Investigating the Impact of Parking Violations on the Performance of a Curbside With-Flow Bus Priority Lanes: A Simulation-Based Approach

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Extended Abstract

A Bus Priority Lane (BPL) is a lane where priority is given to buses over other traffic. Travel time reduction is one of the main benefits expected from implementing a BPL. Literature reveals that the success of a BPL in achieving its expected benefits depends entirely on the adherence by motorists and the enforcement by the enforcement authority of the BPL Rules. Literature classifies BPL violations into two types, namely parking and driving violations (Agrawal, Goldman, & Hannaford, 2012; Mundy, Trompet, Cohen, & Graham, 2017). The impact of Parking Violations (PV) is explored in this study. A PV is when an unauthorised vehicle enters the BPL and parks in the BPL for a period of time. A driving violation is when an unauthorized vehicle drives in the BPL without stopping. Curbside with-flow BPLs, such as in the case of Colombo, Sri Lanka, are most at risk for parking violations due to high number of curbside activities.

Experimenting PVs on the ground is not only costly but also risky. Microsimulation is a valuable traffic engineering tool that offers many benefits in evaluating traffic scenarios before implementation. However, as it is an approximation of the real world, the models should closely reflect the real world for the outputs to be credible. This credibility is achieved by calibrating parameters influencing the vehicle trajectory decisions in the simulations. Many studies have used microsimulation to analyse bus priority strategies by calibrating several parameters. These include vehicle-specific parameters such as dimensions, speed, lateral and longitudinal gap acceptance, etc., and simulation model-specific parameters such as car-following and lane-changing models. “SUMO TraCI” has been used successfully to simulate the stopping of a vehicle in a lane for a predetermined time period, which was used to simulate the PV s in this study.

The output showed that the average travel time of buses increases exponentially with increasing frequency of PVs, duration of PVs and the flow of buses (headways). While both increase of duration of PVs and flow of buses causes the average bus travel times to increase at an increasing rate, further analysis showed that the duration of PVs increases the travel time at an increased rate higher than that of the flow of buses increases (shorter headways).

The investigation of the impact of PVs on the travel time of buses in BPLs is identified as a research gap. Anwar, Fujiwara, & Zhang (2011) modelled the impact of illegal on-street occupancy on the

impact of link travel time as a reduction in the link capacity using the Bureau of Public Roads (BPR) function developed in the USA. The parameters of BPR function have been recalibrated considering the effect of illegal on-street occupancy on travel time prediction.

The microsimulation model developed in this study has been calibrated for Sri Lankan Traffic conditions. The model comply with Greenshield's traffic flow model. Microsimulation is used to obtain the average travel time of buses in the BPL for varying flow of buses, frequency of PVs and the duration of parking. The output is then used to calibrate the BPR function to model the impact of PVs on the travel time of buses in a BPL.

The α and β values of the calibrated BPR function are 3.403 and 2.493, which is similar to the parameters used by the authorities who estimate travel time on national roads in Sri Lanka. Thus, the overall travel time in BPLs increases more than three times (340%) compared to that in free-flow conditions due to PVs, while the increase is random as of occurrence of PV.

Since the study is focused on modelling the travel time of buses on BPLs, the impact of violator vehicle movements on the travel times of the general traffic is not investigated. Another limitation of this study is that it considers only one vehicle type to perform PVs. Therefore, expanding this study to include different types of vehicles as violators and investigating the impact of PVs in BPL on the general traffic on other lanes in the same direction is recommended as future research avenues.

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Lastly, I wish to acknowledge my husband and my parents, for their constant and unwavering support, which made it possible for me to come this far.

Abbreviations

BPL	Bus Priority Lane
PV	Parking Violations
SUMO	Simulations of Urban Mobility
TraCI	Traffic Control Interface
BPR	Bureau of Public Roads
HCM	Highway Capacity Manual

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1 Introduction

1.1 Background

Public Transport is widely hailed as the answer to reducing traffic congestion in urban areas. Among the public transport modes, buses hold the major mode share in passenger transportation in Asian countries (around 60% in Sri Lanka). Therefore, priority treatment for buses is inevitable, especially as augmentations to infrastructure can be highly expensive. The Bus Priority Lane (BPL) are one such priority measure where the buses are given priority in a dedicated lane (Litman, 2016).

A BPL is a traffic congestion relief measure that typically doesn't involve grade separation of lanes.

Some BPLs, such as the one in operation in Colombo, Sri Lanka, have a fixed operational time period (usually during recurrent congestion period) where the priority is given to buses. Therefore, it is very easy for general traffic to encroach and violate the BPL regulation. This causes BPLs to be as effective as their enforcement in their contribution to congestion relief (Agrawal et al., 2012).

It has been proven that the performance of BPL operations is negatively affected by drivers with poor lane discipline (Basbas, 2007a; Trivedi & Gor, 2017). The curbside of a road has abundance of activities like loading/unloading, parking, pick-ups and drop-offs (Gavanas, Tsakalidis, Aggelakakis, & Pitsiava-Latinopoulou, 2013). These activities demand vehicles (unauthorised on BPLs) to move into the bus priority lane, stay parked until their intended activity is completed, and move out of the lane after pick-up/drop-off or loading/unloading activity is completed. This lane changing maneuvers and parking disrupts the flow of authorized vehicle traffic in the BPL, causing the buses to incur delays (Seraj, Bie, & Qiu, 2017).

For this study, entering these unauthorised vehicles into the BPL and parking for a short period is considered a Parking Violation (PV). As considered in this study, a PV is shown in the Figure 1 below.

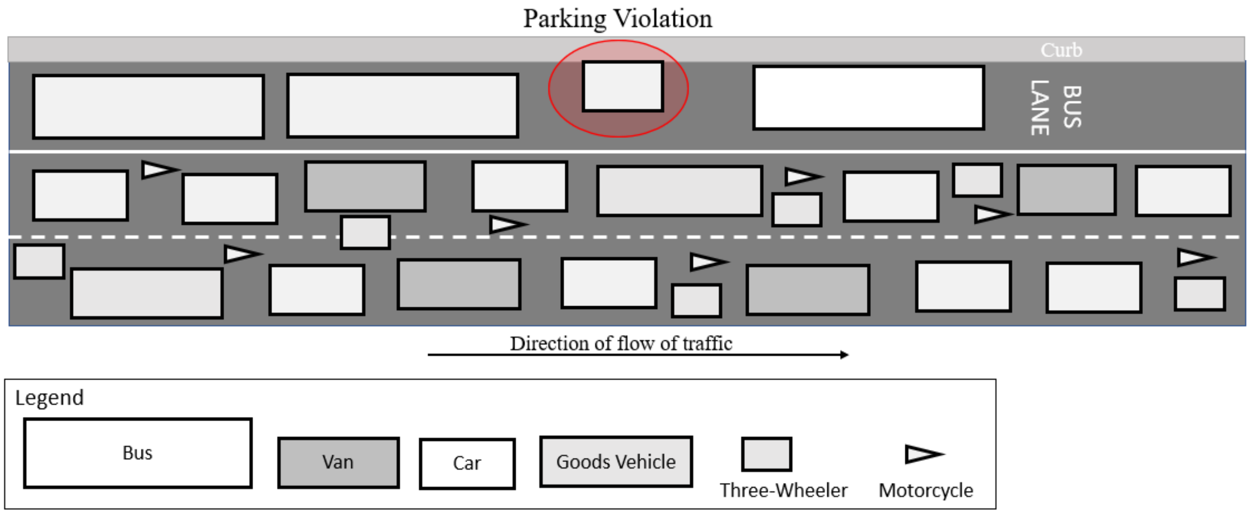

Figure 1: Illustration of a PV

These PVs negatively impacts the benefits that can be gained by implementing a BPL, which has a wider impact on its expected economic benefits as well (Mackie, Jara-Diaz, & Fowkes, 2001). PVs incurs a cost in terms of prolonging the travel time to commuters in public transport. The prolonged travel time could cause time loss to the commuters, increase fuel consumption/cost to the bus operators, and burning of greater amount of fuel also results in greater pollution of the environment and thereby increasing healthcare costs to the people and the government. Therefore, investigating the impact of these PVs on the performance of curbside BPLs is crucial in planning and operation of a successful BPL (Safran, Beaton, & Thompson, 2014).

The traditional method of investigating different scenarios involves conducting pilot studies and analysing the data gathered. But this approach faces many difficulties. Not all scenarios could be piloted. Conducting these pilot studies is expensive and causes much inconvenience to road users. Even after a successful pilot study, various issues such as data accuracy can hinder the quality of the study. Simulation can be used to overcome these difficulties by modelling these scenarios in a virtual environment (Srikanth, Mehar, & Praveen, 2020).

Simulating a traffic scenario offers numerous benefits to traffic planners and society as there is no inconvenience to the public (Muzyka, 1975). Simulation offers the traffic planner a degree of control that far surpasses the control over many variables that could be offered in any pilot study (Lay-Yee & Cotterell, 2015). The simulation also offers the advantage of reproducibility of output and thus guarantees greater accuracy of the data gathered compared to a pilot study. A well-calibrated simulation model can replicate a real-world scenario with over 90% accuracy (Desta & Tóth, 2021; Lopez et al., 2018).

There are 3 levels of traffic simulation: macroscopic, mesoscopic and microscopic. The choice of the simulation model used depends on the details required to be simulated and analysed (Papageorgiou, Ioannou, Pitsillides, Aphamis, & Maimaris, 2009). Microscopic simulations focus on the behaviour of individual vehicles and thus can accurately model individual vehicles' longitudinal car-following and lateral lane-changing behaviour (Yin & Qiu, 2012).

Simulation of Urban Mobility (SUMO) is an open-source microscopic simulation software. SUMO simulates the behaviour of vehicles considering the vehicle‘s mechanical capabilities to move (speed, acceleration, deceleration, etc.) and the driver‘s controlling behaviour (impatience, gap-acceptance, etc.) (Krajzewicz, Hertkorn, Wagner, & Rössel, 2003). It can model car-following and lane-changing models defined by many parameters, allowing a modeller an increased control over the simulations. Therefore, this study uses microscopic simulation using SUMO to evaluate the impact of PVs on the performance of BPMs, in a model calibrated using traffic conditions in Colombo, Sri Lanka.

1.2 Significance of the Study

Obtaining the desired travel time improvement outcome from a BPL depends on the level of adherence by motorists and enforcement. However, even with tight enforcement, violations are inevitable. The challenge is to identify the level of violations to be tolerated to obtain the desired performance of the BPL.

While many studies have confirmed reduced BPL performance due to PVs, the quantification of both the duration of parking and frequency of PVs has not been mapped for authorities to identify the level of enforcement necessary to achieve the desired performance, which is addressed in this study.

1.3 Objectives of this Research

The overall objective of this study is to investigate the performance of BPLs with regard to PVs. The specific objective of this study are to:

- Build a simulation model that will emulate lane discipline behaviours of vehicles and drivers.
- Develop a model to predict the changes in BPL performance due to PVs in terms of travel time of buses.
- Predict the changes in BPL performance caused by durations and frequency of PVs.

1.4 Limitations

The study has the limitation of deploying the simulations in a test network that is designed for only parking violations to impact the bus travel times. Other contributors to increased bus travel time in the real world such as jaywalking pedestrians, traffic lights, etc. is not included in the test network, so that only the impact of PVs to be reflected in the travel time changes.

2 Literature Review

This section is a critical review of selective existing literature on:

1. Violations of BPL Rules
2. Impact of BPL Rule Violations
3. Simulation of BPL rule violations

2.1 Violations of BPL Rules

Studies divide violations into two categories: driving and parking. Driving violations include unauthorised vehicles encroaching into the BPL, while parking violations include parking of unauthorised vehicles entirely or partly into the BPL. Mundy, Trompet, Cohen, & Graham (2017) studied violations in these two categories with the rate of violations per km as the unit of measure of frequency. Agrawal, Goldman, & Hannaford (2012), in their analysis of shared-use bus priority lanes in 7 cities around the world, have also analysed violations in terms of driving and parking violations.

Very few case studies on the frequency of BPL violations are available. While parking and driving violations were analysed together, Basbas (2007a) observed from four BPLs operated in Thessaloniki, Greece, that the highest frequency of violations is 432 violations per hour (108 violations every 15 mins). In contrast, New York BPLs experience the highest number of Violations at 1,128, with Brussels and Barcelona experiencing 224 and 223 violations each. Lisbon, however, is reported to experience only 1 violation (Mundy et al., 2017). This variation in the frequency of violations has been attributed to varying levels of enforcement of BPL rules in those countries, which concludes that a BPL is as successful as its enforcement.

Basbas (2007a) has also concluded that two-wheeled vehicle drivers (56%) and taxis (26%) committed the majority of the violations. Here the duration of violations by violator vehicles has also determined to have lasted less than 15 seconds.

The increased vulnerability of curbside with flow BPLs is noted in several studies. A study has quantified this vulnerability of curbside BPLs to be obstructed 1.39 times more than offset lanes in New York (Safran et al., 2014). Here, some of the most frequent obstructions are listed as illegally parked automobiles, taxi pickups and drop-offs and trucks making deliveries (Safran et al., 2014). Shalaby & Soberman (1994) concluded that mean travel time decreased by as staggering 40.5% when obstructions were removed from the with-flow BPL, highlighting their vulnerability for violations. Here The vulnerability of curbside BPLs for violations has also been noted by Agrawal et al. (2012). There is a need for curbside with-flow BPLs to be investigated, with regard to their impact on travel time, because they are the most vulnerable for violations

2.2 Impact of BPL Rule Violations

Many studies have emphasised the importance of enforcement of the BPL rules as it directly affects the achievement of the performance benefits expected on implementation. A study of BPLs in four cities by Mundy et al. (2017), revealed that the major cause of the disparity in the number of violations observed was due to variations in the level of enforcement in each city.

Out of the total daily traffic in four BPL networks in Greece, the proportion of unauthorised traffic was between 3% and 52.5% (Gavanas et al., 2013). Their study had concluded that these violations decreased the bus speeds in BPL s to the same level as in other lanes, thereby undoing the purpose of BPLs.

The negative impact of PVs on the performance of BPLs has been reported in BPLs implemented in various cities worldwide. A decrease in bus speed by approximately 0.4 km/hr for each additional lane violation by taxis was observed in Athens, Greece (Kepaptsoglou, Pyrialakou, Milioti, Karlaftis, & Tsamboulas 2011). Similarly, elimination of illegal parking and stopping in Toronto (Canada) has decreased the mean travel time of buses by 40.5% in a particular segment (Shalaby & Soberman, 1994).

The lax enforcement over time is listed as a leading cause of the decline in the performance of BPL implemented in Sri Lanka due to disruptions to the flow in bus lanes (Weerasekera, 2010).

However, to the best knowledge of this author, the impact of PVs on the performance of BPL was not investigated by simulating the behaviour of drivers and vehicle sizes in Sri Lanka.

While the impact of PVs on the performance of a bus priority lane has not been investigated, Anwar, Fujiwara, & Zhang (2011) have studied the influence of illegal on-street occupancy on travel time in a particular link. Here the α and β parameters of Bureau of Public Roads (BPR) function has been calibrated with the reduction of link capacity due to illegal on-street occupancy to describe its impact on travel time. The model developed in the study is given below.

$$T_{a_{i(p)}} = T0_{i(p)} \left[1 + \alpha \left(\frac{V_{i(p)}}{C - C_{io}}\right)^{\beta}\right] \qquad \text{........ Eq. 1}$$

Where,

$T_{a_{i(p)}}$ = Congested travel time in the link i at peak hour;

$T0_{i(p)}$ = Free-flow (60kmph) travel time in the link i at peak hour;

$V_{i(p)}$ = Traffic volume in link i at peak hour;

C = Capacity [1741 PCU per lane per hour (18);

C_{io} = Capacity occupied by on-street parking and street occupancy in the link i;

α and β are parameters to be estimated.

2.3 Simulation of BPL rule violations

There are major advantages of using simulations to model traffic scenarios in lieu of primary data from field surveys. Such advantages have been noted in the evaluation of BPL performance at least since 1975. Muzyka (1975) describes the usage of simulation to evaluate bus priority strategies as "ideal", listing many benefits that are summarised as follows.

- No inconvenience to the public
- The public cannot interfere with an experiment on computer simulation

- A high degree of control afforded on the traffic system allows the impact of variation in any individual component on the whole system to be investigated
- Many strategies can be evaluated in a short period of time as simulation speed can be controlled to a certain extent
- Provide insight into problem areas which allows refining the proposed strategies, thereby leading to more successful demonstration of projects

Muzyka (1975) also points out that while simulation can be a valuable traffic tool, it is only an approximation at best, and hence it is impossible to eliminate field experiments.

Many studies have been conducted since then that have used simulation to investigate bus priority strategies. Shalaby (1999), in his study of evaluating the performance impacts of BPLs, stated the use of simulation for the analysis of the base cases (before scenario) and after scenarios were "essential" in investigating the contributions of BPL introduction to bus and auto performance changes.

Few other studies used simulation to evaluate BPL performance are Desta & Tóth, 2021; Hidayati, 2012; Vu, Sano, Y, & Thanh, 2013. In the simulation model of Shalaby & Soberman (1994) built using TRANSYT-7, the dwell time of buses is kept constant in evaluating the travel time of buses to determine the effect of with-flow BPLs. This was done so that the variations in dwell time will not be reflected in the total travel time as a reduced dwell time might lead to being interpreted as an improved performance and vice versa. The impact of PVs has also been investigated in the form of eliminating illegal parking and stopping using simulation.

In using SUMO to simulate parking violations, Smith, Djahel, & Murphy (2014) have used SUMO's Traffic Control Interface (TraCI) to simulate prolonged vehicle parking in a lane. The study was undertaken to simulate a traffic incident, after which the output was used to study the resulting capacity reduction of the link.

Hadi, Sinha, & Wang (2007) have provided recommendations in developing a microscopic simulation model to analyse reduction in freeway capacity due to incidents. The study has considered three of the available simulation platforms; CorSim, AIMSUN and VISSIM. Here, a three-lane freeway segment with a free flow speed of 70 kmph was used. The capacity of the segment was calculated by increasing the traffic demand volume untill the maximum throughout in vehicles per hour, in a no incident scenario. In all three software, the incident blockages have been simulated either explicitly or by using other events that affects traffic operations similarly such as bus stops. This study recommends that lane-changing behaviour by vehicle type should be included to emulate the behaviours at incident locations. It also states that the modeling of cooperative lane-changing behavior should be considered. SUMO provides parameters that allows calibration of lane-change behaviours to vehicle types, which includes, but is not limited to corporative lane changing.

2.4 Simulation of heterogeneous traffic

Various parameters must be calibrated in developing any simulation model to generate a traffic scenario that is a close approximation of the real world and get a credible output. In modelling heterogeneous traffic, such as in Sri Lanka, lateral interactions are essential to simulate driver behaviours. Matcha et al. (2020) have reviewed the strategies for simulating mixed traffic conditions using 9 simulation software. SUMO is the only open-source software package with 9 different vehicle-based parameters to calibrate the model. SUMO uses a strip-based model applicable to modelling heterogeneous traffic in freeways and intersections. Thus, SUMO can simulate the lane change behaviours required for PVs.

Mahmud, Ferreira, Hoque, & Tavassoli (2019) have summarised the major variables used and the strengths and weaknesses of three major simulation software packages (VISSIM, PARAMICS and AIMSUN) in microscopic modelling of heterogeneous traffic. While all three packages support lane changing, each package has drawbacks. VISSIM is reported to not model vehicle trajectories in a realistic way, while PARAMICS uses an origin-destination matrix to derive traffic volume, and AIMSUN doesn't explicitly calculate link delays (Mahmud, Ferreira, Hoque, & Tavassoli, 2019).

When developing a microscopic simulation of heterogenous traffic, microscopic characteristics include vehicle characteristics such as physical and mechanical characteristics and driver characteristics such as acceptable lateral and longitudinal gaps (Mallikarjuna & Rao, 2011). This lateral and longitudinal gap acceptance is a criterion that is commonly considered in developing a lane-change model (Seraj, Bie, & Qiu, 2017; Wang & Coifman, 2008; Arasan & Vedagiri, 2008). Arasan & Vedagiri (2008) has calculated the gap acceptance by vehicle types for Indian road traffic is given in Figure 2. Arasan & Vedagiri (2010) used vehicle dimensions, lateral and longitudinal gap acceptance, vehicle speed, acceleration and deceleration to calibrate the simulation model.

Vehicle Type	Dimensions in m		Lateral Clearance allowance in m		Free Speed in km/h	
	Length	Breadth	Minimum	Maximum	Mean	S.D.
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bus	10.3	2.5	0.3	0.6	67	7
Truck	7.5	2.5	0.3	0.6	62	9
LCV	5.0	2.0	0.3	0.5	61	7
Car	4.0	1.6	0.3	0.5	72	7
M.Th.W.	2.6	1.4	0.2	0.4	48	8
M.T.W.	1.8	0.6	0.1	0.3	61	10
Bicycle	1.9	0.5	0.1	0.3	15	2

LCV- light commercial vehicle, M.Th.W – Motorised Three Wheelers, M.T.W - Motorised Two Wheelers

Figure 2: Vehicle parameters calibrated for Indian Traffic Conditions

Gap acceptance is influenced by density rather than speed (Knoop et al., 2016). This is reiterated by Munigety & Mathew (2016) as the tendency of drivers in mixed traffic to maintain shorter gaps compared to that in lane-based traffic. Therefore, it can be dependent on the road-geometry and thus road network-specific. The gap acceptance is also attributed to the aggressiveness of drivers (Srikanth et al., 2020), which SUMO allows being defined for each vehicle.

In simulating vehicles in developing countries, vehicle size, mechanical characteristics, lateral distribution of vehicles, and the lateral gaps maintained by them are most suitable (Mallikarjuna & Rao, 2011). However, Arkatkar et al. (2016) have calibrated a simulation model using the vehicle's acceleration/deceleration and mechanical characteristics, minimum safety distance, minimum lateral distance, and driving behaviour characteristics.

A Low-Cost Urban Test Scenario has been generated using SUMO for microscopic traffic simulation of Shenzhen, China (Yue, Shi, Wang, & Lin, 2020). The scenario employed a lane-changing model with a *sublane* parameter of 0.01m. However, this model has considered all vehicles to be cars with the exact dimensions.

SUMO enables the users to calibrate all of these parameters (German Aerospace Center (DLR), 2020a). Jayasinghe, Sivakumar, & Kumarage (2021) has calibrated all these parameters for SUMO for Sri Lankan Traffic Conditions, except for the lateral gap acceptance.

3 Methodology

3.1 Overview

This research considers the various degrees of adherence to BPL rules and analyses their impact on the performance of BPL. The impact on travel time is measured in terms of the travel time of buses in the BPL. As literature shows, both frequency and the duration of PVs are the two major determinants of the degree of impact and therefore, both frequency and duration were investigated. The output generated is then analysed to understand the impact of the frequency and duration of PVs on travel time and reliability of buses in a BPL.

3.2 Research Methodology

The **S**imulation **O**f **U**rban **MO**bility (SUMO) is an open-source microscopic simulator used in this study to simulate traffic and PVs. The development of the microsimulation model is described in detail in Chapter 4.

The factors affecting the impact of PVs identified in the literature were the frequency and duration of the PVs. Starting from 0 PVs per 15 mins, an increasing frequency of violations (PVs per 15 min) was simulated to understand its impact on BPL performance. That is, an increasing no. of violations generated at random timesteps in a 15 minute duration simulation run.

Five different parking durations of PVs were simulated to identify their impact on BPL performance. The simulated PV durations were selected based on the study by Basbas (2007), in which the frequency of violations was classified according to their durations. The durations of PVs selected were 10 seconds (10s), 15s, 30s, 45s and 60s.

Due to the relationship between flow-and speed explained in traffic theories, different flows of buses were also simulated. Four different bus flows were simulated in this study. They are 20 veh/hr (3 min headway), 60 veh/hr (1 min headway), 120 veh/hr (30s headway) and 180 veh/hr (20s headway). Depending on the traffic levels (peak or off-peak), the flow of buses also changes, which prompted the investigation into the impact of bus flow on the travel time of buses while encountering PVs.

The microsimulation model was repeatedly run after changing the 3 input variables each time, the frequency of PVs per scenario in each run, the duration of a violation and the bus flow, to obtain the impact of the frequency of PVs on the average bus travel time in BPLs. That is, for each run of the microsimulation, a unique combination of the frequency of PVs, the duration of PVs and the bus flow was used. For example, one simulation run could have 0.5 violations per second occurring for 10s per each violation, while the bus flow is 60 veh/hr. This workflow is illustrated in figure 1 below.

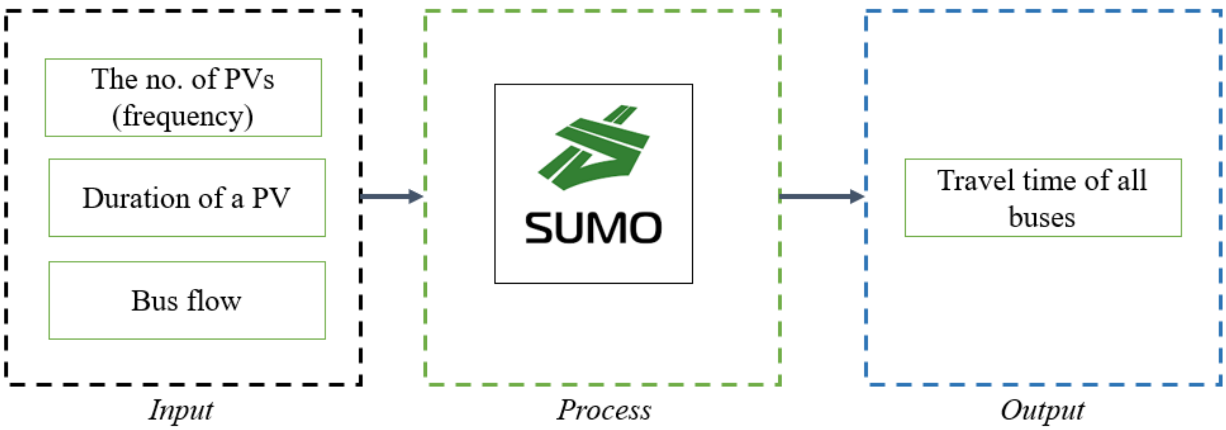

Figure 3: Workflow of a single run of the microsimulation model

The average travel time of buses in each simulation run was obtained along with the frequency of PVs, duration of a PV and the bus flow of that run as output. The outputs obtained were analysed to identify the impact of PVs on the performance of a BPL in terms of travel time, with changing frequency and duration of PVs and bus flow.

3.3 Assumptions

This research has a few assumptions that were maintained to isolate the impact of PVs on the BPLs, by excluding some behaviours that also impact the travel time of buses.

1. Buses do not violate.

   Buses do not engage in any traffic law violations and conform to all the BPL laws. Thus, the impact of violations by buses is not observed in the output gathered by microsimulation.

2. A constant dwell time of 10 seconds at bus stops

   As stated by Shalaby & Soberman (1994), the total travel time of buses is influenced by their dwell time at stops. Thus, variations in dwell times can make it challenging to identify the impact of PVs exclusively from the microsimulation output. Therefore, the dwell time of buses at each stop was maintained constant, at 10 seconds per bus stop.

3. No jaywalking pedestrians

   Jaywalking pedestrians can impact the bus travel times in BPL as they interrupt the flow, causing the vehicles to decelerate and/or stop till the pedestrian is no longer in their way. This deceleration and/or stop is also reflected in the final bus travel time. Hence, it is assumed that no jaywalking pedestrians are present.

4. The parking duration and frequency are assumed to be independent from each other.

4 Development of the SUMO Microsimulation Model

4.1 Simulation of a PV in SUMO

A traffic scenario developed in SUMO microscopic simulation primarily has three files: the route file (.rou.xml), the network file (.net.xml) and the additional data file (.add.xml). All three files are called in the configuration file (.sumocfg) to build the simulation. Therefore, the simulation is run by executing the SUMO configuration file. The descriptions of each file are given in Table 1 below.

Table 1. SUMO simulation files and contents

File	Contents
Route file (.rou)	This contains the vehicle routes and flows. Here vehicle specific routes can be defined (vehicle routes) and repeated vehicle routes such as buses (flows), in which the frequency of the vehicle generation is given.
Network file (.net)	This contains the road network where the simulation is created.
Additional file (.add)	This includes all the other information such as traffic signal plans, bus stop locations, traffic counters, etc.
Configuration file (.sumoconfig)	This is where all the above files are called. It also includes the SUMO model used in the car following model and/or lane changing model.

The most basic methodology for simulating PVs in SUMO would be to include a vehicle flow that follows the behaviour of a PV in the route file (.rou.xml). However, to investigate the impact of violations, the parameters of this flow would have to be manually adjusted every time for each of the parameters defining the violation scenario is changed: namely, the frequency of violations and the duration of a violation. Furthermore, the simulation will only include all violator vehicles to stop at one location, while all violations would happen at similar intervals. But this is not the case with PVs observed in the real world. In the real world, the violations happen at random intervals at random positions in a given road stretch.

SUMO has introduced TraCI (which is an Application Programming Interface (API)), which gives real-time access to a running road traffic simulation. It allows the retrieval values of simulated objects and manipulates their behaviour "online". TraCI uses the traffic simulation scenario developed as a base scenario, where it then manipulates vehicles during their run time (Figure 4). The simulation is run by executing the commands in TraCI. TraCI calls for the SUMO configuration file, which then calls for the network, route and additional file.

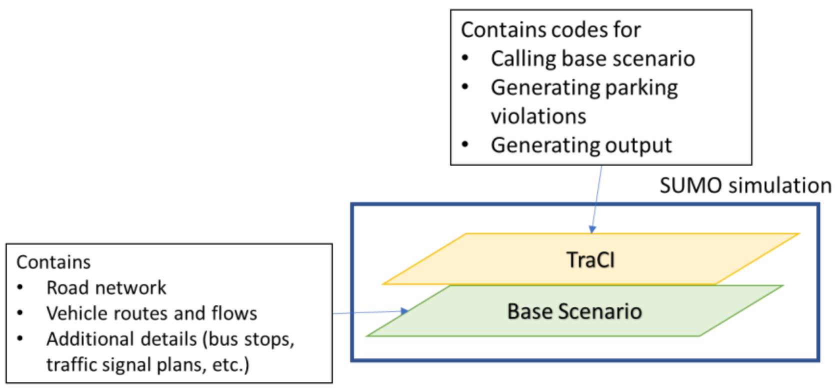

Figure 4. TraCI inside SUMO Simulation Environment

TraCI contains commands that can perform various manipulations, including but not limited to vehicle insertion, changing vehicle routes, and value retrievals such as lane-based values, edge-based values, and individual vehicle-based values such as travel time, and speed, etc.

4.1.1 The Base Scenario

The base scenario developed is explained using the 3 files used in the microsimulation using SUMO.

4.1.1.1 The network file (.net)

The network developed consists of a single road stretch that is 1.05km long, with 0.05km allocated as a warm-up distance. When all the vehicles are loaded into the simulation, their speed is 0. Therefore, this warm-up distance is allocated so that the vehicles entering the simulation would adjust their behaviours, such as speeds and enter the 1km stretch, similar to that observed in traffic in an urban road segment in the real world.

The road stretch used in the simulation has 3 lanes, one of which is a BPL where buses and HOVs are permitted. It also includes a pedestrian walkway.

Figure 5: The road stretch used in the simulation

4.1.1.2 The additional file (.add)

The additional file contains the locations of 2 bus stops beside the BPL lane. The two bus stops are 400m apart, as per international standards.

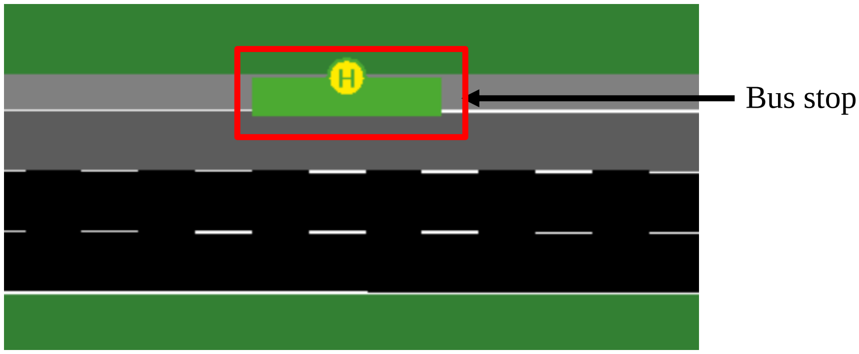

Figure 6: Bus stop in the simulation as seen in GUI

4.1.1.3 The route file (.rou)

The vehicles input to the simulation is defined as flows in the route file. The calibration parameters used to define each vehicle type in these flows are as follows.

- Vehicle dimension (length/width)
- Vehicle acceleration and deceleration
- Lateral Gap Acceptance of each vehicle type
- Lane changing behaviours

The base scenario utilises the SUMO lane change model in simulating the behaviour of vehicles in the simulation (Erdmann, 2015). This lane-change model was used instead of just the standard car following model because PVs involve a violator vehicle moving in and out of the BPL. In this lane change model, the SUMO computes the lane change decision of a vehicle for a single simulation step based on the route of the vehicle and the traffic conditions, as well as the changes in the velocity for the vehicle performing the lane change as well as the vehicles that are obstructing for the successful execution of the desired lane-change manoeuvre. The lane change model used executes all the lane change decisions unless they conflict with vehicle manoeuvring requests issued by TraCI. The requests received from TraCI are handled urgently (with cooperative speed adaptations by the vehicle that intends to change lanes as well as the surrounding traffic) but with full consideration for safety constraints ("Change Vehicle State - SUMO Documentation," n.d.).

Four different parameters in lane-changing behaviour are considered and defined for each vehicle. The four behaviours defined by these parameters are as follows.

1. The eagerness to perform strategic lane changes to be able to reach the next edge
2. The eagerness to perform a lane change to help another vehicle to change into the desired lane
3. The eagerness to realise speed gains such as overtaking a slow leader
4. Willingness to encroach laterally on other vehicles

Both vehicle dimensions and acceleration, deceleration and lane change model parameters are available for simulation of Sri Lankan traffic in SUMO (Jayasinghe et al., 2021). In the absence of data due to difficulties in data collection as a result of COVID-19, the gap acceptance parameters that are used to calibrate the simulation of heterogeneous traffic in India will be used (V. T. Arasan & Vedagiri, 2010).

The types and the number of vehicles, their flows and the calibration parameters are shown in Table 2 (page 20). Each of the flows is defined for 15 minutes. Therefore, one run of the microsimulation model is 15 minutes long. The vehicles declared in the base scenario are inserted for this 15 min period based on their defined flows. For example, if the bus flow is defined as 180 veh/hr, exactly 45 buses will be entered into the simulation at regular intervals.

Since the target output was the travel time of buses, the tripinfo device has been enabled in buses and disabled in all other vehicle types (German Aerospace Center (DLR), 2020b).

4.1.1.4 The configuration file (.sumoconfig)

This file includes codes to call all the above three files. The SUMO simulation model, whether the car following model or lane changing model, is also declared here. In this study, to facilitate lane changes or performing of PVs, the SUMO lane changing model (SL2015) was implemented with a sublane parameter of 0.01m (Yue et al., 2020).

Table 2: Flows and the Calibration Parameters of the Vehicles in the Base Scenario

Parameter	**Bus**	**Car**	**Van**	**Motorcycle**	**Three-wheeler**	**Light good truck**	**Medium goods truck**	**Heavy goods truck**
Flow (veh/hr)	Varied*	120	40	200	200	40	40	40
Longitudinal Acceleration and Deceleration	1.0 0.88	2.87 5.0	2.23 5.9	1.96 1.33	0.6 1.14	1.0 0.88	1.0 0.88	1.0 0.88
Lateral gap acceptance (minGapLat)	0.3	0.3	0.3	0.1	0.2	0.3	0.3	0.3
sigma	0.7938	0.5	0.7938	0.7938	0.7938	0.7938	0.7938	0.7938
lcPushy	0.7939							
lcStrategic	5.9138							
lcSpeedGain	5.2227							
lcCooperative	0.9991							

*Varied flows were simulated during the study

4.1.2 Simulating PVs using TraCI

The workflow of the simulation of PVs in SUMO using TraCI is shown in Figure 7 below (Samarakoon & Sivakumar, 2022).

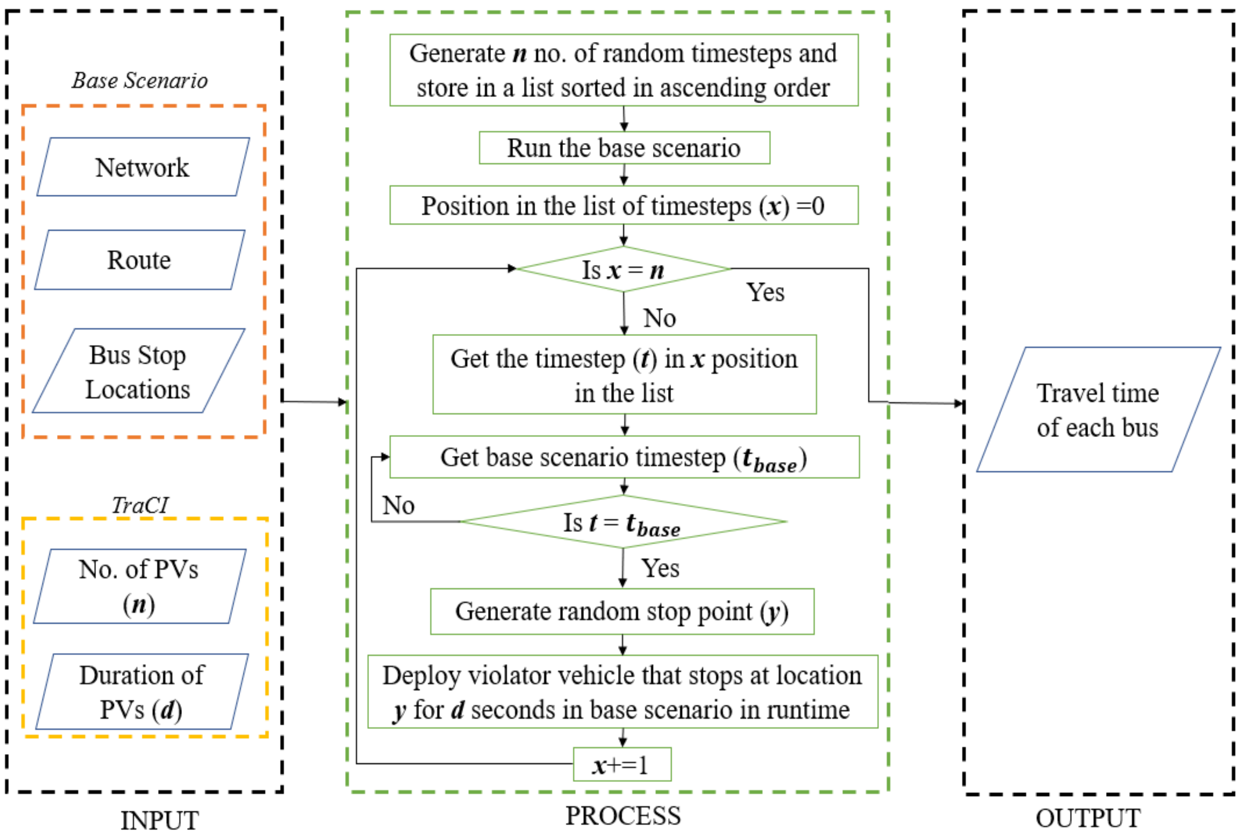

Figure 7: Workflow of the simulation of Violations with TraCI

Here, TraCI is used to insert Violators and make them perform a violation of a given duration by making the Violator vehicle stop in the BPL. This is done by inserting violator vehicles into the base scenario at random timesteps within the simulation period by assigning each violator vehicle a path with a random stop location. Hence, the randomness observed in the performance of PVs in the real-world scenario is reflected in the simulation of a PV in the developed scenario.

The no. of violator vehicles in one simulation run and their duration of PV is input by the TraCI. After generating a list of random insertion times (into the base scenario), it then calls the SUMO configuration file of the base scenario to run and then inputs the violators into it during the assigned timesteps during runtime. These vehicles are assigned random stop locations as well as a stopping duration to make them perform a PV. After all the vehicles have left the simulation, the travel time of all buses in the BPL is generated as the output. The travel time of buses were obtained by assigning a trip info device to buses.

The path of travel of a vehicle performing a PV at location ***y*** is illustrated in Figure 8 below.

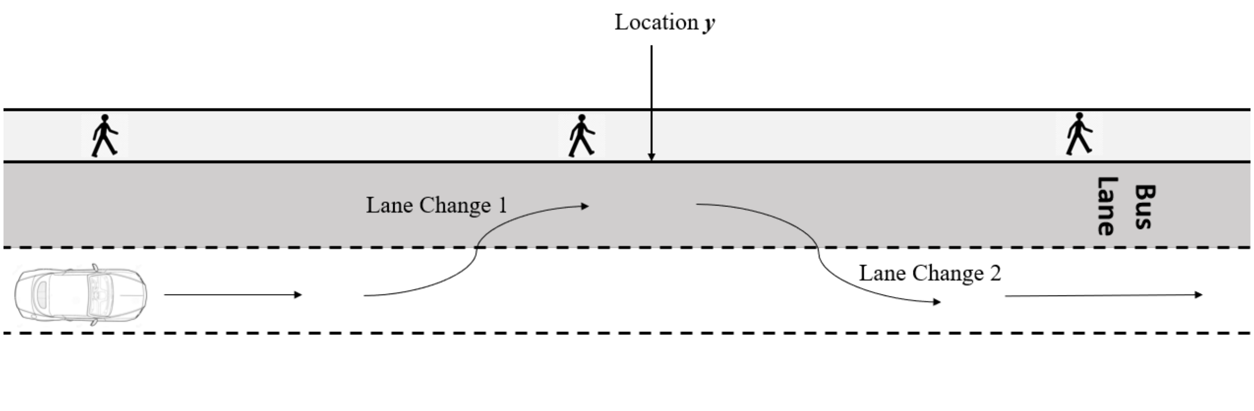

Figure 8: Path of travel of a vehicle performing a PV

The point at which both the lane changes happen depends on the availability of space in the BPL and the adjacent lane. Lane Change 1 will happen anywhere between 0 and ***y*** km in length in the road stretch, depending on the availability of space in the BPL. After completing the PV, the vehicle can choose to perform Lane Change 2, depending on the availability of space in the BPL and the adjacent lane. If the BPL is not obstructed, the violator vehicle will continue its journey on the BPL, as long as it's not obstructed (by a stopped vehicle, bus or another violator vehicle/s). If it comes across an obstruction of a stopped vehicle, depending on the availability of space in the adjacent lane, it will change into the adjacent lane. Therefore, Lane Change 2 happens anywhere between ***y*** and 1.05 km in length in the road stretch. The simulator computes these lane change decisions within the parameters of the SUMO lane change model that is defined for each vehicle type to determine the positions where the lane changes take place.

4.1.3 Parking Violations Simulation Code

The python script containing TraCI commands developed to simulate the PVs is called ParkingViolations.py. As described by the process section of the workflow illustrated in Figure 5, the script developed generates the violator vehicles that stop at assigned random locations for a specific duration into the simulation during runtime. Here, TraCI also iterates the input of frequency of PVs, starting from 0 to 1 violation vehicle emitted per second. It also generates the output of the travel time of each bus in the simulation run as a .xml file.

The random timestep and location are generated through the random python library. Therefore, the randomness generated is constrained through a random seed (Srikanth et al., 2020). For the reproducibility of the microsimulation output, the randomness was constrained by defining a random seed for each simulation run. With all other inputs kept constant, the output of the simulation also varies with varying random seeds. Therefore, the average output of 30 random seeds was obtained as output for a simulation run with a particular combination of frequency, duration and bus flow.

The workflow of ParkingViolations.py is shown in Figure 9 below.

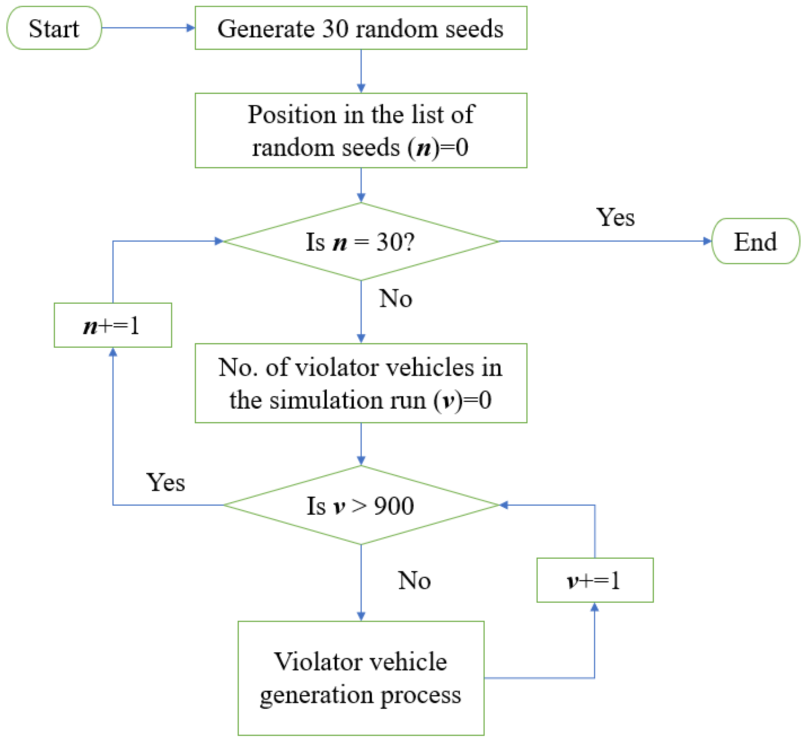

Figure 9: Workflow of ParkingViolations.py

First, a list of 30 random seeds is generated and stored in a list. Then for each random seed, simulations are run for varying no. of violator vehicles per run using a model with a set bus flow and duration of PVs. Since the no. of violator vehicles per run changes from 0 to 1 violator vehicle generated per second, a total of 901 simulation runs were executed for each combination of bus flow and duration of violation (0 violation vehicles – 900 violation vehicles since one simulation run is 900 seconds (15 mins) long). For the 5 different PV durations and 4 different bus flows investigated in this study, 18,020 simulation runs (901 × 5 × 4) were executed, and outputs were generated in this study.

The full code is given in the Appendix.

4.2 Fundamental Diagrams

The fundamental traffic diagrams were drawn for the obtained simulation outputs. As shown in Figure 7 below, the model output follows Greenshield's traffic flow model (Greenshield, 1935).

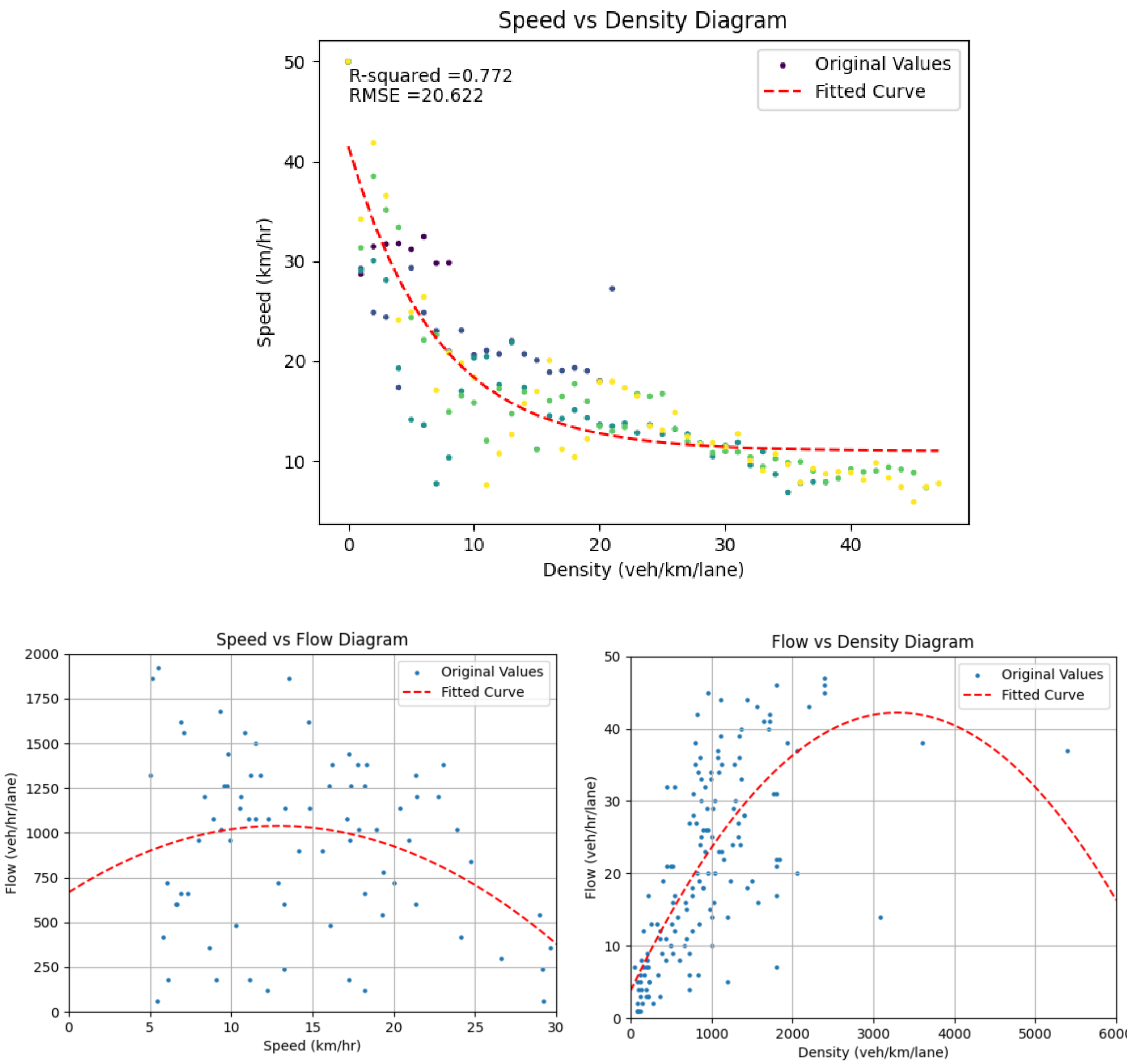

Figure 10: Fundamental Diagrams of Traffic Flow in simulating PVs in SUMO

4.3 Model Constraints

4.3.1 Time Constraints

The computational time per run was a significant constraint faced in this study. Various measures were taken to decrease the calculation time, including running simulations without GUI, using 5 computers to run different simulations simultaneously, etc. The total time taken for the simulation runs is given in Table 3 below.

Table 3: Total Computational Time of Microsimulation

Bus Flow (veh/hr)	**Approximate time per random seed (hr)**	**No. of scenarios (5 parking durations * 30 random seeds)**	**Total Time (hr)**
20	4	150	600
60	6	150	900
120	8	150	1200
180	12	150	1800
Total			4500 hr
			187.5 days
			~27 weeks

A simulation run must be uninterrupted to obtain the necessary outputs, meaning that the developed codes need to run continuously for 4-12 hours.

4.3.2 Vehicle Type Constraints

The model only uses cars as violator vehicles to perform PVs. This was done as SUMO does not contain the vehicle class Three-wheeler. Therefore, it interprets Three-wheelers as small cars with the given dimensions (of a Three-wheeler). Thus, car was used as violator vehicles.

4.3.3 Output from the simulations

The travel time of each bus is used to obtain the average travel time of buses in each scenario. The graphs below show the average travel time of buses with changing flow of buses (f), duration of parking (d) in performing a PV and the frequency of PVs.

The Figures 11,12,13 and 14 show that the average travel time of the buses in BPL increases exponentially with the increasing no. of PVs. But the degree of increase in average travel time varies with the duration of parking as well as the flow of buses.

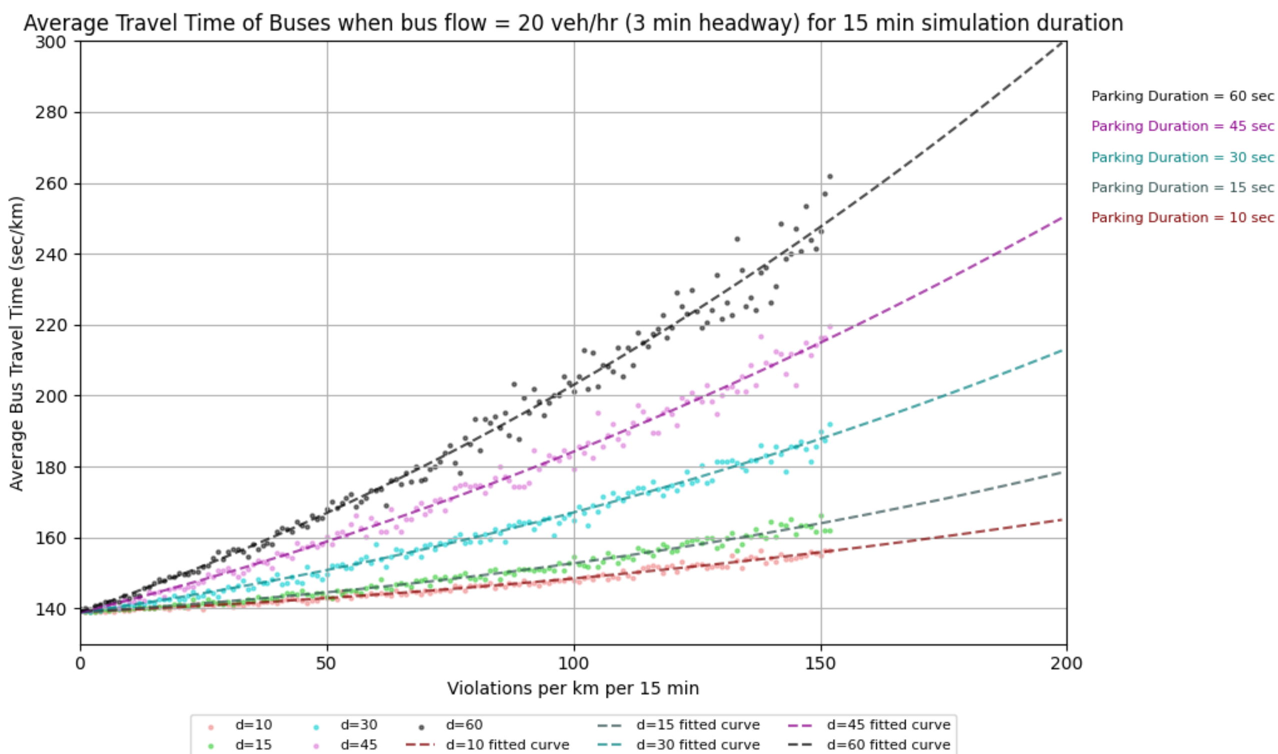

Figure 11: Average Travel Time of Buses when bus flow= 20 veh/hr (3 min headway) for 15 min simulation duration

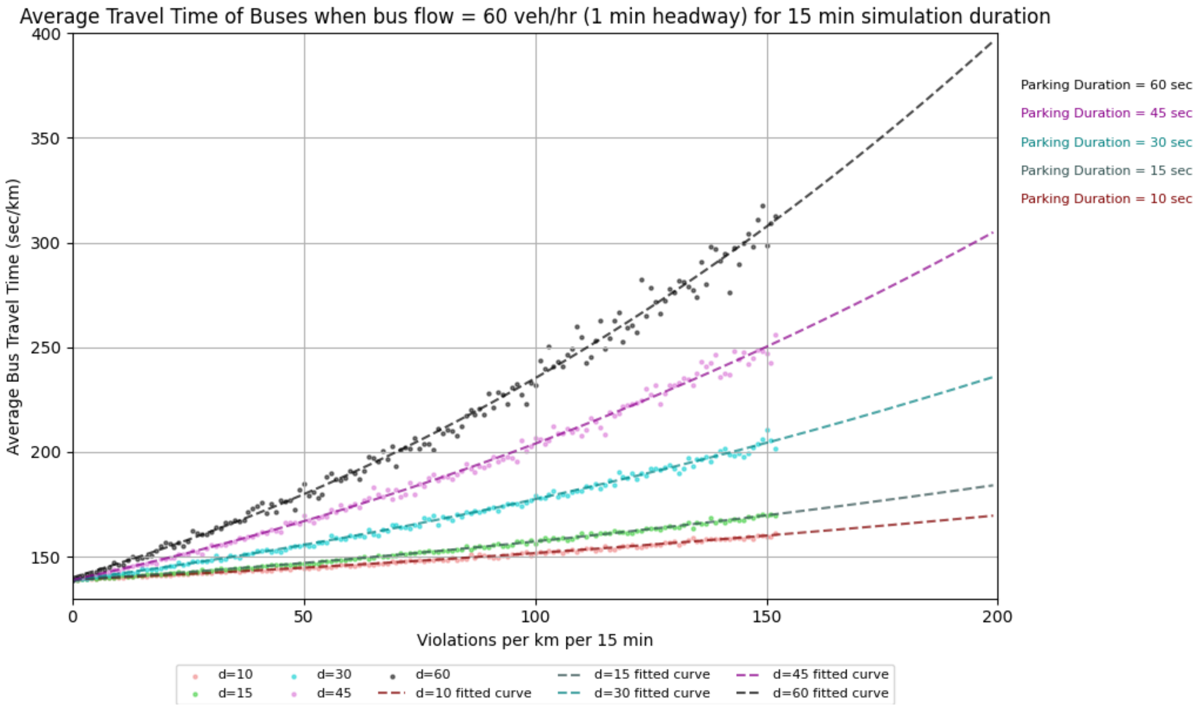

Figure 12: Average Travel Time of Buses when bus flow = 60 veh/hr (1 min headway) for 15 min simulation duration

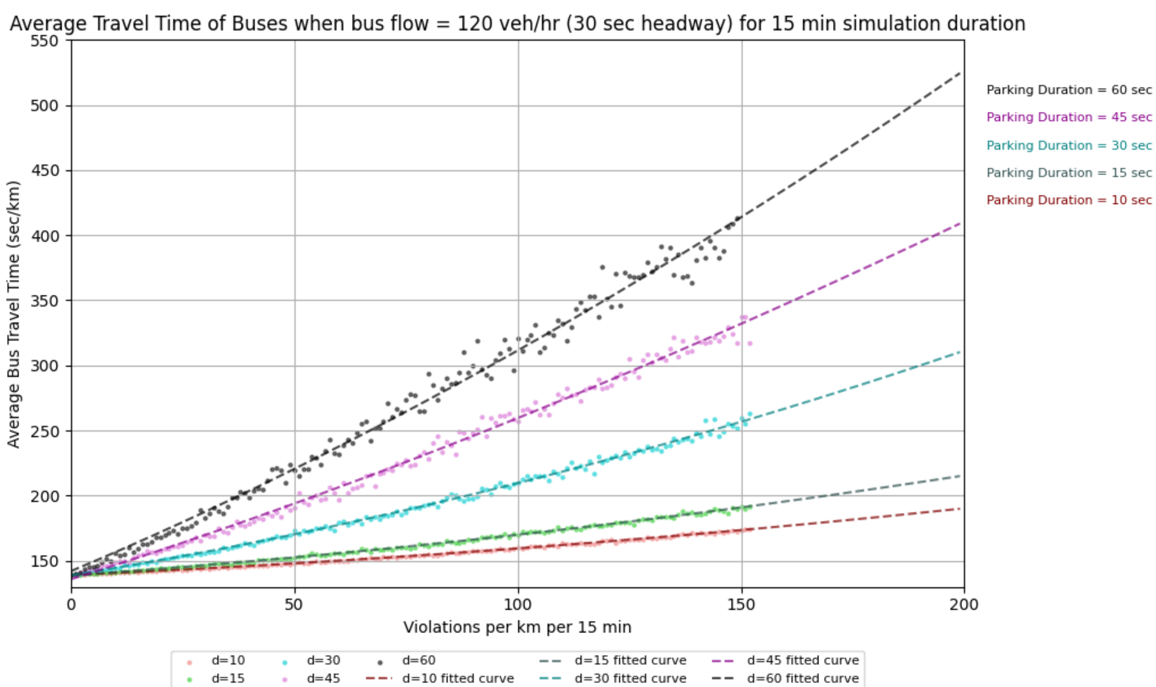

Figure 13: Average Travel Time of Buses when bus flow = 120 veh/hr (30 sec headway) for 15 min simulation duration

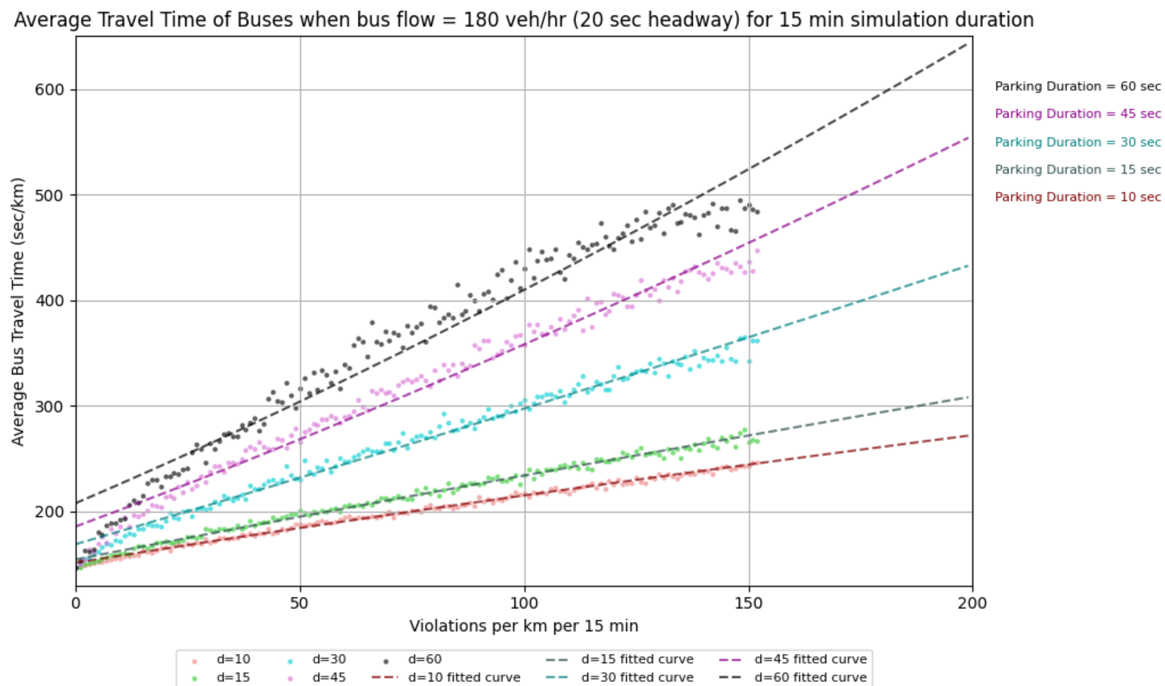

Figure 14: Average Travel Time of Buses when bus flow = 180 veh/hr (20 sec headway) for 15 min simulation duration

On further analysis, as shown by Figure 15, the increase of parking duration (d) in a PV impacts the average bus travel time in the BPL more than the impact by the increased bus flow (shorter headway between buses).

In Figure 15, the red curve (bottom curve) is the increase in average bus travel time with increasing frequency of PVs when the flow of buses is 20 vehicles per hour (3 minute headway between buses) and the duration of each PV is 15 seconds. The green curve (middle curve) is the increase in average bus travel time w frequency of PVs when the flow of buses is 20 vehicles per hour (3 minute headway between buses) and the duration of each PV is 60 seconds. The blue curve (top curve) is the increase in average bus travel time w frequency of PVs when the flow of buses is 60 vehicles per hour (1 minute headway between buses) and the duration of each PV is 15 seconds.

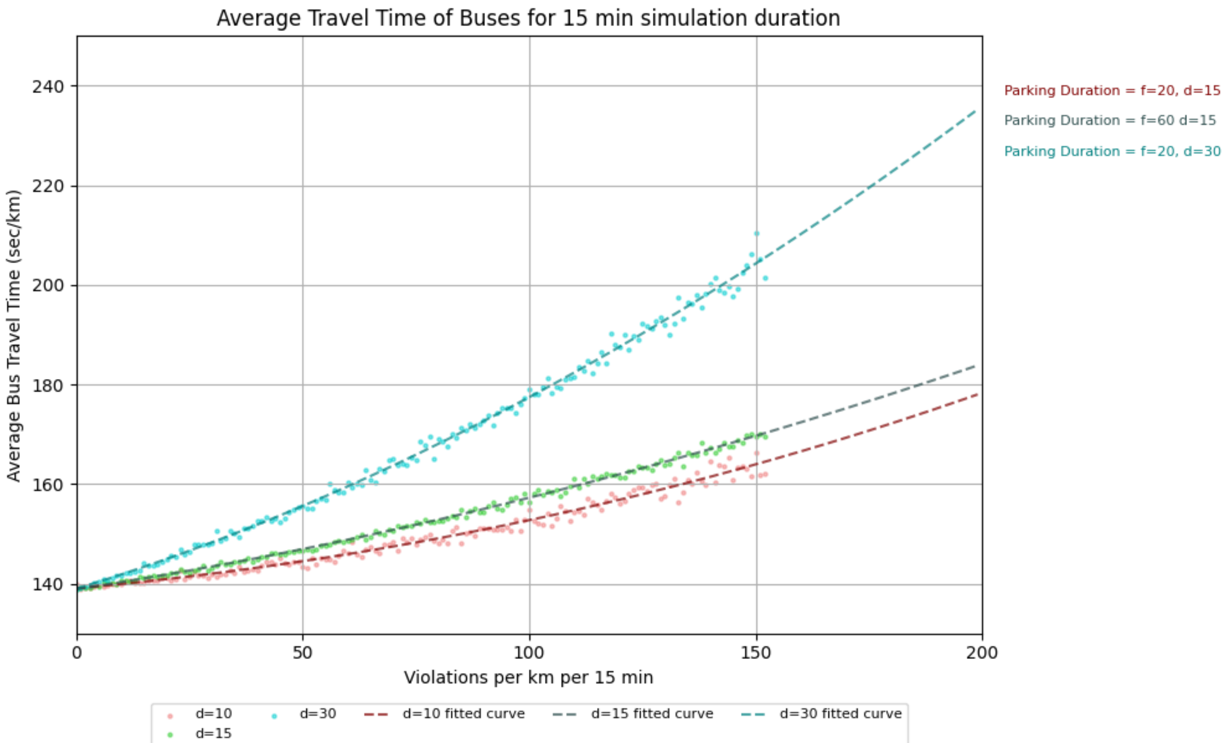

Figure 15: Comparison of the effect of increased parking duration and increased bus flow on average bus travel time

The increase of average bus travel time for increased duration of PVs when bus flow (headway) is kept constant is higher than that of increased bus flows (shorter headways) when duration of PVs is kept constant. The rate of increase in bus travel times is also higher with increasing duration of each PVs (with headways kept constant) than that of shorter headways (duration kept constant).

5 Evaluation of the Impact of PV s on the Travel Time of Buses on BPL

This chapter focuses on the development of the microsimulation model to predict the travel time variability of buses with varying numbers of PVs in a BPL.

5.1 BPR Function

The Bureau of Public Roads function is proposed by the Federal Highway Administration of the Department of Transportation USA as a volume-delay function that adjusts the travel impedance in terms of a predetermined relationship between the capacity of the link and the volumes assigned to the link. Anwar, Fujiwara, & Zhang (2011) has modified the BPR function to incorporate the influence of on-street occupancy by calibrating the function using the effective capacity of the link with illegal on-street parking rather than the total capacity of the link. The model developed in the study is as follows.

$$T_{a_{i(p)}} = T0_{i(p)} \left[1 + \alpha \left(\frac{V_{i(p)}}{C - C_{io}} \right)^{\beta} \right] \qquad \text{....... Eq. 2}$$

Where,

$T_{a_{i(p)}}$ = Congested travel time in the link i at peak hour;

$T0_{i(p)}$ = Free-flow (60kmph) travel time in the link i at peak hour;

$V_{i(p)}$ = Traffic volume in link i at peak hour;

C = Capacity;

C_{io} = Capacity occupied by on-street parking and street occupancy in the link i;

α = Parameter describing the ratio of travel time per unit distance at practical capacity to that at free flow;

β = Parameter describing how fast the estimated average link speed decreases from free-flow to congested conditions.

In this study, the C_{io} will be replaced by C_{pv}, which is termed as the Capacity occupied by violator vehicles performing a PV. Therefore, the final equation is given below.

$$T_{bus} = T0_{bus(bpl)} \left[1 + \alpha \left(\frac{V_{bpl}}{C - C_{pv}} \right)^{\beta} \right] \qquad \text{........ Eq. 3}$$

Where,

T_{bus} = Congested travel time in BPL;

$T0_{bus(bpl)}$ = Free-flow travel time in BPL;

V_{bpl} = Traffic volume BPL;

C = Capacity;

C_{pv} = Capacity occupied by violator vehicles in the BPL;

α and β are parameters to be estimated.

The parameters α and β will be calibrated using the output obtained from the microsimulations.

5.2 Travel Time at Free-Flow Conditions ($T0_{i(p)}$)

Highway Capacity Manual (HCM) describes free flow conditions as when drivers drive at their desired speed under low-volume conditions on a given facility (National Academies of Sciences Engineering and Medicine, 2000). In this simulation study, the low-volume scenario is taken as the scenario where there are no PVs and no queuing of buses. Both these conditions were observed in the no PVs scenarios where the flow was 20, 60 and 120 veh/hr. The free flow travel time of buses in these conditions is 139 seconds (2.32 min) and is hence considered as the travel time in free-flow conditions ($T0_{i(p)}$).

5.3 Capacity (C) Calculation

The capacity of a link is the maximum number of vehicles the link can accommodate per unit time. The capacity of the BPL was calculated using the traffic flow models. The free-flow speed (v_f) is calculated using the travel time at free-flow conditions as 25.9 km/h. The jammed density (k_j) was obtained from the microsimulation model. A microsimulation run with 1-second headway of buses (flow of 3600 buses/hr) where they are not allowed on other lanes was developed and run to get the jammed density. As shown in Figure 1 below, at jammed density, 32 buses can be counted on a 450m stretch. Therefore, using the PCU value of 3.54 for buses, the jammed density in the BPL was calculated as 251.73 PCU/km.

Figure 16: Jammed Density modelled in the Microsimulation

The Greenshield model (Greenshield, 1935) was then used to calculate the capacity (q_{max}) of the simulated edge where,

$$q_{max} = \frac{v_f \times k_j}{2} \qquad \text{........ Eq. 4}$$

The total capacity of the BPL was calculated as 1629.93 PCU/hr/lane. The capacity calculated for Sri Lankan freeways is 2000 PCU/hr/lane (Road Development Authority, 1998). However, these values were calculated in 1998 for data obtained in a link without BPLs.

In BPLs, some reduction in the capacity is inherent due to dwell times at bus stops. Since 4 different bus flows were used in this study, the capacity available while the buses travelled in free-flow conditions is different. Hence, the capacity of the BPL depending on the bus flow was calculated to be used as the **C** in the V/C calculations.

$$C = C_{bus\,flow_i} = C_{total} - C_{bus\,dwell\,time} \qquad \text{........ Eq. 5}$$

$$C_{bus\,dwell\,time} = \frac{n_{bus} \times d_{dwell\,time\,at\,planned\,stops}}{d_{duration\,of\,simulation}} \qquad \text{........ Eq. 6}$$

Where,

$C_{bus\,flow_i}$ = Available Capacity for bus flow I;

C_{total} = Tatal Capacity (1629.93 PCU/hr/lane);

$C_{bus\,dwell\,time}$ = Capacity reduced by buses occupying road due to planned stops;

n_{bus} = No. of buses in the lane;

$d_{dwell\,time\,at\,planned\,stops}$ = Total dwell time duration of one bus at planned stops in the lane in its journey;

$d_{duration\,of\,simulation}$ = Duration of the simulation.

5.4 Capacity Reduction due to PVs (C_{pv}) Calculation

The capacity reduction in the BPL due to PVs was calculated using the following equation.

$$C_{pv} = \frac{n_{pv} \times d_{pv}}{d_{duration\,of\,simulation}} \qquad \text{........ Eq. 7}$$

Where,

C_{pv} = Capacity reduced by violator vehicles occupying the BPL by the performance of a PV;

n_{pv} = No. of violator vehicles performing PVs;

d_{pv} = Duration of a PV;

$d_{duration\,of\,simulation}$ = Duration of the simulation.

5.5 Volume (V_{bpl}) Calculation

The volume of vehicles in the BPL was calculated using the equation below.

$$V_{bpl} = (n_{bus} \times PCU_{bus}) + (n_{violators} \times PCU_{violaters}) \quad \text{........ Eq. 8}$$

Where,

n_{bus} = No. of buses that travelled in the BPL in a unit of time;
$n_{violators}$ = No. of violator vehicles that travelled in the BPL in a unit of time;
PCU_{bus} = PCU value of a bus (3.54 PCU);
$PCU_{violaters}$ = PCU value of a violator vehicle (1 PCU).

The PCU values used in the study were calculated by (Dhananjaya, Fernando, & Sivakumar, 2022) for Sri Lankan traffic conditions.

5.6 Calibration of α and β parameters

The V/C ratio was first calculated using the V_{bpl} , C and C_{pv} Values obtained from Equations 4-7 above. The values α and β parameters were then calibrated for the microsimulation output of the average travel time of buses with different frequencies and duration of PVs at different bus flows. Python curve fit was used in the calibration.

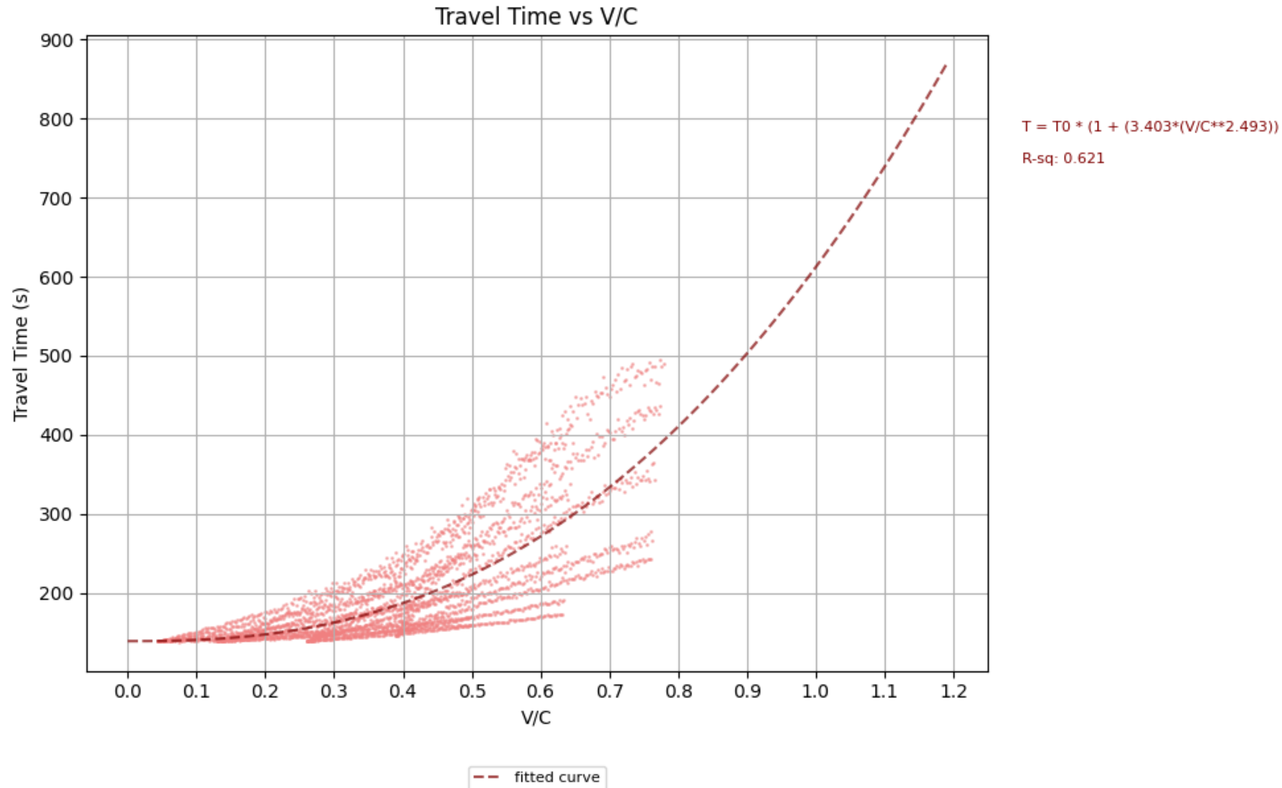

Figure 17: Calibrated α and β parameters

Figure 12 above shows the fitted BPR function for the BPL. The calibrated α value is 3.403, which is similar to the α value calibrated for a link with illegal on-street occupancy in Dhaka, Bangladesh (Anwar et al., 2011). However, the calibrated β value is higher than Dhaka at 2.493. These α and β values mean that the travel time increased 340% due to PVs compared to free flow. This decrease in speed has occurred somewhat abruptly. The calibrated parameters showed an R square value of 0.621, deemed acceptable (Anwar et al., 2011).

The α and β parameters calibrated by the Road Development Authority of Sri Lanka use the values 3 for α and 2.5 for β for the BPR function for national roads. Therefore, the α and β parameters calibrated in this study align with the national values used in practice.

The following graph shows the delay caused by increasing V/C ratio in a BPL.

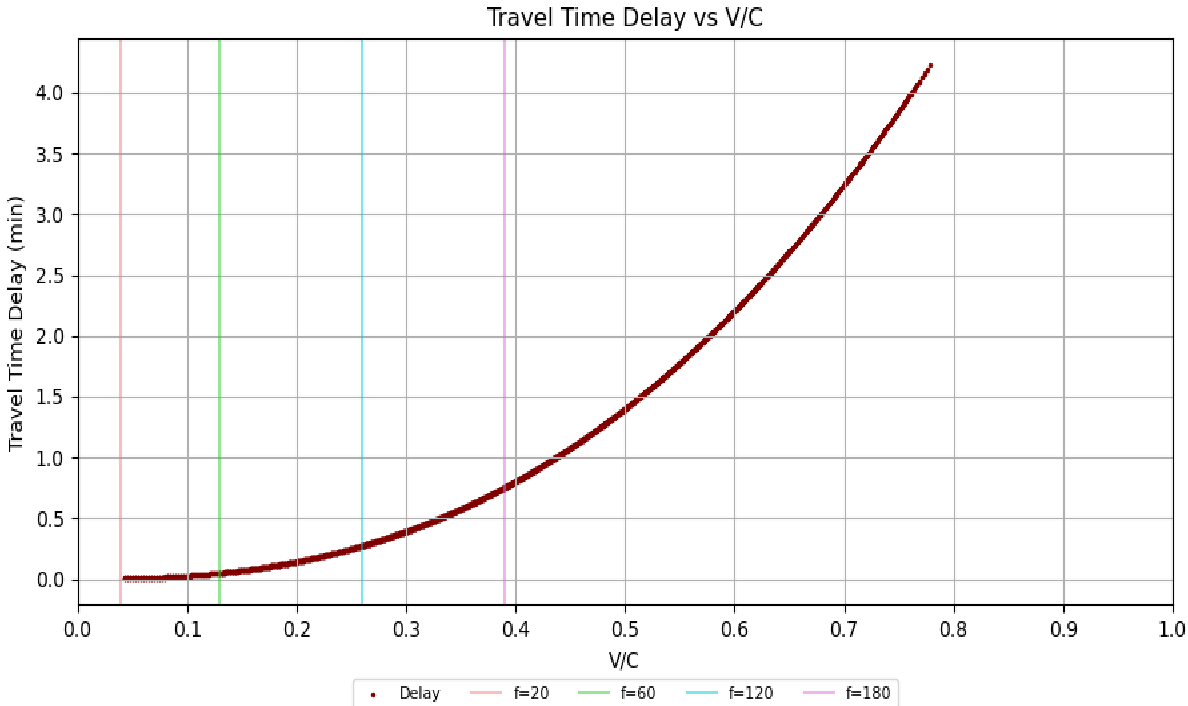

Figure 18: Travel time delay (min) vs V/C ratio

The graph shows that when the V/C ratio approaches 0.8, the travel time delay increases exponentially. The V/C ratios with zero violations for each bus flow (f) in veh/hr is also indicated in the graph. Each vertical line indicates the starting point for analysis of delays caused by parking violations for scenarios with each bus flow.

When the bus flow is 20 veh/hr, the delay caused by parking violations will increase at a comparatively lower rate at first. In contrast, if the bus flow is 180 veh/hr (i.e. 20 sec headway between two buses), the delay caused by each parking violation will be higher. This is further clarified using table 3.

For each bus flow, 0.1 change in V/C will be reached when 38 violations with 10s parking durations are performed. However, the delay caused to bus travel times increase at an increased rate with increasing bus flow.

Table 3: Delay caused by 0.1 change in V/C when d=10

Bus flow (veh/hr)	**Delay caused by 0.1 change in V/C (min) when d=10s**	**No. of violations**
20	0.05	38 violations
60	0.07	38 violations
120	0.12	38 violations
180	0.67	38 violations

The V/C ratio where the BPL reaches jammed condition is 0.8. Since the V/C ratio of base scenario (no violations) scenario when bus flow is 180 veh/hr is higher than that of a bus flow of 20 veh/hr, the no. of parking violations to reach jammed conditions is lower at bus flow of 180 veh/hr.

This interpretation will be useful for both planners and enforcers, as it gives a clear understanding of the limitations in parking violations in order to keep delays to a desired level. Based on the desired level of delays and the bus flow of the planned BPL, the planners and enforcers can identify how many parking violations and corresponding duration of parking per each violation that can be allowed in the BPL. If data can be collected on the average duration of parking in a planned BPL corridor, planners can identify the maximum no. of parking violations that can be allowed per certain time period using the developed model.

This can aid the enforcers as it sets a clear goal for them in terms of enforcement of the BPL, thus enabling the implemented BPL to reach its planned performance goals.

6 Conclusions and Recommendations

This chapter focuses on concluding the research findings and future research recommendations.

6.1 Conclusions

The literature concludes that the success of a BPL in achieving its expected performance benefits depends on the enforcement of the BPL rule. The curbside with flow BPLs, such as the case in Colombo, Sri Lanka, are most at risk for BPL rule violations. The PVs, where unauthorised vehicles enter the BPL and park illegally, cause delays in the travel time of buses in BPLs by reducing the lane's capacity.

A microsimulation model that is calibrated to Sri Lankan traffic conditions to investigate how the illegal parking behaviours affect the performance of a BPL. The simulation was conducted on a 1km 3-lane edge with one lane allocated for BPL Vehicle flows were simulated for 15 minutes. Average bus travel times were obtained as output by varying the bus flow, duration of illegal parking and the frequency of illegal parking.

Output showed that the average bus travel time increased exponentially with increasing frequency of violations (Figures 11,12,13,14). The average bus travel time increased at an increasing rate when the bus flow was increased keeping the duration of parking as well as frequency of parking constant. The average bus travel time also increased at an increasing rate when the duration of parking was increased keeping the bus flow as well as frequency of parking constant (Figure 15). The increased duration of parking was found to impact the average bus travel time more than the increased bus flow, that is buses with shorter headways.

To model the increase of travel time, a modified BPR function was developed, building on the work of Anwar et al., (2011). The α and β parameters of the BPR function were calibrated for the travel time of buses in the BPL by microsimulation of a BPL calibrated for Sri Lankan traffic conditions. The α and β values of the BPL are 3.403 and 2.493, which is close to the values used by national planners. This implies that while the decrease in speed due to PVs in BPL is similar to the decrease of speed observed on national roads, the percentage of this decrease is higher than that of national values.

The model developed can be used by planners as well as enforcement agencies to understand the level of enforcement needed to keep delays to bus travel times to desired levels (Figure 19). With the varying bus flows, the V/C ratio in scenarios with no violations also varies. The base scenario (no violations scenario) V/C ratio increases with increasing bus flow. The model explains an exponential increase in delay with increasing V/C ratio. Around a V/C ratio of 0.8, the travel time delay approaches infinity. The base scenario V/C ratio when bus flow is 60 is 0.04 and that of 180 veh/hr is 0.39. If the bus flow is 180 veh/hr, each additional parking violation causes V/C ratio to approach 0.8 faster than when bus flow is 20 veh/hr. This means that the delays caused by an additional parking violation is higher when bus flow is 180 veh/hr than when bus flow is 20 veh/hr. Furthermore, the no. of parking violations that can be performed before the BPL reaches jammed conditions is lower when bus flow is 180 veh/hr than when bus flow is 20 veh/hr.

This knowledge can aid planners as well as enforcement agencies to determine the level of enforcement needed in terms of maximum allowable no. of parking violations when designing and implementing a BPL.

6.2 Recommendations

This study considered only the travel time of buses in the BPL. However, the general traffic could also be impacted by the reduced capacity in BPL due to PVs from the movements of violator vehicles, such as lane changes to and from adjacent lanes, creeping, etc. Therefore, the study could be extended to analyse the impact of travel time on general traffic.

A limitation of this study was that it used only one vehicle type as a violator vehicle. However, in the real world, different types of vehicles perform PVs. Depending on the vehicle that performs a violation, the reduction in capacity is different due to different PCU values. Therefore, extending this study to include different vehicle types as violators is recommended.

The code developed to generate parking violations in this study can be plugged into a SUMO model developed for a real-world network, in order to simulate the impact of parking violations on the real-world traffic scenarios (Jayasinghe, 2023) .

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Appendix

ParkingViolations.py

```
#importing libraries
import os
import random
import subprocess
import sys
import optparse
from random import seed
from random import randint

import numpy as np
import pandas as pd
from xml.etree import ElementTree as et

#importing TraCI
if 'SUMO_HOME' in os.environ:
    tools = os.path.join(os.environ['SUMO_HOME'], 'tools')
    sys.path.append(tools)
else:
    sys.exit("Please declare enviornment variable 'SUMO_HOME'")

from sumolib import checkBinary
import traci

#Setting the base scenario sumo configuration file
sumo_config_file = 'BPL.sumocfg'
tree = et.parse(sumo_config_file)
run_summary=pd.DataFrame()
root = tree.getroot()
```

```
def get_options():
    opt_parser = optparse.OptionParser()
    opt_parser.add_option("--nogui", action="store_true",
                          default=False, help="run the commandline version of SUMO")
    options, args = opt_parser.parse_args()
    return options

# TraCI control loop
def run(vio, ra_se):
    # check binary
    if options.nogui:
        sumoBinary = checkBinary('sumo')
    else:
        sumoBinary = checkBinary('sumo-gui')

    # Script connecting TraCI to run sumo
    sumoCMD= ['sumo', "-c", "BPL.sumocfg", "--tripinfo-output", str(seed)+" "+str(ra_se) + "
Violations.xml", "--start", "--quit-on-end"]
    traci.start(sumoCMD)

    # Generating random timesteps for violator vehicle generation
    step = 0;
    x = 0
    t_steps = []

    for vi in range(0, int(vio)):
        vi_no = randint(0, 900)
        t_steps.append(vi_no)

    t_steps.sort()
```

```
    # Generating violator vehicles
    while traci.simulation.getMinExpectedNumber() > 0:
        traci.simulationStep()

        #Checking for the timestep to generate the vehicle
        for w in t_steps:
            if step == w:
                #Generating the random stopping location
                 y = randint(50, 1050)
                #Generating the violator vehicle
                 traci.vehicle.add("Violater" + str(x), "", typeID="HOV", arrivalPos="1050", departLane="2")
                #Assigning the violator vehicle the random stop location
                 traci.vehicle.setStop("Violater" + str(x), "-gneE0", y, "1", "15")
                 x += 1

        step += 1

    #Close TraCI
    traci.close(False)

# Main entry point
if __name__ == "__main__":
    options = get_options()

    #Generate random seeds
    rand = np.random.randint(10000, 99999, 50).tolist()

    for seed in rand:
        print(seed)
        run_summary[str(seed)]=np.nan
```

```
#Calling TraCI control loop with a certain violation frequency for each random seed
for qwe in range(0, 901):
    run(qwe,seed)
```