study proposes a proactive traffic control strategy using advanced technologies. The approach involves deep learning convolutional neural network models (YOLOv7-DeepSORT) for vehicle counting and long short-term memory model for short-term arrival rate prediction. When projected arrival rates exceed a threshold, the strategy proactively activates Variable Speed Limits (VSL) and Ramp Metering (RM) strategies during peak hours. Validated through a case study at Ravi Toll Plaza using PTV VISSIM, the proposed method reduces queue length by 57% and vehicle delays by 47%, while cutting fuel consumption and pollutant emissions by 28.4% and 34%, respectively. Additionally, an implementation framework alongside the proposed strategy, this study aims to bridge the gap between theory and practice, making it easier for toll plaza operators and transportation authorities to adopt and benefit from the advanced traffic management techniques. Ultimately, this study underscores the importance of integrated and proactive traffic control strategies in enhancing traffic management, minimizing congestion, and fostering a more sustainable transportation system. Intelligent Transportation System, Variable Speed Limits, Ramp Metering and Deep Learning, YOLOV7-Deep-SORT and LSTM

Keywords: Intelligent Transportation System, Variable Speed Limits, Ramp Metering and Deep Learning, YOLOV7-Deep-SORT and LSTM

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CHAPTER 1: INTRODUCTION

Traffic congestion is a global challenge for asset planning and management, driven by urban sprawl and rapid traffic growth. According to INRIX Analytics in 2017, congestion is expected to cost U.S. drivers $480 billion in the next decade, encompassing lost time, fuel wastage, and carbon emissions [1]. Likewise, the U.S. Federal Highway Administration (FHWA) anticipates a 23% rise in vehicle miles travelled by 2032, signifying a 1.04% annual growth[2]. Similarly, the European Commission estimates an annual cost of over €110 billion due to road congestion, accounting for 1% of Europe's GDP [3]. In Pakistan, vehicle numbers have surged by 8%, accompanied by a 5.5% increase in average annual growth from 2001 to 2020 (Ecomonic Survey of Pakistan 2021-22). Consequently, high demand-induced traffic congestion significantly impacts travel time[5], infrastructure mobility, and triggers severe environmental [6], social, and economic repercussions [7].

As cities expand and commuter numbers increase, efficient transportation infrastructure becomes increasingly vital. Similarly, toll plazas play a pivotal role in contemporary transportation systems, functioning as gateways that ensure the fluidity of traffic and generate revenue through toll fees, critical for maintaining and expanding essential road networks. However, these toll plazas often encounter challenges linked to traffic congestion, resulted in lengthy queues, prolonged travel times, and adverse environmental impacts. With advancements in artificial intelligence (AI), Intelligent Transportation Systems (ITS) have been proposed to proactively manage traffic flow and congestion reduction. For instance, few studies proposed proactive control measures to optimize traffic flow and reduce congestion. Some studies mainly focused on implementing strategies like Electronic Toll Collection (ETC), lane configuration, and freeway capacity control techniques to optimize traffic flow and mitigate congestion at toll plazas. Moreover, a fundamental element of ITS is vehicle counting, which provides valuable traffic flow parameters [8]. ITS utilizes these predictive traffic flow parameters to optimize traffic control strategies, plan alternative routes, assist policymakers in informed infrastructure management decisions, and facilitate sustainable transportation solutions.

In particular, to mitigate the adverse toll plaza congestion effects, this study proposes a proactive traffic control approach for pre-emptive management of traffic demand and flow at toll plazas. The first phase of this proactive strategy entails accurate vehicles counting through video cameras. To achieve this, the study utilizes two deep learning Convolutional Neural Network (CNN) models: YOLOV7 and DeepSORT. YOLOV7 handles vehicle detection, accurately recognizing vehicles within a frame, while DeepSORT manages vehicle tracking across consecutive frames. Subsequent post-processing refines the models' outcomes to ensure accurate vehicle counting and calculation of the arrival rate. For better traffic management, this study examines variations in arrival rates across weekdays and utilizes Long Short-Term Memory (LSTM) model for short-term predictions of arrival rates within the next 15 minutes. This predictive model aids in estimating anticipated vehicle arrival rate, thus facilitating real-time traffic management. To effectively regulate vehicle flow during peak hours, a combination of Variable Speed Limits (VSL) and ALINEA Ramp Metering (RM) control strategies are implemented at the toll plaza when the arrival rate exceeds a predefined threshold.

This study encompasses a comprehensive approach to traffic demand management and environmental sustainability. It aims to optimize traffic demand through proactive strategies like Ramp Metering, to regulate the merging rate of vehicles onto the main freeway lanes, to prevent excessive queue formation at toll plazas. The integration of Variable Speed Limits (VSLs) allows real-time adjustments to speed limits, ensuring smoother traffic flow. Furthermore, the study seeks to minimize the environmental impact of congestion by optimizing traffic flow, thereby decreasing fuel consumption and emissions through reduced idling and stop-and-go traffic. This ultimately contributing to a more sustainable and eco-friendly transportation system.

1.1 Problem Statement

Urban sprawl and exponential increasing traffic volumes have led to widespread traffic congestion, making asset planning and management challenging worldwide. Moreover, as cities grow and the number of commuters increases, the demand for efficient transportation infrastructure becomes vital. Toll plazas on freeways play a pivotal role in modern transportation systems, serving as gateways that facilitate the smooth flow of traffic and generate revenue through toll fees, which are critical for the maintenance and development of essential road networks. Simultaneously, these toll plazas encounter challenges related to traffic congestion, leading to extended queues, increased travel times, and negative environmental impacts.

1.2 Study Area

To validate the effectiveness of the proposed control strategy, Ravi Toll Plaza Lahore is taken as the case study as shown in Figure 1. Ravi Toll Plaza is one of the busiest toll plazas in the country, situated on the exit of the M-2 motorway that connects two large metropolitan cites: Lahore and Islamabad. The extensive traffic volume and diverse traffic patterns make it an ideal testing ground for the proposed control strategy. This study used VISSIM, a powerful traffic simulation software, to simulate results. A VISSIM model of Ravi Toll Plaza is created, and the control strategy algorithm is integrated using VisVAP software. This simulation provides a realistic environment to evaluate the effectiveness of the proposed control strategy and its impact on traffic flow.

Figure 1 - Ravi Toll Plaza

1.3 Research Objectives

To simulate the results, the study compares various scenarios, such as Existing, VSL only, and RM only, with the proposed strategy. Through a comprehensive analysis, the study demonstrates that the proposed strategy outperforms all other scenarios, offering the most efficient and effective approach to manage traffic flow at Ravi Toll Plaza and potentially other similar busy toll plazas. The results validate the significance of combining advanced computer vision (YOLOv7-DeepSORT), predictive modeling (LSTM), and control strategies (VSL-RM) to enhance traffic management and optimize toll plaza operations. To simulate the results, the study compares various scenarios, such as Existing, VSL only, and RM only, with the proposed strategy. Through a comprehensive analysis, the study demonstrates that the proposed strategy outperforms all other scenarios, offering the most efficient and effective approach to manage traffic flow at Ravi Toll Plaza and potentially other similar busy toll plazas. The results validate the significance of combining advanced computer vision (YOLOv7-DeepSORT), predictive modeling (LSTM), and control strategies (VSL-RM) to enhance traffic management and optimize toll plaza operations. The primary objectives of this study are as follows:

1- **Optimizing Traffic Demand:** The proactive traffic control strategy leverages Ramp Metering, a traffic control technique used at freeway on-ramps, to regulate the rate at which vehicles merge onto the main freeway lanes. By efficiently managing the flow of vehicles entering the freeway, the control system aims to prevent excessive queue formation at toll plazas and optimize traffic demand.

2- **Dynamic Traffic Flow Control:** The integration of Variable Speed Limits allows for real-time adjustments of speed limits based on traffic conditions. During periods of congestion, the control system can dynamically lower speed limits to maintain a smoother traffic flow, reducing the potential for stop-and-go conditions and enhancing overall road safety.

3- **Reducing Congestion:** By managing traffic demand and flow proactively, the proposed strategy aims to reduce congestion at toll plazas, enhancing the overall efficiency of the transportation network and improving the commuting experience for travelers.

4- **Minimizing Environmental Impact:** Through the optimization of traffic flow, the proactive strategy aims to minimize the environmental impact associated with congestion. By reducing prolonged idling and stop-and-go traffic, the control system seeks to decrease fuel consumption and emissions, contributing to a greener and more sustainable transportation system.

CHAPTER 2: LITERATURE REVIEW

2.1 Estimation and Prediction of Traffic Parameters

Traditional transportation systems relied on specialized sensors such as magnetic coils, microwave, or ultrasonic detectors for vehicle counting. However, these sensors have limitations in capturing detailed information and were expensive to install [9]. The advancement of computer vision and image processing technologies has led to the rise of video-based vehicle counting systems. These technologies offer a wider range of traffic parameters, including vehicle category, density, speed, and even the capability to detect traffic accidents; these are cost-effective, easy to install, and simple to maintain [10].

The computer vision method for vehicle counting encompasses three integrated procedures: detection, tracking, and trajectory processing [11]. Initially, computer vision vehicle detection used basic image processing techniques like edge detection, blob detection, Hough transform, and stereo vision for tracking. However, these methods lacked accuracy and required manual adjustments. Subsequently, more sophisticated feature extraction methods, such as Haar cascades, SIFT, and HOG, combined with Kalman filters and support vector machines, significantly enhanced vehicle detection and tracking, particularly for surveillance and traffic monitoring purposes [12]. While, existing vehicle counting approaches can be categorized into regression-based, cluster-based, and detection-based approaches [13]–[15]. Regression-based methods involve learning the regression function using characteristics of detection region. Cluster-based methods track object features to establish trajectories, which are then clustered to determine object counts. Detection-based methods encompass four main categories:

1. Frame difference method [16]

2. Optical flow method [17]
3. Background subtraction (BS) method[18]
4. Convolutional neural network (CNN) method [19]

Convolutional neural networks (CNNs) have emerged as the popular object detection technique, achieving significant advancements in vehicle detection and tracking [20]. Utilizing GPUs, CNNs have become the leading approach for accurate vehicle detection and classification, effectively handling complex appearance changes and occlusions[21]. Two primary CNN-based strategies for vehicle detection include one-stage detectors (e.g., YOLO) and two-stage detectors (e.g., R-CNN). R-CNN and its variants propose region-based CNNs, while YOLO and its variants pass the entire image through a CNN for generating boundaries boxes and class probability. CNN-based approaches have been extensively employed for vehicle counting by researchers. For instance, [22] proposed a YOLO-based approach for object detection combined with Kalman filtering and the Hungarian algorithm for tracking. [23] presented a vehicle counting framework using aerial videos from UAVs, offering flexibility in deployment and a larger perspective for traffic monitoring compared to traditional sensors. Similarly, [24] introduced a vehicle counting system using deep learning Mask R-CNN for vehicle classification and counting. Additionally, [9] developed a video-based vehicle counting framework comprising object detection, tracking, and trajectory processing, yielding accurate traffic flow data. [11] explored video-based vehicle counting through object detection and tracking algorithms, achieving precise counts with YOLOv4 and DeepSORT. Leveraging the development of YOLOv5, [25] proposed a deep learning model based on YOLOv5 and DeepSORT for vehicle detection and tracking, resulting in enhanced accuracy.

2.2 Freeway Proactive Traffic Control

Real-time traffic parameters collection is vital in Intelligent Transportation Systems (ITS). Equally crucial are traffic prediction models that offer insights into both current and future traffic conditions. By accurately forecasting congestion, travel times, and traffic flow, these models enable efficient traffic management and resource allocation. For example, [26] presented the Congestion-based Traffic Prediction Model (CTPM), which enhances traffic forecasts in large cities by incorporating congestion data. This model provides invaluable for optimizing road infrastructure and enhancing traffic prediction accuracy.[27] developed machine learning and genetic algorithms to predict traffic flow, managing big data in the transportation system. Similarly, [28] proposed LSTM and Gated Recurrent Unit (GRU) neural network to predict short-term traffic flow for optimal control implementation.

Proactive freeway traffic control strategies are major interventions that improve traffic efficiency and safety on existing infrastructure. These controls utilize real-time data, coordinating various strategies based on short-term traffic flow forecasting to manage demand and mitigate accident risks [29]. Various strategies, such as VSL, ramp metering (RM), and integrated controls, have emerged in recent years. For example, from the perspective of traffic efficiency, [30] designed a VSL method based on a second-order discrete macroscopic traffic model, METANET, analyzing VSL's impact on freeway traffic flow by accounting for segment capacities, critical densities, and driver compliances. Notably, this VSL algorithm achieved high prediction accuracy in model calibration and validation. Han et al. proposed VSL control [31] and RM control [32] strategies using reinforcement learning methods. Similarly, [33] used reinforcement learning to coordinate VSL and RM controls, alleviating freeway network congestion. By integrating future traffic flow predictions, [34][35] applied a discrete first-order model to predict future traffic flow and optimize freeway VSLs. This control effectively resolved jam waves compared to traditional second-order traffic flow models. Integrating multiple control strategies into future traffic flow prediction models also shows promise in achieving cooperative control. For example, [36]applied a traffic prediction model to coordinate VSL and RM, relieving road network congestion and overall time spent.

2.3 Traffic Control for Toll Plazas

Numerous studies have investigated and optimized toll booth operations, often employing different microsimulation software. PTV Vissim software microsimulation is mostly used in some studies to model toll operations[37][38][39], while some studies modeled the microsimulation based on PARAMICS program [40]. The TPSIM microsimulation program was also used to model toll booth areas [41]. Additionally, microsimulation models within VISSUM software were used by [42][43] to analyze toll booth performance and mitigate traffic congestion effects. [43] built a toll lane configuration optimization model that considered various payment methods and vehicle-type proportions. [44] showcased decreased delay values with the use of electronic toll collection over manual toll booths. Furthermore, microsimulations have effectively demonstrated their utility in evaluating toll plaza traffic control strategies, including plate recognition technology [45], separating passenger cars and heavy vehicles[45][46], and employing ETC system applications [47]. However, limited research has focused on proactive traffic control at freeway toll plazas. [48] used LSTM to predict traffic flow for the implementation of proactive control strategies, including variable speed limits (VSLs) and lane configuration, before toll plazas. [49][50] proposed a comprehensive conceptual framework for real-time merging traffic using the local ALINEA RM strategy, improving toll plaza efficiency by reducing vehicle delay and queue length. Similarly, [51] proposed an integrated VSL-RM control strategy to improve freeway mainline efficiency. This strategy coordinates traffic flow between the mainline and toll plaza, adjusting traffic density in the mainline merging zone.

The literature review reveals several significant research gaps in vehicle counting and traffic management at toll plazas in developing countries. Firstly, the use of deep learning CNN models for vehicle counting encounters limitations in efficiency, especially with low-resolution videos, making accurate counting a challenge in such surveillance footage. Secondly, some studies propose increasing the number of lanes for toll plaza optimization. However, this solution can be costly and may encounter Right-of-Way (ROW) issues, particularly in densely populated regions. Thirdly, certain approaches involve configuring lanes based on vehicle classification and payment methods like ETC and MTC. Yet, challenges arise when MTC-equipped vehicles use ETC lanes and vice versa due to a lack of awareness and education among the population in developing countries. Lastly, some research offers proactive control solutions using RM and VSL to manage freeway or mainline capacity, without considering the actual capacity at the toll plaza in real-time. Neglecting the current and future traffic load at the toll plaza can lead in an inefficient traffic management system, causing congestion and delays, particularly during peak hours. Furthermore, the implementation of these strategies in developing countries has been inflexible, with some lacking a well-defined implementation scheme.

To address these research gaps, our proposed study employs the latest version of YOLO, YOLOv7, in conjunction with DeepSORT to achieve high accuracy in vehicle detection, tracking, and counting. Additionally, this study proposes an integrated control method to implement Variable Speed Limits (VSL) and Ramp Metering (RM), while considering short term future capacity at the toll plaza area using LSTM. By dynamically adjusting traffic flow by VSL and regulating vehicle entry via RM, this proactive approach aims to reduce delays and congestion during peak hours, leading a smoother traffic experience for motorway commuters at toll plaza section. Moreover, the study provides a well-defined implementation scheme, demonstrating its feasibility and ease of installation in developing countries. This comprehensive strategy holds significant promise in optimizing toll plaza operations, addressing unique challenges, and benefiting both travelers and toll operators alike.

CHAPTER 3: METHODOLOGY

The proposed proactive traffic control method operates in a time-step manner. It estimates the current traffic state at the toll section and uses it to predict future traffic demand (pred flow). Based on these predictions, the control system determines the appropriate actions to effectively regulate the traffic flow. When the predicted flow is projected to exceed 2500 vehicles per hour, the system implements Variable Speed Limits (VSL). This involves adjusting the speed limits displayed on overhead signs to encourage smoother traffic flow and prevent congestion. If the predicted flow is anticipated to surpass 3400 vehicles per hour, Ramp Metering (RM) comes into play, a combination of both VSL and RM is implemented to efficiently control the traffic situation. Figure 1, visually represents the entire control process of proposed strategy. Furthermore, the following subsection explains the methodology in detail.

3.1 Traffic Flow Estimation

This study utilizes the YOLOv7 deep-learning detection algorithm and the DeepSORT tracker for vehicle counting. YOLOv7 is known for the speed and accuracy in real-time object detection tasks among the YOLO family [52]. It employs convolutional neural networks (CNN) with an efficient network architecture, leading to better features integration and more precise object detection. Additionally, it uses a more robust loss function, improves label assignment, and enhances model training efficiency [52] . Whilst, the DeepSORT algorithm is an advanced object tracking approach that incorporates appearance information through a ReID model. This integration enhances tracking accuracy and reduces ID switching, resulting in more robust and accurate object tracking results [53].

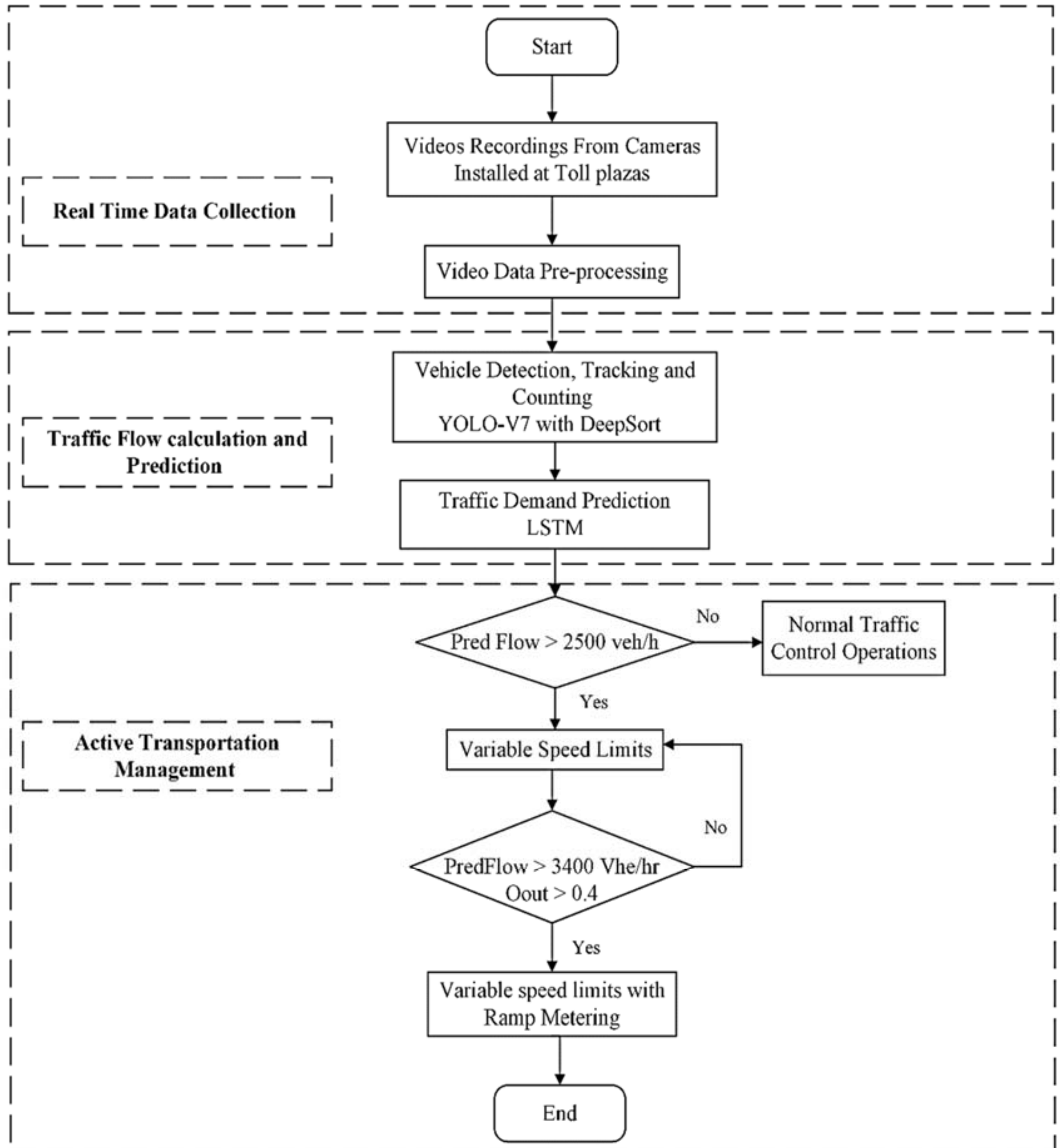

Figure 2: Methodology framework

3.2 YOLOv-7 and DeepSORT

In YOLO family, the real-time object detection model for computer vision tasks with the highest accuracy and speed is YOLOv7. In general, YOLOv7 [52] offers a quicker and more robust network architecture that offers a better feature integration approach, more precise object detection performance, a more robust loss function, and an improved label assignment and model training efficiency. YOLOv7 is the fastest and most accurate real-time object detection model for computer vision tasks in the YOLO family. It has a more efficient and robust network architecture that integrates features better, provides more accurate object detection performance, uses a more robust loss function, and improves label assignment and model training efficiency. The backbone of YOLOv7 is based on extended efficient layer aggregation networks, which consider the number of parameters and computational density of the model as the two primary factors for efficiency. The ratio of input and output channels and element-wise operations can affect the speed of network inference, as shown by the VovNet and CSPVNet models. These models use convolutional neural networks (CNNs) to make DenseNet more efficient by integrating all features in the last feature map. For YOLOV7, the author proposed an architecture called E-ELAN that used expand, shuffle, merge cardinality to improve the learning ability of the network while preserving the original gradient path. E-ELAN guided different computational blocks to learn diverse features. Compound model scaling method to maintain the initial design properties and the optimal structure was also introduced. Re-parameterization is a technique used to improve model performance after training. Although it increases the training time, it can lead to better inference results. Two types of re-parameterization, model-level, and module-level ensemble, are used to complete the models. Model-level ensemble involves training multiple models with the same parameters and different training data, then averaging their weights to obtain the final model. Module-level ensemble involves dividing the model training process into several phases and ensembling the outputs to create the final model. YOLOv7's re-parameterized convolution architecture uses RepConv, which does not have an identity connection (RepConvN), to prevent connections that may harm the network's structure. The Lead Head in YOLOv7 makes predictions, and the Auxiliary Head helps with middle-layer training. The Label Assigner method uses ground truth and network prediction outcomes to assign soft labels, which are used to calculate loss for both the Lead Head and Auxiliary Head. Soft labels are generated identically to ensure consistency in the loss calculation. This makes the yolov7 having most efficient architecture, as shown in the

Figure 3.

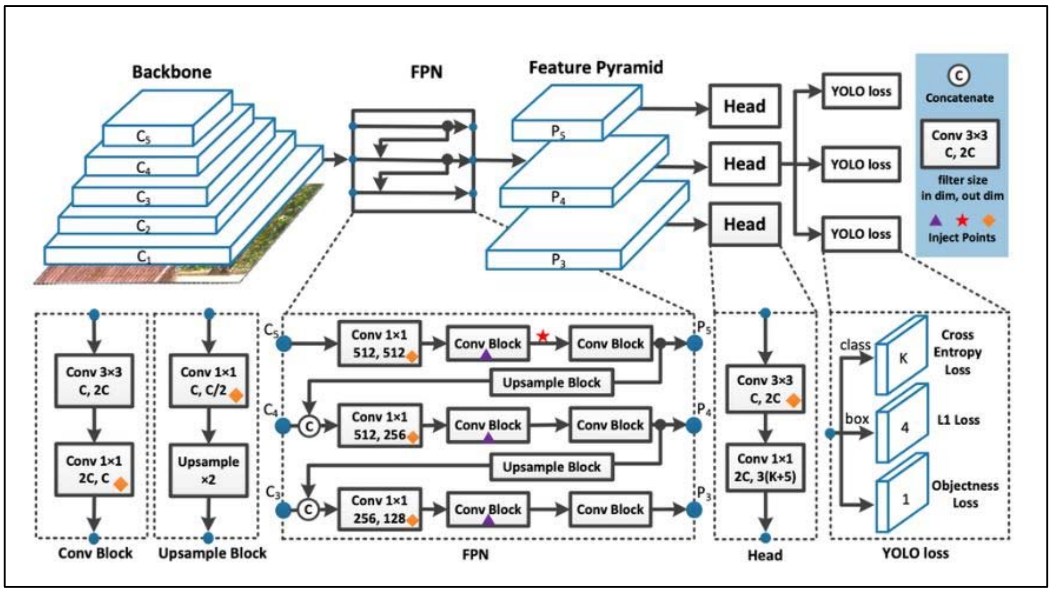

Figure 3 Model Architecture of Yolo-v7

On the other hand, SORT algorithm is an effective approach for object tracking at high frame rates, utilizing a Kalman filter to account for correlation between frames and the Hungarian algorithm to measure correlation. However, it only performs well when target state estimation uncertainty is low since it ignores appearance features of detected targets. SORT also tends to delete targets that are not matched in consecutive frames, leading to the issue of ID switching, where assigned IDs can change frequently. To address these issues, the DeepSORT [53] algorithm incorporates appearance information by using a ReID model to extract feature embeddings. This reduces ID switching by 45% since targets can be more reliably identified by their appearance. DeepSORT also improves SORT's matching mechanism by introducing a Matching Cascade approach that prioritizes track matching to frequently-occurring targets over long-term occluded targets, solving the problem of matching targets that have been hidden for a while. Furthermore, IoU matching is applied to unmatched tracks and detection targets in the final stage of matching to alleviate changes caused by apparent mutations or partial occlusion. By requiring a well-distinguishing feature embedding from the object detection network's output for calculating similarity, DeepSORT borrows the ReID model to improve tracking accuracy. Overall, DeepSORT is a more robust and accurate approach to object tracking that incorporates appearance features and improves upon SORT's matching mechanism.

3.3 Current Traffic Flow Estimation

The proposed approach combines YOLOv7 for vehicle detection in video frames, providing bounding box information for each detected vehicle. These detected vehicles are then processed by DeepSORT, which assigns a unique ID to each bounding box across frames, ensuring consistent and accurate tracking of individual vehicles. With this combined approach, vehicle counting is achieved by tracking the same vehicle across multiple frames, counting it only once. Additionally, the proposed technique performs vehicle classification detection, enabling the counting of vehicles with their specific classifications (i.e., cars, trucks, buses). As a result, vehicles with their classifications are counted for each time interval, and the arrival rate for each interval is estimated. Overall, this approach provides a powerful solution for accurate and efficient real-time flow rate estimation, visually represented in figure 2.

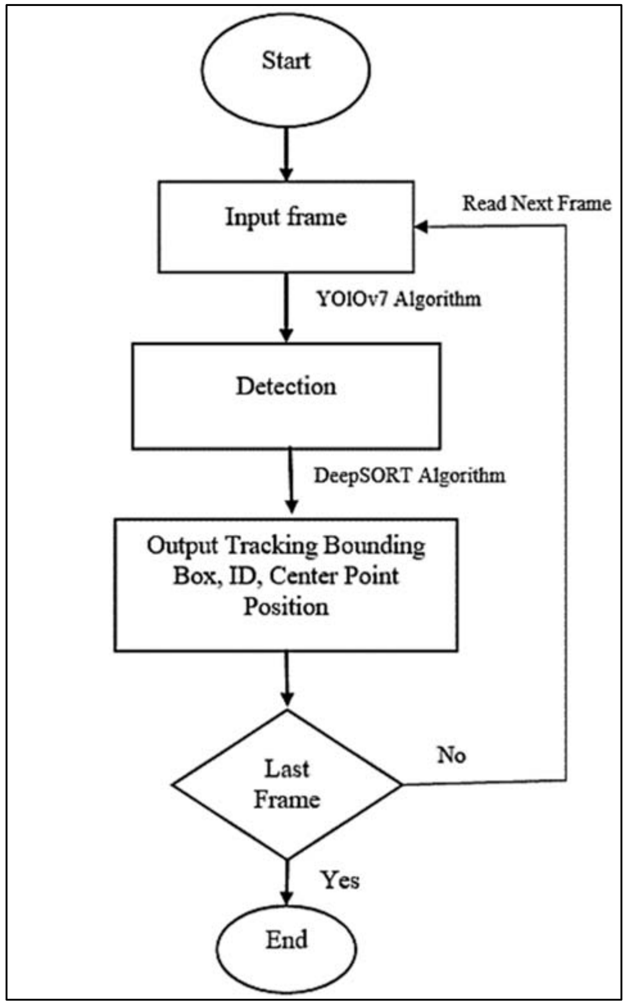

Figure 4: Flow chart for vehicle counting

3.4 Future Traffic Demand Prediction - LSTM

Following the estimation of the current flow rate at toll plaza for every 15-minute intervals, the LSTM model underwent training by analyzing distinct trends for each day of the week to predict traffic flow for subsequent intervals. LSTM is a type of recurrent neural network (RNN) architecture specifically designed to handle long-term dependencies in sequential data - a challenge that traditional RNNs often encounter [28]. Throughout the training phase, the model learned patterns and characteristics unique to each day of the week individually. Consequently, the model was utilized to predict traffic flow for upcoming time interval based on these learned trends. Upon completion of the training process, the model's performance was evaluated using a testing dataset.

3.5 Implementing Proactive Control Strategies

After predicting the short-term future traffic flow, proactive traffic control strategies, namely Variable Speed Limits (VSL) and Ramp Metering (RM), were implemented in advance. These control measures were aimed at mitigating the possibility of congestion in future and ensuring smooth traffic flow at the toll section. The following are brief details of the control strategies i.e., VSL and RM.

3.5.1 Variable Speed Limit Control

The proposed methodology utilizes Variable Speed Limits (VSL) to efficiently control congestion at toll sections. Real-time data analysis dynamically adjusts speed limits with respect to traffic conditions. The fundamental model of traffic flow theory, which establishes a connection between traffic flow (q), traffic speed (u), and traffic density (ρ) through the equation $q = \rho \ x \ u$, is utilized. Additionally, the core equation derived from the Lighthill-Whitham-Richards (LWR) traffic model is also employed, expressed as equation 1.

$$\mathrm{\rho(x,t)} + \partial(\mathrm{\rho u}\ (\mathrm{x,t}))/\ \partial \mathrm{x} = 0 \qquad (1)$$

where:

$\mathrm{\rho(x,t)}$ represents the traffic density at location x and time t, and

$\mathrm{u(x,t)}$ denotes the traffic velocity at location x and time t.

Based on this model, VSL is calculated using the Eq.2.

$$\mathrm{VSL}(x,t) = u\_max - (q(x,t) - q\_min) * (u\_max - u\_min) / (q_{crit} - q\_min)$$

(2)

where:

$\mathrm{VSL}(x,t)$	representing the Variable Speed Limit at location x and time t,
u_max	the maximum speed limit under ideal traffic conditions,
u_min	the minimum speed limit (often set to 0 to represent stopped traffic),
$q(x,t)$	the flow rate of vehicles at location x and time t
q_min	the minimum flow rate (usually set to a small non-zero value to avoid division by zero)
q_crit	the critical flow rate, which represents the threshold beyond which congestion begins to build up.

The proposed methodology continuously applies the traffic flow equation and updates the VSL values based on the real-time flow rate data as shown in equation 2. This effectively regulates traffic flow, optimizes travel conditions, and prevents congestion build-up in the upstream area of toll plaza sections. The proposed approach is visually represented in the Figure 5.

3.5.2 Ramp Metering Control

The proposed strategy also includes ramp metering to regulate the entry of vehicles onto freeways through on-ramps. The fundamental objective of ramp metering is to improve the overall freeway throughput and maintain a smoother traffic flow by using traffic signals at the on-ramps. In this study, the chosen ramp metering strategy is ALINEA (Asservissement Linéaire d'Entrée Autoroutière), widely recognized for its adaptive and proactive approach in handling fluctuating traffic conditions. ALINEA ramp metering uses the following equation for calculating the ramp metering rate [54].

$$r(k) = r(k-1) + K * [\hat{o} - Oout(k)] \tag{3}$$

where:

$r(k)$	the current ramp metering rate in seconds,
$r(k-1)$	the previous iteration ramp metering rate in seconds,
K	a regulator parameter (smoothing factor),
$\hat{o}$	the desired downstream occupancy, and
$Oout$	the measured occupancy in vehicles per mile.

The proposed mechanism for ramp metering control is outlined through a series of steps. Initially, the measurement of traffic outflow $Oout(k)$ on the main freeway near toll plaza sections is undertaken using mainline sensors for the current time step k. Second step is to calculate the difference between the desired rate $\hat{o}$ and the measured or current occupancy $Oout(k)$ at toll plaza sections. The negative sign ensures that the system tries to match the desired rate with the actual outflow. In the third step, difference is multiplied by the control gain (K). The control gain represents the sensitivity of the ramp metering system to changes in traffic conditions. Higher values of K indicate a more aggressive adjustment of the ramp metering rate, while lower values result in a more gradual response. In the last step, product of K and the difference of occupancies to the previous ramp metering rate $r(k-1)$ is added to get the new ramp metering rate $r(k)$, which will be send to the signals. Through signals, the entry of vehicles on freeway to approach toll plaza sections is being controlled as shown in Figure 6. Through the iteratively applying of this control mechanism at each time step, the ramp metering system can continuously adapt and regulate the rate of vehicle entry onto freeway.

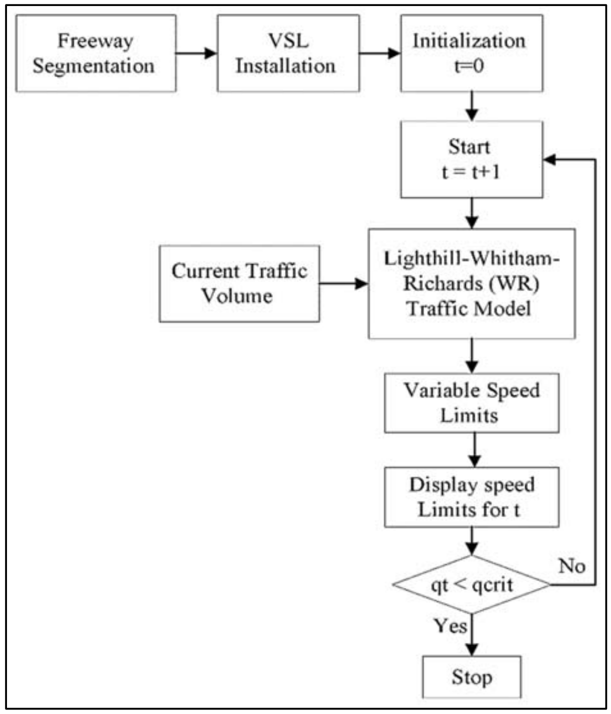

Figure 5: Framework for variable speed limit

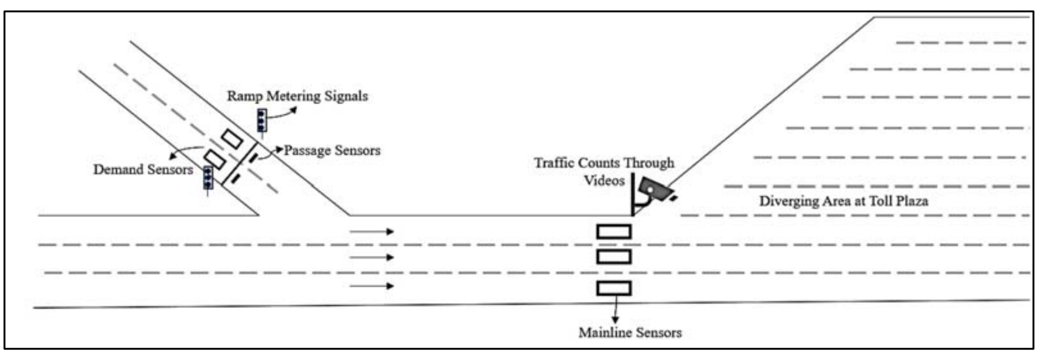

Figure 6: Ramp metering at On-Ramps

CHAPTER 4: SIMULATION MODEL DEVELOPMENT

4.1 Study Site

The selected site for this study is Ravi toll plaza in Lahore, Pakistan, which serves as a hybrid toll plaza on the M-2 motorway, connecting two metropolitan cities: Islamabad and Lahore. This toll plaza encompasses a length of 540 meters, inclusive of both diverging and merging sections. It comprises of total of 25 lanes, with 15 designated for traffic bound for Lahore and 10 for traffic headed to Islamabad. The individual toll booths span a length of 140 m. While all interchanges along the M-2 have been upgraded with the provision of M-Tag (ETC) system for toll payment, yet the public awareness still remains an issue and impacting system efficiency. Variable Message Signs (VMSs) are installed in front of the toll booths, capable of displaying lane types - ETC or MTC. The current study focuses exclusively on traffic flow in the exit direction, especially Lahore bound. Site location is shown in the Figure 7.

Figure 7: Study site: Ravi Toll Plaza Lahore

4.2 Data Collection and Analysis

To gather data for this study, video cameras were positioned at the toll plaza's diverging section outsets, capturing vehicle trajectories. This collected data enabled the recognition of traffic patterns, as well as the prediction of traffic flow and composition at the studied toll plaza section. The video footage spans a week, encompassing 168 hours from 30th January to 5th February 2017. The Camera's position is at an angle of approximately 30 degrees to the vehicles' travel direction, providing a comprehensive view of the toll plaza's diverging area. The recorded video frames possess dimensions of 720 pixels in width and 480 pixels in height, with a fame rate of 29.5 frames per seconds.

Once the camera videos were collected, a series of pre-processing, video decoding, frame resizing, and frame normalization, were executed. Subsequently, the pre-processed videos were used as input for YOLOV7-DeepSORT algorithm. This methodology enabled the acquisition of traffic counts for every 15-minute interval. In total, this process involving handling 168 videos, each spanning one hour, culminating the final outcomes. Screenshot of the output video is displayed in the

Figure 8.

The outcome showed distinct traffic patterns. During weekdays, the morning and evening peaks starts at 0800 and 1700hrs respectively. However, on weekends, the morning and evening peaks begins at 1000 and 1900hrs. The trend is visually shown in the

Figure 9. On weekdays, the observed maximum flow rate is 3400 vehicles per hour; whereas, weekends witness 3800 vehicles per hour flow rata, especially on Sundays. Further data analysis revealed four distinct traffic flow trends. From Monday morning until Thursday, a consistent flow patterns prevails. Fridays showing a noticeable deviation in flow pattern behaviour, indicating a distinct traffic dynamic.

Saturdays exhibit a unique flow trend distinct from weekdays, Fridays, and Sundays. Sundays displays a flow trend entirely distinct from rest of the week as shown in the

Figure 10. Additionally, the results of mode share analysis showed that, across the entire week, 81.85% of incoming vehicles were passenger cars, while 10.8% constituted trucks and 7.3% were buses. Whereas, these mode shares varied over time; the proportion of trucks and buses slightly increased during night-time.

Figure 8: Screenshot of output video

To evaluate the accuracy of the proposed traffic counting method, the vehicle counts obtained through this approach were compared with manually calculated counts. The process involved in manual counting the number of vehicles passing through 15-minutes videos under different weather conditions, and these counts were then compared with the estimated counts derived through the proposed methodology. The outcomes of this comparison indicated a substantial degree of accuracy achieved by our approach. Specially, under normal daylight conditions (sunlight), the approach exhibited an impressive accuracy of 91%. However, the accuracy dropped in other scenarios, with accuracy rates of 87% during morning dawn, 85% during evening twilight, 81% during night, and 68% in foggy morning conditions, as showed in the Table 1.

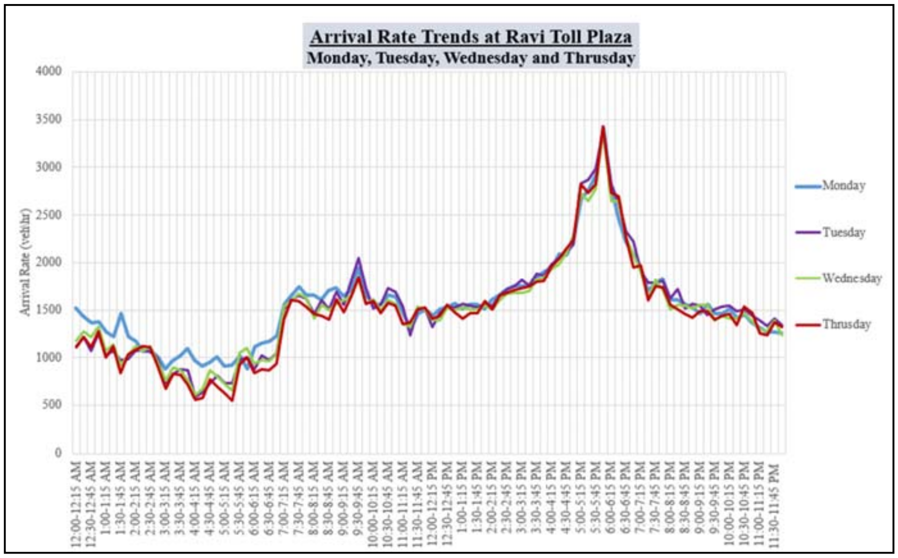

Figure 9: Arrival rate profile from Monday to Thursday

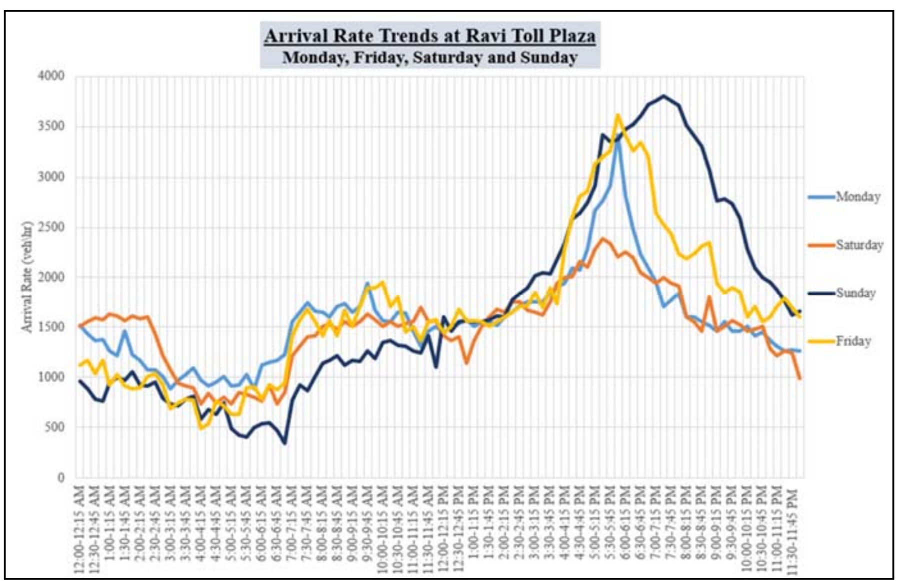

Figure 10: Arrival rate profile of Monday, Friday, Saturday and Sunday

Moreover, to enhance the comprehension of the accuracy achieved by the proposed counting approach, confusion matrices have been utilized to evaluate the classification of vehicles and ascertain how effectively they were counted. An illustration of the confusion matrix for the same 15-minute video recorded under sunlight conditions is shown in Figure 11. Figure 11 displays the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions generated by the algorithm. The results showed in the confusion matrix reveals that 98% of car, 86% of trucks, and 70% of buses were correctly counted.

Following the estimation of the number of vehicles passing in 15-minute intervals, the LSTM model underwent training by analysing distinct trends for each day of the week to predict traffic count for subsequent intervals. This evaluation yielded encouraging results, with the model achieving a mean squared error (MSE) of 128.18, a mean absolute error (MAE) of 8.55, and a root mean squared error (RMSE) of 11.93. Additionally, the R-squared value of 0.94 indicated a strong correlation between the model's predictions and the actual traffic counts. This underscores the LSTM model’s capability in forecasting traffic trends by leveraging the distinct day-specific trends it learned during the training phase.

True Labels	Predicted Labels: Car	Truck	Bus
Car	256	9	3
Truck	7	32	2
Bus	3	1	14

True Labels	Predicted Labels: Car	Truck	Bus
Car	0.98	0.24	0.15
Truck	0.02	0.86	0.1
Bus	0.01	0.028	0.7

Figure 11: Confusion Matrix for estimated vehicle classification

Table 1 Arrival rate profile of Monday, Friday, Saturday and Sunday

Weather Condition	**Vehicle Type**	**Manual Counts**	**Proposed Method**	**Percentage Error (%)**	**Overall Accuracy (%)**
Sunlight	Car	262	266	98.5	90.5
	Truck	37	42	88.0	
	Bus	20	17	85.0	
Morning Dawn	Car	140	137	93.0	86.8
	Truck	16	19	84.0	
	Bus	6	4	83.3	
Evening Twilight	Car	287	264	92.0	84.7
	Truck	32	38	82.0	
	Bus	21	17	80.0	
Night	Car	250	240	94.0	81.2
	Truck	39	45	86.6	
	Bus	27	17	63.0	
Fog	Car	112	62	55.4	67.8
	Truck	13	17	76.5	
	Bus	7	5	71.4	
Rain	Car	160	130	81.2	64.5
	Truck	21	16	76.2	
	Bus	11	4	36.0	

4.3 Model Development on PTV VISSIM

Micro-simulation tests were carried out to validate the proposed integrated control method before its actual development. To this end, the PTV Vissim software was used to simulate the proposed control strategies during the peak hour at Ravi toll plaza. PTV VISSIM is widely recognized for its capacity to visually represent traffic flow across various modes, making it an exceptional tool for both graphical presentations and detailed traffic flow analysis at specific points within a transportation system. To accurately model the system's geometry in VISSIM, a detailed design process was undertaken using links and connectors. The initial step involved importing and appropriately scaling a background image. Next, links and connectors were added to build the roadways. Specifically, two on-ramps were incorporated upstream of the mainline freeway section. Downstream, the toll plaza was meticulously designed. A zone for desired speed limits (Variable Speed limits) was introduced 8 km before the start of the toll plaza's diverging section. In addition, a variable message sign board was deployed ahead of VSL zone.

The toll plaza was divided into two sections: a diverging section spanning 238 meters and a merging section extending over 220 meters. Both sections were meticulously drafted in VISSIM to accurately mirror the as-built design. With the diverging area, the 3-lane mainline link was subdivided into 15 toll lanes, seamlessly connected to the mainline link using connectors. Static routes were also assigned to every toll lane. This configuration allowed a smooth traffic transition from the mainline to the toll lanes. In order to manage speed within the diverging section, a speed limit of 60 km/hr was considered, ensuring safe and controlled vehicle movement.

For the mainline motorway section, varying speed limits were introduced: 120 km/hr for cars, 110 km/hr for buses, and 100 km/hr for trucks, respectively. At the toll plaza, the dwell time of the stop sign was synchronized with service time. Moreover, to gather relevant data, queue counters and data collection points were placed before the stop sign. This allowed the measurement of queue length and the count of vehicles passing through the toll plaza, providing essential insights into traffic flow and operational efficiency. Furthermore, vehicle travel time collection points were integrated into the network to measure travel time across scenarios. Additionally, a node was formed throughout the network to ascertain vehicle delay and CO-emissions.

In this study, the LSTM (Long Short-Term Memory) model's predicted flow measurements were considered as the actual vehicle input for the network in VISSIM. To introduce this input into the simulation, 40 percent of the predicted flow was allocated as the vehicle input for both on-ramps links, while the remaining 60 percent was directed as the vehicle input for the mainline motorway link. To accurately replicate driver behaviours like following, merging, and diverging, the CC0, CC1, and CC2 parameters in the Wiedemann 99 model were calibrated and validated within the simulation model for their respective segments.

Moreover, there were no hard separations between lanes at the toll booths, allowing for smooth vehicle flow and lane changes. In line with the real scenarios at Ravi toll plaza, vehicles equipped with Electronic Toll Collection (ETC) and Manual Toll Collection (MTC) were permitted to travel in both lane types (ETC and MTC lanes). The network was configured so that 60 percent of vehicles used MTC for toll payment, while the remaining 40 percent utilized the ETC payment method. Service times were set at 5 seconds for ETC and 22 seconds for MTC. VISSIM Simulation model for Ravi toll Plaza as illustrated in the Figure 13, while, 3D view of toll booths is shown in the Figure 12.

Figure 12: - 3D view of Ravi Toll Plaza on PTV VISSIM

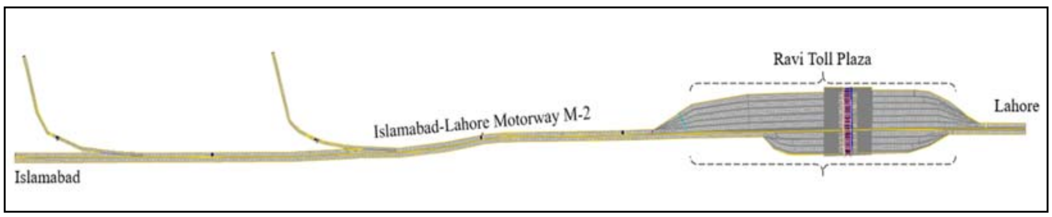

Figure 13: 2D view of Simulation Model on PTV VISSIM

4.4 Model Calibration

Prior to implementing the control strategy within the VISSIM network, a meticulous calibration of the model's parameters was conducted. Traffic data collectors were strategically positioned throughout the network to collect essential traffic parameters, including queue length, delays, and vehicle travel time. Furthermore, during the field data collection process using video recordings, actual queue length, delays, and travel time were calculated. The comparison between the model's predictions and the field data showed that the model achieved a Mean Absolute Percentage Error (MAPE) of 6.5%. This low MAPE value signifies that the calibrated VISSIM model accurately predicted traffic patterns in both free-flow and congestion situations, understanding its reliability for proactive control. The delay, vehicle travel time, and queue length profiles presented in Figure 14, Figure 15 and

Figure 16 respectively, further support the precision of the calibrated VISSIM model.

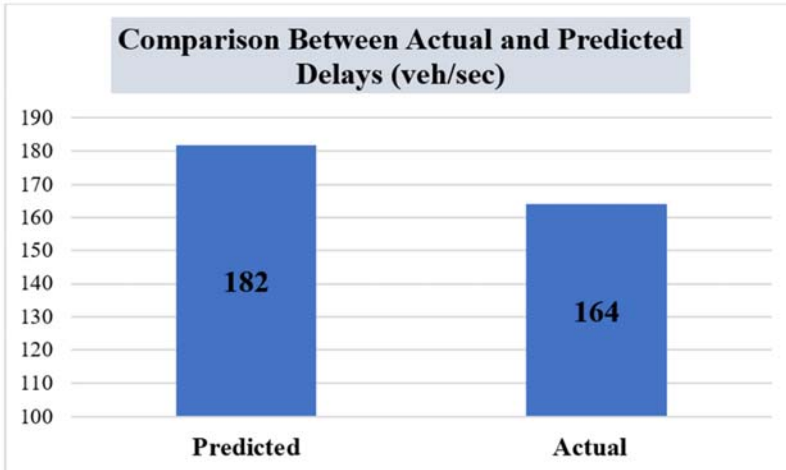

Figure 14: Comparison of actual and predicted delays

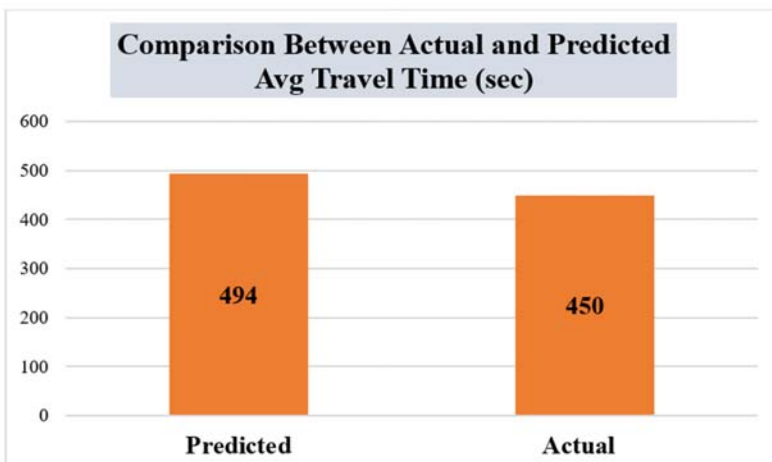

Figure 15: Comparison of actual and predicted travel time

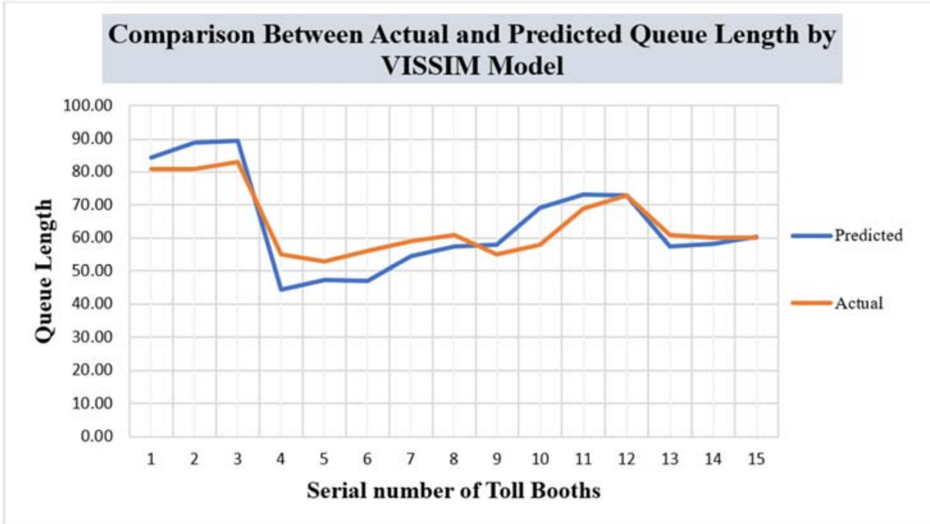

Figure 16: Comparison of actual and predicted queue length

4.5 Proposed Logic development using VisVAP

After the toll plaza model development, the control strategy was programmed using a VisVAP based approach on VISSIM. Brief methodology for establishing the control strategy utilized in this research study is presented in the

Figure 17. As indicated in

Figure 17, the PTV VISSIM annex software, known as VisVAP, was used to development changes in speed limits and apply ramp metering throughout the simulation. The development of a program within VisVAP was undertaken to facilitate the initiation of the simulation process and optimization of the control variables. This logic was literately executed for each time interval. For every interval, the current traffic parameters were extracted, passed into the logical program, which then generated optimal control inputs. Subsequently, these optimal inputs were returned into the VISSIM environment. When there was a change in the current flow, the VisVAP program replaced the original control parameters with new optimized controls within the VISSIM simulation.

Specifically, when the flow exceeded 2500 vehicles per hour, the program removed the initial limits and introduced new desired speed limits of 100 km/h based on the Lighthill-Whitham-Richards (LWR) traffic model, as explained in methodology part. When the flow exceeded 3000 vehicles per hour, the program set a desired speed limit of 80 km/h, and similarly, when it went beyond 3400 vehicles per hour, the program established a desired speed limit of 60 km/h. Concurrently, the program was designed from the outset to monitor whether the ramp metering rate and cycle length exceeded 4 seconds after each time interval, utilizing the calculation method explained in methodology. If the metering rate was below then the cycle length of 4 seconds, the ramp metering signal remained green. However, when the flow exceeded 3400 vehicles per hour and the measured occupancy increased, causing the cycle length to exceed 4 seconds, the ramp metering was triggered. In short, when the vehicle flow rate surpassed 3400 vehicles per hour, both Variable Speed Limit (VSL) and Ramp Metering (RM) controls were activated to optimize traffic flow at the toll plaza.

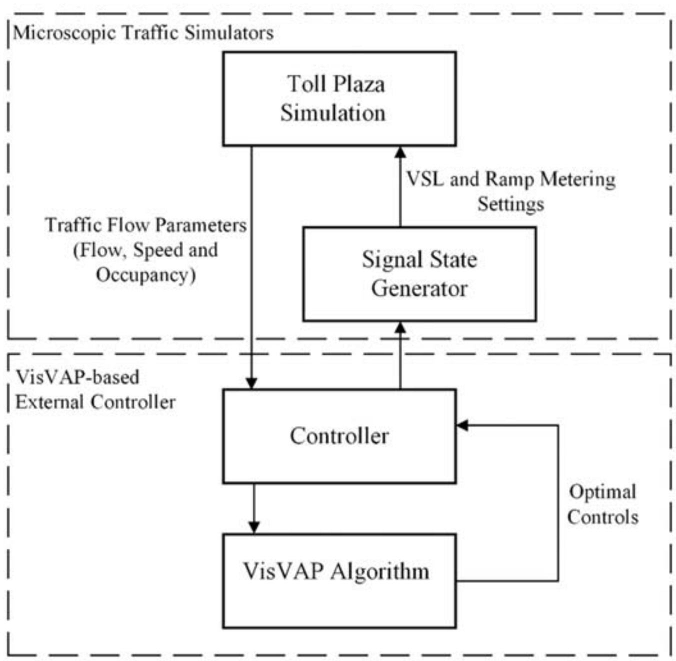

Figure 17: Microsimulation setup for VisVAP

CHAPTER 5: RESULTS AND DISCUSSION

The proposed study was conducted at Ravi Toll Plaza, analyzing various control strategy scenarios. The outcomes were evaluated based on four efficiency criteria: queue length, travel time, vehicle delay, and environmental impact. The efficiency of the proposed scenario (VSL+RM) was evaluated by comparing it with three other alternative scenarios: the existing scenario, variable speed limits only (VSL), and ramp metering only (RM). In the VSL only control scenario, ramp metering wasn't employed alongside VSL when vehicles flow exceeded 3400 vehicles per hour. Conversely, in the RM control scenario, only ramp metering was activated when the vehicles flow exceeded 3400 vehicles per hour. These scenarios were analyzed and evaluated based on their influence on queue length, travel time, vehicle delay, and environmental factors.

5.1 Traffic Impact Analysis

Traffic impact analysed based on their influence on queue length, travel time and vehicle delay by all scenarios. The queue lengths (measured in meters) for all scenarios at toll booths, numbered 1 to 15, are depicted in

Figure 18. The simulation results reveal that the highest average queue length is observed in the existing scenario (64.18 m). This observation aligns with the real-world experience of long queues forming on weekends during peak-hours (04:00 – 10:00 PM) when traffic from Islamabad to Lahore is at its peak. The average queue lengths for the VSL-only and RM-only scenarios were 33.40 m and 53.18 m, respectively. However, when both controls, VSL and RM, were jointly operational, an average queue length of 27.60 m was recorded. The average queue lengths are shown in

Figure 19.

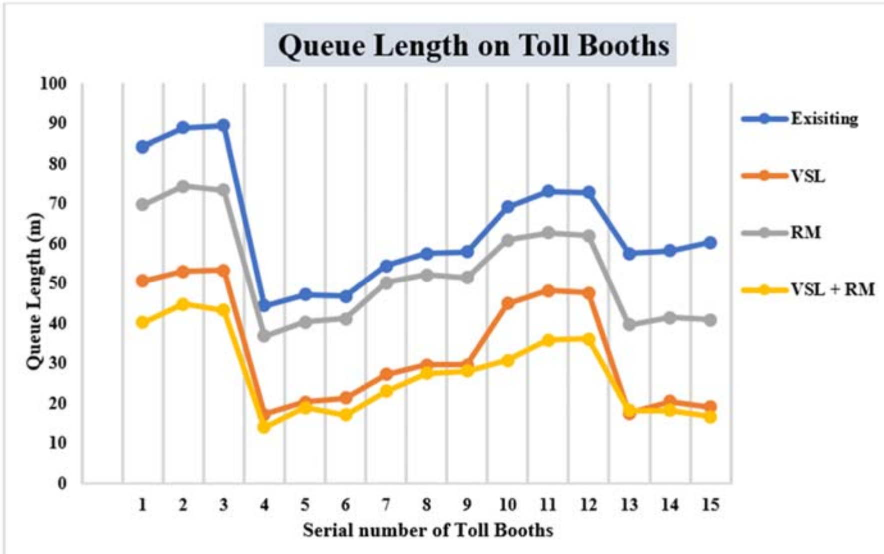

Figure 18: Queue lengths on toll booths in all scenarios

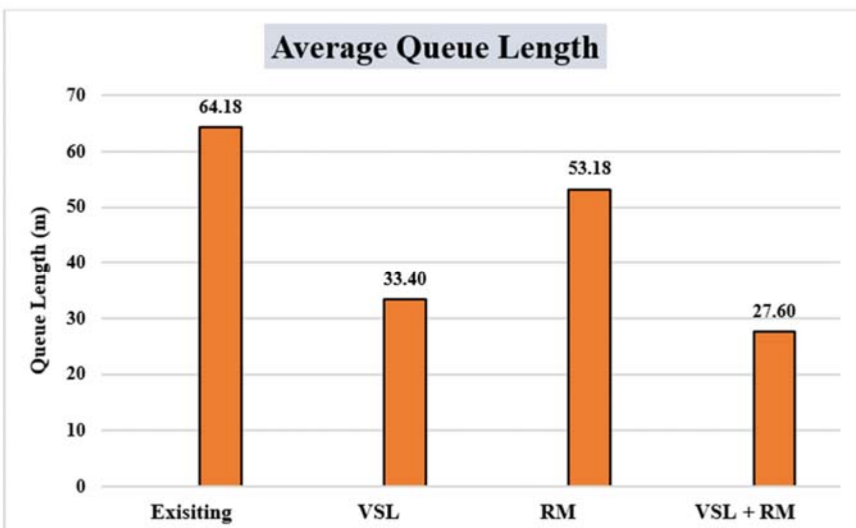

Figure 19: Average queue lengths against all scenarios

Average vehicular and stop delays were recorded from the node outcomes. The encompassing node covered the entire network, resulted in recorded vehicle delays that included acceleration and deceleration due to variable speed limits. Recorded stop delays included waiting delays at the ramp when the signal was red, along with waiting time for service at the toll plaza. The outcomes showed that the scenario involving the combination of VSL and RM had average vehicle and stop delays of 95 and 43 seconds, respectively. In comparison, vehicle delays for the VSL-only, RM-only, and existing scenarios were 125, 148, and 182 seconds (about 3 minutes), respectively. Stop delays for VSL-only, RM-only, and existing scenarios were 55, 75, and 78 seconds, as depicted in

Figure 20. These results collectively underscore the deduction of traffic impact by the VSL and RM combined strategy.

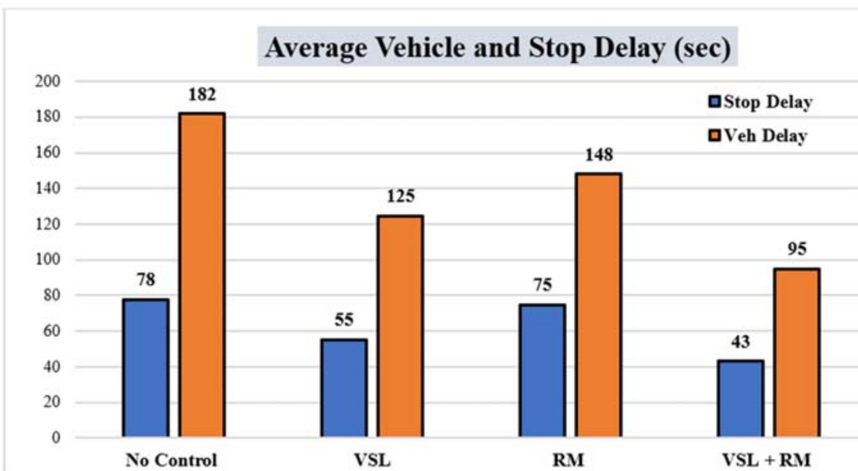

Figure 20: Average vehicle and stop delay for all scenarios

5.2 Environmental Impact Analysis

Environmental impact analysed based on fuel consumption and carbon emissions by all scenarios. As a result, it is observed that VSL and RM scenarios notably reduced carbon monoxide (CO), volatile organic compounds (VOC), and nitrogen oxides (NOx) emission. Specifically, the VSL+RM scenario demonstrated significant decreases, including a remarkable 28.4% reduction in fuel consumption, lowering from 936 gallons in the existing scenario to 670 in the proposed scenarios as shown in the Figure 21. Additionally, CO emissions were reduced by 34.4%, as depicted in the

Figure 22, while VOC emissions exhibited a reduction of 32%. The NOx emissions also saw a substantial reduction of 35%, as illustrated in the

Figure 23. These results collectively underscore the substantial environmental benefits of implementing the VSL and RM combined strategy.

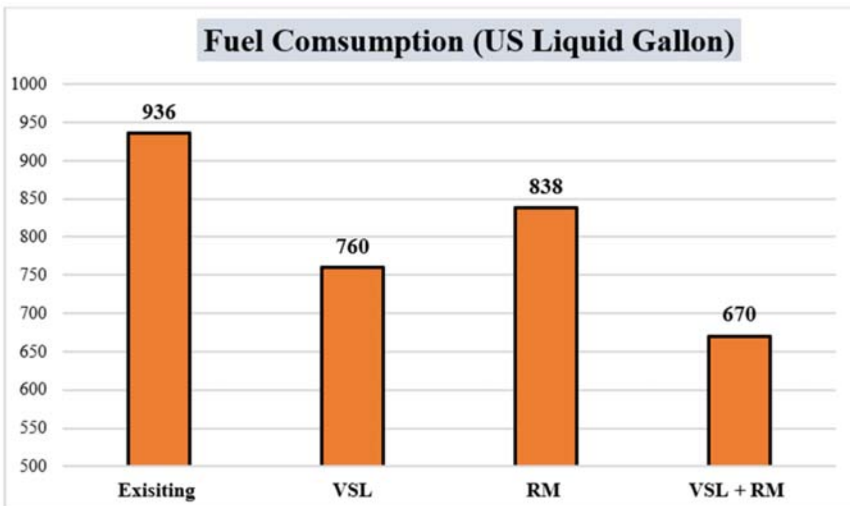

Figure 21: Fuel consumption by all scenarios

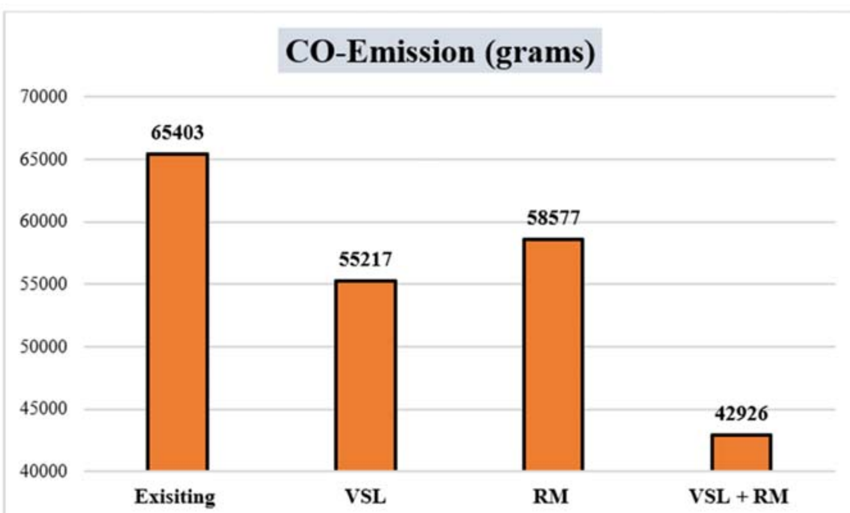

Figure 22: CO-emission by all scenarios

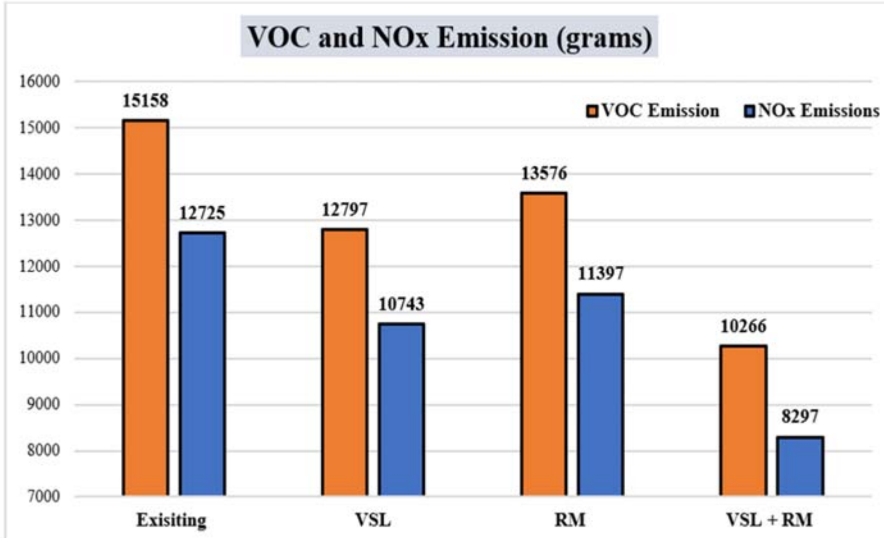

Figure 23: VOC and NOx emission by all scenarios

To summarize the traffic and environmental analysis, the combination of VSL and RM strategies resulted in a substantial 57% reduction in queue length at the toll plaza. This combined approach also significantly curtailed vehicle delays by around 47%, and stop delays by 44.8%. Specifically, the VSL+RM scenario achieved a 28.4% decline in fuel consumption and a 34% reduction in air pollutant emissions, highlighting the importance of integrated and proactive traffic control strategies in mitigating environmental impacts, enhancing air quality, and fostering a sustainable transportation system. It is important to emphasize that the objectives of achieving smooth traffic flow, minimizing environmental impact, and alleviating tool plaza congestion were prominently achieved using the VSL and RM combination deployed ahead of the toll plaza.

5.3 Implementation of Proposed Proactive Control Strategy

Developing countries face a significant challenge when it comes to active transportation strategies due to insufficient public awareness and acceptance. Proposed study tackles this concern by proposing a comprehensive implementation strategy to enhance the successful adoption of proactive control measures. This strategy not only facilitates governing bodies and law enforcement agencies but also benefits the users of the system. Users are facilitated through the deployment of variable message signs boards ahead of the RM and VSL zones. These signs offer real time information about the ongoing queue length, estimated waiting times, and travel durations required to navigate the toll plaza. Such information empowers users to make decisions at the right movement. Simultaneously, enforcement agencies are facilitated by the system to identify non-compliant users. A pre-trained model designed for signal violation detection is used for this purpose. When a vehicle fails to stop at a red signal during ramp metering, the system captures its ID. Whenever the model detects a violation, the vehicle's ID is recorded as traffic signal violator. Furthermore, when all vehicles enter the VSL zone, their IDs, geolocation, and entry time are recorded. The system also estimates the anticipated time for each vehicle to approach the toll plaza. If a vehicle enters the toll plaza before its estimated arrival time, it could indicate a speed violation (exceeding the speed limit) within the VSL zone. In such instances, the system flags the vehicle as a defaulter.

With a very limited utilization of resources, not only monitoring would become easy, but it will add value to treasury, as violations are very common in developing countries resulted in highest accident rate in low-and middle-income countries according to WHO[55]. Upon toll payment, the system generates fines for all defaulter, aligning with their respective violations, whether they are involved in violation of VSL or RM or both. This study has suggested an obligated fine payment, alongside the toll tax, collected as vehicle pass through the toll plaza, to enhance transparency and early recovery aspect. The intricate proposal framework for violation detection is outlined in Figure 24.

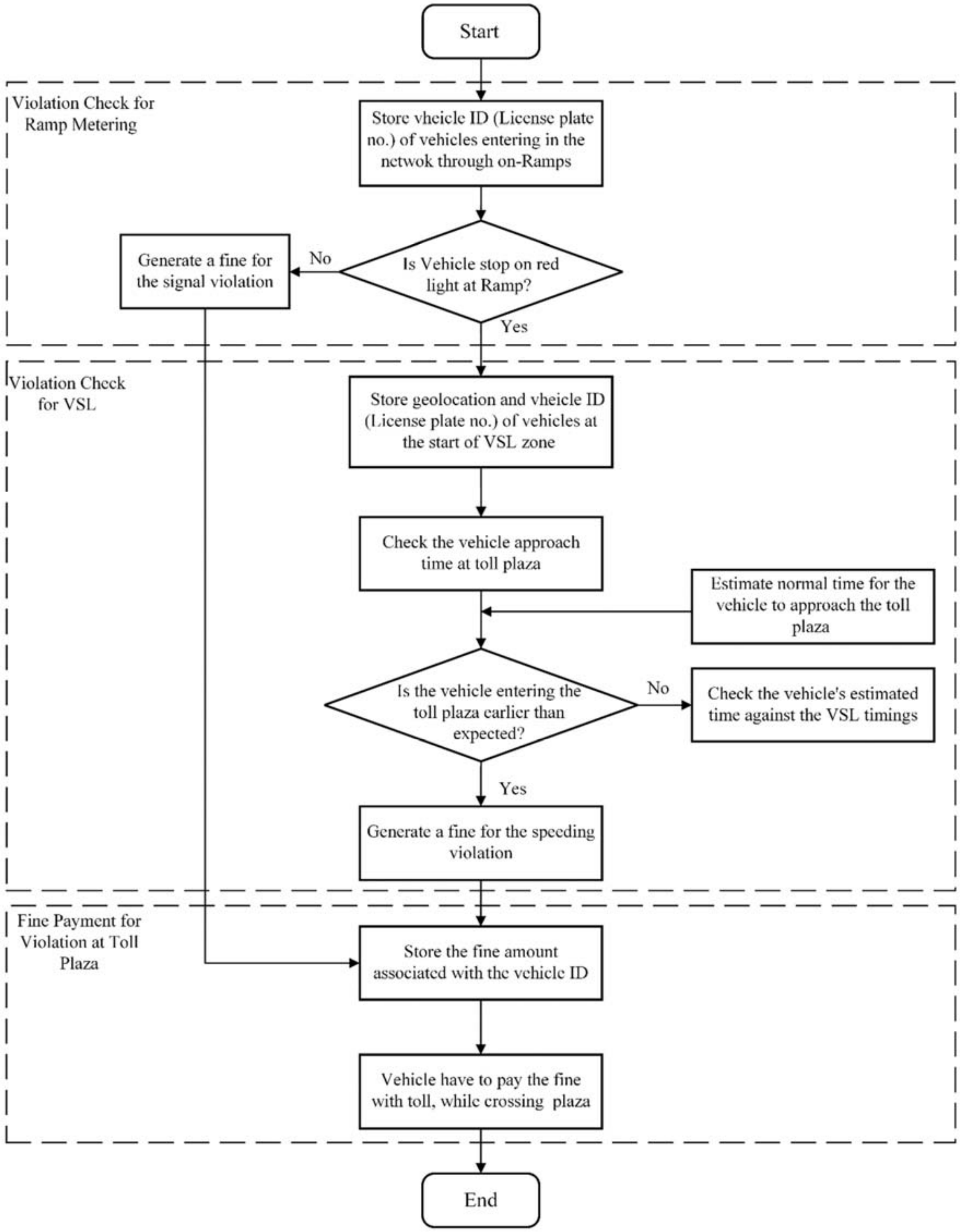

Figure 24: Implementation framework for proposed strategy

CHAPTER 6: CONCLUSION

Toll plazas positioned on freeways hold a vital role in managing traffic flow and generating revenue. However, these critical junctions frequently grapple with congestion concerns, causing delays and environmental repercussions. To address these challenges, the present study introduces a sophisticated traffic control strategy that harnesses cutting-edge technologies and strategic control mechanisms. The cornerstone of this approach involves the utilization of deep learning CNN models, specifically YOLOv7-DeepSORT, to accurately count vehicles. Additionally, the study employs LSTM model to predict short-term arrival rates. Guided by these predictions, the strategy orchestrates timely interventions, deploying Variable Speed Limits (VSL) and Ramp Metering (RM) when projected arrival rates surpass a predefined threshold. Validation of the proposed methodology is meticulously executed through a tangible case study conducted at Ravi Toll Plaza. The simulation outcomes demonstrate the strategy efficiency, revealing a remarkable 75% reduction in queue length and a substantial 47% decrease in vehicle delays. Beyond these tangible improvements, the proactive strategy holds far-reaching implications for environmental welfare. It significantly curtails fuel consumption by an impressive 28.4% and diminishes air pollutant emissions by a substantial 34%. However, successful implementation of such an innovative strategy necessitates more than theoretical insights. To facilitate its practical adoption, the study proposes a comprehensive implementation framework. This blueprint serves as a strategic guide, facilitating the transition from theory to real-world application. This study bridges the gap between theoretical innovation and tangible impact, illustrating a pathway toward enhanced traffic management and sustainable transportation systems.

RECOMMENDATIONS AND LIMITATIONS

The proposed strategy offers an effective approach to alleviate congestion. However, certain limitations exist in the strategy that can be addressed through the recommendations for future work. Following are the recommendations:

1. **Expanded Vehicle Classification:** In the current study, all vehicles were classified into three categories: cars, buses, and trucks. Additionally, within these categories, further mode shares of vehicles were approximately estimated after the manually calculated in a peak hour. There is potential to expand the vehicle classification to improve real-time arrival rate calculations.
2. **Exploring Advanced Traffic Models:** in future, Cell Transmission Model (CTM) can be integrated into the prediction framework. This advanced model can provide detailed insights into traffic parameter evolutions, enabling more precise control strategies and better alignment with actual traffic dynamics.
3. **Refined LSTM Training:** To improve short-term arrival rate predictions, refine the training of the Long Short-Term Memory (LSTM) model by incorporating factors such as seasonal patterns and public holidays. This would boost the model accuracy in capturing diverse traffic conditions.
4. **Integration with Autonomous Vehicles**: Explore synergies with autonomous vehicle systems by incorporating the proposed strategy into connected environments. Collaborating with autonomous systems can optimize traffic flow and coordination, enhancing the strategy's impact.

By being mindful of these recommendations and recognizing the limitations, the strategy's potential can be maximized, paving the way for effective traffic management, congestion alleviation, and a more sustainable transportation system.

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