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Improving Highway Efficiency Using Dedicated Lanes

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of the requirements for the degree of
Msc Computer Science

Declaration

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Abstract

Over recent years, Connected Autonomous Vehicles (CAVs) have been a trending research area due to their promising benefits and advanced technology. A large array of studies have shown that CAVs can improve traffic efficiency and safety in mixed traffic modes. The researchers in this domain have proposed several traffic management techniques utilizing the potential of CAVs to increase highway capacity, and reduce travel time, road accidents, and fuel consumption. A dedicated lane for CAVs is one of the proposed techniques. However, the dedicated lane is a relatively new area, and thus the research based on the impact of the dedicated lane on traffic mode with both CAVs and HDVs is limited. Recent studies in this domain have utilized mixed traffic modes with different distributions of CAVs and HDVs, and varying numbers of dedicated lanes. The majority of these studies have shown that at a higher CAV penetration rate, the dedicated lane technique improves traffic efficiency. However, the impact of the dedicated lane on a realistic highway network with real-time traffic flow is unclear.

This study aims to analyze the expected impact of dedicated lanes on traffic efficiency in a realistic motorway network with real-time traffic data. For this purpose, the performance of several dedicated lane strategies has been studied for varied CAV penetration rates and traffic volumes. The significance of the deployment of dedicated lanes from both the left side and right sides of the motorway has also been studied.

The simulation experiments in this study are designed based on the position of the dedicated lane, the number of dedicated lanes, CAV penetration rates, and several traffic scenarios with both validation and a realistic highway network. The experiments are highly resource and time-consuming, and also generate a large amount of data. The results show that the assignment of dedicated lanes shows improvement in traffic efficiency. For saturated flow, one dedicated lane shows improvement in trip duration for CAV MPR 70% to 90%. For congested flow, one dedicated lane shows improvement in traffic efficiency for CAV MPR 30% to 70% and two dedicated lanes for CAV MPR 70% to 90%. No impact was observed during the free-flow traffic scenario. We also find that the optimal position and location of the dedicated lane are highly dependent on the complexity of the highway network. Based on the simulation experiments, a rule-based adaptive approach to dynamically assign the dedicated lane. The performance of this approach is evaluated with 24-hour real traffic data with all other lane strategies implemented in this work.

Acknowledgements

I would like to thank and express my gratitude to my supervisor Assistant Professor Dr. Mélanie Bouroche. With her expertise in the area of smart cities, I was able to explore the various research gaps in the research area. She continuously motivated me to focus on analysing the research topic and novel techniques that can be introduced in this study. I would also like to thank Mr. Mohit Garg. With his experience with the several simulation platforms, I was able to resolve the implementation issues quickly. His inputs were also helpful to complete the project. I would also like to express my gratitude to my family and friends for their continuous support.

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1 Introduction

This chapter states the motivation for this work in Section 1.1. Section 1.2 gives a brief introduction to the dedicated lane strategy, its benefits, and research gaps.

1.1 Motivation

Traffic congestion is an eternal problem for the area of road transportation and road infrastructure. Traffic congestion can be termed as a phenomenon where the road demand is more than the road capacity (3). Congestion occurs when the regular traffic flow is disrupted by unnecessary lane changes, shock waves produced due to declarations, and bottlenecks increasing in overall travel time. High population density and insufficient road infrastructure are also reasons for the increased traffic congestion. Traffic congestion does not only affect travel time but also has impacts on environmental and economic factors. Increased travel time results in increased fuel purchases. In 2014, traffic congestion in the United States resulted in 6.9 billion additional hours of travel with 3.1 billion gallons of excess fuel purchased compared to usual (35).

As per the World Health Organization (WHO) [1], every year on average 1.35 million people are killed due to road traffic injuries across the globe. 20-50 million other injuries are reported which also result in partial or permanent disability. Road traffic accidents are the world's ninth leading cause of death and are anticipated to become the fifth leading cause by 2030 (28). Also, with increased road congestion, road transportation accounts for three-quarters of transport emissions which significantly increases the level of air pollution.

Human Driven Vehicles [HDVs] have an imperfection driving factor that majorly depends on the driver's habits. Also, Humans Driven vehicles are prone to degradation of traffic performance due to human errors (6). Connected Autonomous Vehicles [CAVs] are designed with the primary purpose of improving traffic situations and road safety. CAVs can communicate with other Autonomous Vehicles and infrastructure, and this allows CAVs to obtain and share data between vehicles. In the near future, we would expect a mixed traffic mode with both human-driven and CAVs on the road. In recent times, multiple studies have been conducted to understand the impact of CAV in such mixed traffic flows in both ideal and realistic conditions. Results from these studies show that CAVs can improve traffic efficiency, and reduce traffic congestion (17) (11). The Insurance Institute for Highway Safety [IIHS] states that level 4 Autonomous

[1] World Health Organization : https://www.who.int/news-room/fact-sheets/detail/road-traffic-injuries

Vehicles can reduce traffic crashes and fatalities caused due to road accidents (6). Several traffic management and lane management techniques such as congestion prediction, traffic flow control, speed limit policies, Adaptive Cruise Control, and Cooperative Adaptive Cruise Control have been suggested to improve traffic efficiency using CAVs. However, the presence of Human Drive Vehicles (HDVs) in the traffic flow is likely to impact the potential benefits promised by CAVs. The movements of HDVs can not be entirely controlled and manipulated as compared to that of CAVs. Because of this HDVs tend not to follow the road policies which can result in randomness and uncertainty. This in turn can reduce the overall performance of the CAVs in mixed traffic mode.

As mentioned earlier, CAVs can communicate with each other which enables data sharing between a group of CAVs. This information sharing is very useful in traffic and congestion management. For example, the leader vehicle can transfer the message of an accident that occurred in the lane to the following vehicles. Based on this information, the following CAVs can adjust their route and avoid creating congestion on the lane. The communication technologies used in these vehicles vary in range and thus the presence of HDVs can impact the connectivity between two or more CAVs (43) (15). The vehicle-to-vehicle (V2V) communication is also focused on vehicle safety and reducing collisions (36). The HDVs primarily depends on the visual and hearing perception of the driver. HDVs also lack information about the road and surrounding conditions which increases the risk factor. Hence the presence of HDVs along with CAVs in the traffic can overall increases traffic accidents (46). The studies conducted on the evaluation of safety parameters under mixed traffic mode show that the traffic safety index increases with an increase in the CAV penetration rate. CAVs are also modeled with cautious driving and car following models which is another reason cited that leads to improvement of the traffic safety (46) (48).

1.2 Dedicated Lane Management

A dedicated lane management (41) is one of the plausible solutions to improve traffic efficiency in mixed traffic mode. Dedicated lanes or Managed lanes are a type of lanes used to improve the traffic flow, and vehicle throughput. These lanes allow only a specific type or class of vehicles to travel. The application of managed lanes can further be extended to environmental benefits such as air quality improvement, emission reduction with improved traffic, and highway efficiency. The term managed lanes refers to highway facilities with operational strategies effectively deployed and managed in response to changing conditions. (2) Managed lanes are meant to be a congestion management strategy and its benefits can only be utilized when there is frequent traffic congestion that results in significant travel time delays. Understanding and analysis of traffic demand in the given geographical areas play a vital role to draft managed lane strategies. Examples of dedicated lane strategies: High occupancy vehicle lanes, Bus lanes, etc (30). A dedicated lane for CAVs is an extension of the aforementioned strategy. A specific lane setup only for CAVs allows the CAVs to follow each other with minimum inter-vehicle distance. Also, CAVs traveling in close proximity can increase the vehicle to vehicle communication and data sharing. The dedicated lane strategy also helps to mitigate the p the degradation of CAVs to AVs. For example, in a mixed traffic mode when a CAV is followed by or is following an HDV, it is no longer a connected vehicle. With only CAVs traveling in a specific lane, the chances of this situation would reduce. A dedicated lane would allow CAVs to follow CAVs which in turn would allow these vehicles to with minimum inter-vehicle distance. This can increase the number of vehicles traveling over the same period. Setting up the dedicated lane(s) would also allow CAVs to understand the surrounding environment with the help of sensors and other CAVs, sharing information and adapting control measures based on the situation which would increase overall highway and traffic efficiency. Improvement in traffic efficiency will lead to reducing air pollution and fuel consumption.

In recent times, several studies have been performed to understand the impact of the dedicated lane on traffic congestion. The impact of dedicated lanes in mixed traffic mode has been studied under different traffic volumes. Some of the works, also considered the number of dedicated lanes, the width of the dedicated lanes, and the CAV penetration rate. Some of the studies have also suggested different strategies for different traffic situations based on the aforementioned factors. The result shows that the dedicated lane strategies improve the traffic capacity, and traffic safety and reduce the effect of traffic shock waves (44) (47). It is also observed that the effect of a dedicated lane is seen at a higher rate of CAV penetration. Also, the number of dedicated lanes required to achieve the desired results depend on the traffic volume and CAV penetration rate. However, the majority of these studies consider a hypothetical and simple highway network and static traffic flow. Thus the applicability of a dedicated lane is not thoroughly validated in realistic conditions. The dedicated lane is a relatively new domain and provides a great opportunity for a detailed analysis of the impact of dedicated lanes. It is important to validate the feasibility and impact of dedicated lanes considering multiple factors such as the complexity of the highway network, CAV penetration rate, etc. The rest of this paper is organized in the following manner: Chapter 2 provides the background for CAVs, and the terminology related to CAVs. Chapter 3 analyses the related work and states the research question for this study. Chapter 4 states the simulation experiments, experiment design in detail. Chapter 5 states the observations from the simulation experiments. Finally, chapter 6 summarises the conclusion and states the future scope of this study.

2 Background

This chapter gives a brief background about Autonomous Vehicles (AVs) in section 2.1, Connected Autonomous Vehicles (CAVs) 2.2. Section 2.3 explains the various terminologies related to the vehicular system. Section 2.4 explains the state-of-the-art simulation models for microscopic simulations. Section 4.2 compared the several simulation platforms available for microscopic simulation.

2.1 Autonomous Vehicles

Smart urban mobility is a way of transforming cities with the combination of advanced vehicular technologies and intelligent transport systems. An autonomous vehicle (AV) is one of the most advanced concepts that utilize technology and is capable of taking driving decisions without any human involvement. As per the definition, an Autonomous vehicle is supposed to undertake all the driving tasks using its underlying software system. However, based on the functions performed by the vehicles, the Society of Automotive Engineers International (SAE) defines six levels of automation (23). These six levels can be broadly classified into two categories, one where Humans are driving the vehicle along with driving support functions offered by the vehicle and one where Humans are not driving the vehicle (6).

- Level 0: No Automation Level 0 can be considered a Human Driven Vehicle where there is no automation involved. Although the vehicle can have driver assistance features limited to providing warnings and short-term assistance. (6)
- Level 1: Driver Assistance Level 1 driving assistance features are capable of performing vehicular movement control tasks in the lateral or longitudinal direction. Although, these systems are capable of limited Object and Event Detection Response (OEDR) and are not capable of dealing with some Driving Dynamic Task (DDT) situations. Therefore, the driver has to constantly supervise the performance of these features (6).
- Level 2: Partial Automation Compared to Level 1, in Level 2 the vehicle is capable of performing vehicular movement control tasks in both lateral and longitudinal directions. Similar to that of level1, these systems are also capable of limited Object and Event Detection Response (OEDR) and are not capable of dealing with some Driving Dynamic Task (DDT) situations. Therefore, the driver has to constantly supervise the performance of these features (6). It is important that the driver continuously monitor the driving environment and be in a position to take over the vehicle control immediately when necessary with both Level 1 and

2 systems providing driving comfort and convenience (6).

- Level 3: Conditional Automation Unlike Level 1 and Level 2, Level 3 Automated Driving System (ADS) features are capable of monitoring and controlling the Dynamic Driving Tasks. The driver need not require to supervise the operation and performance when these features are engaged. This level of automation allows the driver to get involved in other activities but the presence of the driver is required to take over the control immediately when the system requests the driver to do so. Hence Vehicle to Human interface plays an important role in this level where the system can notify and easily gain the attention of the user. These features will not operate unless all the required conditions are met (6).
- Level 4: High Automation Similar to that of Level 3, the driver does not need to supervise the Automated Driving System features once it is engaged in Level 4 automation. Along with the features of Level 3 automation, Level 4 ADS is capable of performing DDT fallback. DDT fallback is the response by the driver to perform dynamic driving tasks after ADS DDT-related failure. Level 4 ADS can also achieve minimal risk conditions i.e., bring the vehicle to stable or stop condition if it doesn't receive any response from the user. These two features are the key differences between Level 3 and Level 4. Due to these added features, the driver need not require to take over the control of the vehicle in any situation (6).
- Level 5: Full Automation Full automation in Level 5 means that Automated Driving System can fully operate the vehicle under all road conditions where a traditional human-driven vehicle can operate. These systems are not designed keeping in mind any weather or geographic conditions. Similar to that of Level 3 and Level 4, a user does not need to supervise the Level 5 ADS. A fully autonomous vehicle also has limitations under certain environmental circumstances such as snow storms, and floods, where human expertise might be required (6).

Figure 2.1 summarized these levels of automation with an respective examples.

The futurama exhibit by General Motors in 1939 built the foundation for the concept of automated vehicles. An early depiction of automated cars was done by Norman Bel Geddes. In the 1950s miniature and full-size systems of the automated vehicle were developed by Radio Corporation of America in collaboration with General Motors. From the 1960s to the 2000s several such projects were undertaken in the field of autonomous vehicles. The grand challenges organized by DARPA [Defence Advanced Research Projects Agency] boosted the developments in the vehicular automation field. The DARPA challenges required autonomous driving through various terrain. During the initial series in 2004, none of the participants could complete the challenge. In the consequent challenges in 2005 and 2007, significant advancement was observed and several robots demonstrating autonomous driving capabilities were introduced to the world. (39)

2.2 Connected Autonomous Vehicles

Autonomous driving software consists of three layers: Perception, Planning, and Control. (39) Perception deals with consuming data generated by sensors and surrounding predictions based on sensor data. Planning deals with the dynamic driving tasks and

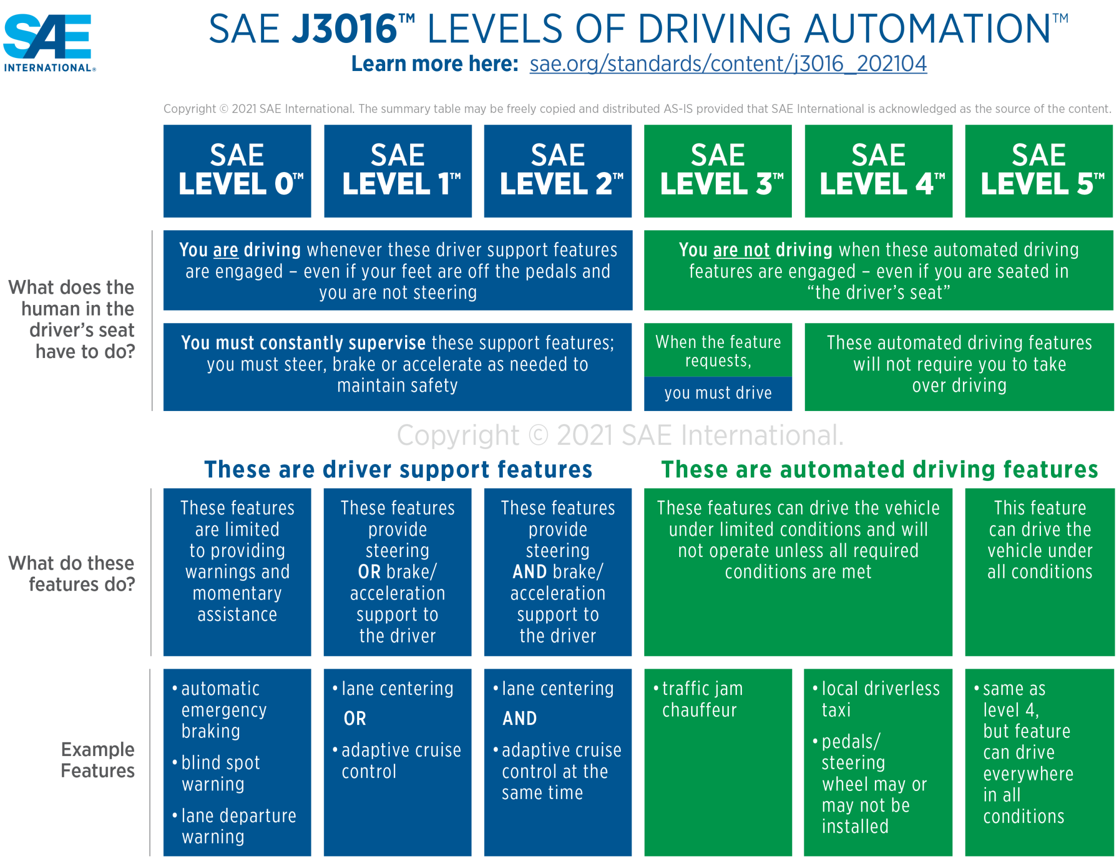


Figure 2.1: Levels of driving automation (23)

control takes care of the actual vehicle controls. Information gathering is the primary key to perception. This information can also be obtained from other infrastructure or other vehicles. This is where the concept of a Connected Autonomous Vehicle comes into the picture. (6) Based on the environments with which the vehicle can interact within the connected network, the connected vehicle's technologies can be classified as:

- V2X (Vehicle to Anything): All the entities that can establish communication with a vehicle fall under the umbrella of Vehicle to Anything. The below-mentioned list gives the most widely established features and is not exhaustive.
- V2V (Vehicle to Vehicle): V2V communication allows vehicles to share information about speed, location, and direction with other vehicles. This is achieved with the help of wireless networks. V2V communication is not limited to a similar type of vehicle and can be achieved by any type of vehicle with the required software setup. Along with the radar and cameras, this information from other vehicles helps increase the performance of vehicle safety systems and avoid fatal crashes and accidents. V2V can also enable applications such as Automatic maneuvering at crossroads and intersections, automated platooning, etc.
- V2I (Vehicle to Infrastructure) and I2V (Infrastructure to Vehicle): V2I communication allows vehicles to share information with road infrastructure and vice versa(I2V). Similar to that V2V, V2I-I2V is also achieved with the help of wireless communication. Road components can store and exchange information about the traffic situation, accidents, and speed limits with vehicles. Similarly, vehicles can also share information about their speed, and system failures with the road infrastructure.
- V2P (Vehicle to Pedestrian): V2P communication enables the communication between vehicles and pedestrians and allows pedestrians to be a part of the Intelligent Transport System. The information exchange between vehicles and pedestrian is important as pedestrians have different movement characteristics. This communication can help reduce pedestrian fatalities due to vehicles.

2.2.1 Communication Technologies in CAVs

Vehicles can communicate with other vehicles and Intelligent Transport System infrastructure components with a variety of communication technologies. Based on the range, type of information, and security constraints these communication technologies can be implemented in a connected vehicular network. (23)

- Dedicated Short-Range Communication (DSRC): This is a wireless licensed and protected technology similar to WiFi designed primarily to use in road infrastructure. This technology has attracted attention due to its features of communicating critical messages over a short distance. However, the application of DSRC is limited to highway transportation. (37)
- WiFi: The usage of WiFi in road transportation is very limited due to its availability and latency over long-distance communications. WiFi is also prone to packet drops and hence lacks the credibility to transfer important messages. (37)

- Cellular communications: This category consists of technologies such as 4G, 5G, WiMAX, etc. This category reduces the dependency on public agencies since the infrastructure for these technologies is easily available in the majority of areas. Based on its usage, users have to pay for the services under this category. (37)
- Satellite communication: The infrastructure setup for satellite communication is costly as compared to other technologies. The system can be used for selected applications such as areas lacking a strong cellular network. (37)
- Bluetooth: Bluetooth is a short-range wireless technology that operates on Ultra High Radio Frequency waves ranging from 2.402 GHz to 2.48 GHz. The application of this technology for Intelligent Transport system is limited due to its shirt range and limited bandwidth.

2.3 Vehicular system terminology

2.3.1 Headway Distribution

Time headways are the time intervals between the passage of successive vehicles passed a point on the highway. Time headways indicate the rate of the flow, hence these can be considered the building blocks of traffic flow. The traffic flow value is inversely proportional to the time headway. The values of time headway depend largely on highway and traffic situations; hence the values can vary depending on the situation. On a lightly trafficked highway, a range of headways will be observed from zero values between overtaking vehicles to longer headways between widely spaced vehicles. Whereas for heavily trafficked highways, there are fewer widely spaced vehicles and all vehicles are traveling at uniform headways. Measurement approaches: 1. Using a device that can record the arrivals of vehicles at a designated time 2. Using aerial photography to record the distribution of headway between successive vehicles (23)

2.3.2 Managed Lanes

Managed lanes are a type of lanes used to improve the traffic flow, and vehicle throughput. The application of managed lanes can further be extended to environmental benefits such as air quality improvement, emission reduction with improved traffic, and highway efficiency. The term managed lanes refers to highway facilities with operational strategies effectively deployed and managed in response to changing conditions. (2) Managed lanes are meant to be a congestion management strategy and its benefits can only be utilized when there is the frequent traffic congestion that results in significant travel time delays. Understanding and analysis of traffic demand in the given geographical areas play a vital role to draft managed lane strategies. Examples of dedicated lane strategies: High occupancy vehicle lanes, Bus lanes, etc (30)

2.3.3 Speed

In kinematics, Speed is defined as the change in position of any object over a period of time. The vehicle speed varies for different vehicle types and plays an important role in traffic management. The average speed of the vehicles is a crucial traffic measure for traffic efficiency. Based on the vehicle speed, several speed management strategies have been proposed. (30)

2.3.4 Volume

Volume is defined as the number of vehicles passing through a particular point. The volume is generally associated with a lane, an edge, or a junction. The traffic volume is directly related to traffic flow and hence plays a significant role as a traffic measure. (30)

2.3.5 Flow (q)

Flow is another traffic measure that is calculated as the number of vehicles passing through a specific point per hour. It is usually denoted by vehicles per hour. For example, if 2000 vehicles are passing through a point on a highway every 20 minutes then the flow rate for that point would be 6000 vehicles/hour. Flow is very widely used to evaluate the capacity of a lane or entire highway. Flow can also be used to calculate the vehicle throughput which is denoted in vehicles per hour per kilometer. (30)

2.3.6 Density (k)

Density can be defined as the number of vehicles occupying a certain roadway length. Density can help identify if the traffic on the roadway is congested or free-flow based on the distance between the vehicles. High density indicates a bumper-to-bumper traffic situation. (30)

2.4 Microscopic Simulation models

There is no standard approach to model CAVs and simulate traffic with CAVs. The simulation can vary from macroscopic level to mesoscopic level to microscopic level based on the level of detail required (16) (7). In the microscopic model, vehicle behavior and intersections are described at a low level of detail. The traffic flow is represented by speed, flow, and density. This method is an accurate and simple way of modeling traffic simulation. However, this method is not suitable to demonstrate interactions among the vehicles. (8) The basic idea behind mesoscopic models is to explain traffic flow dynamics in aggregate while describing individual driver behavior with probability distribution functions (20). Mesoscopic models are a combination of microscopic modeling and macroscopic modeling. In this model, platoon dispersion is stimulated. There are two methods of mesoscopic modeling which are platoon dispersion and vehicle platoon behavior. Microscopic models provide highly detailed vehicle motions where an individual vehicle is viewed as a distinct agent that must adhere to particular governing criteria. The goal of microscopic modeling is to collect data factors such as flow, density, speed, travel and delay time, and shock waves. Microscopic modeling includes car following models, and lane changing models. For this study, microscopic traffic modeling is followed.

2.4.1 The GM Car following model

As the name suggests, the car following models is based on a follower vehicle and leader vehicle [vehicle driving in front] where the follower vehicle reacts as per the leader vehicle's actions. In 1961, General Motors (GM) research laboratories proposed a car following model based on a sensitivity-stimulus framework which predicts acceleration/deceleration using the difference between the leader vehicle's and follower vehicle's current speed [relative speed of leader vehicle](25) (4). Later modified versions were developed based on this model. The GM model is a simple linear car following model based on two parameters: sensitivity as a constant parameter and acceleration of the follower vehicle.

$$a_n(t) = \alpha * \Delta_n^f ront(t - \tau_n)$$

where $a_n(t)$ is the acceleration of the vehicle n at time t. $\Delta_n^f ront(t - \tau_n)$ is the relative speed of leader vehicle at time (). tau_n is the reaction time, alpha is the parameter. Overall, these GM models fail to capture real-life traffic simulations due to their limitations which are caused because of the underlying assumptions. (4)

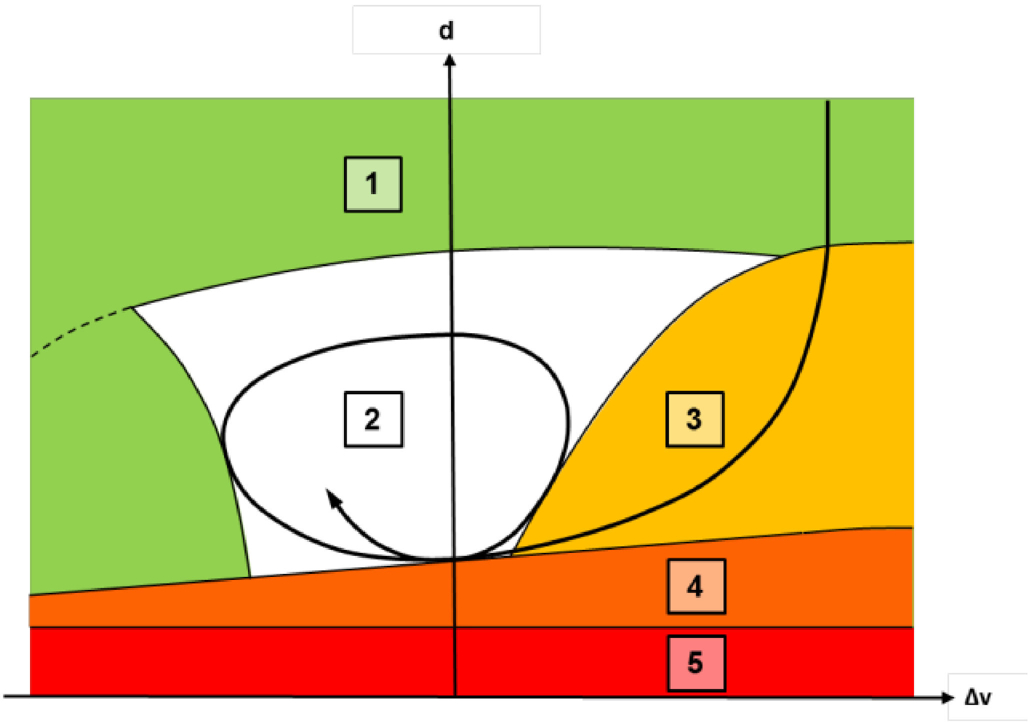
2.4.2 Collision avoidance car following model

Collision avoidance models are also known as safety distance models which are based on the assumption that the collision is unavoidable if the leader vehicle behaves unpredictably. These models always maintain a safe distance between the follower and leader vehicle. In 1981 Gipps developed a general acceleration model which was based on car-following and free-flow situations. The model was designed with characteristics such as mimicking real traffic, model parameters are very close to apparent driver and vehicle characteristics. As per this model, the collision between the follower vehicle and the leader vehicle is completely avoided if the time gap between the two vehicles is equal to or more than 3T/2. This is also referred to as a safe headway. (14). This acceleration model developed by Gipps has two limitations: critical safe headway should be maintained and vehicle speed should not exceed the desired speed (4).

2.4.3 Wiedemann model

Wiedemann car following model is developed by Rainer Wiedemann in 1974[Wiedemann 74] and later updated to Wiedemann 99 in 1999 (19). This model considers the physical and psychological aspects of the driver.

The Wiedemann model works as follows: It considers four driving phases which start with the Free driving phase where the vehicle is driven at the desired speed without any restrictions imposed by surrounding vehicles. As the vehicle approaches a leading vehicle [current vehicle is now considered as the following vehicle], the distance between the two vehicles decreases. Here the driver is expected to observe and react entering the Reaction phase. The driver would see that his/her speed is faster than the leading vehicle. Next, the vehicle enters in perception threshold phase where the following vehicle driver will reduce the speed and will decelerate to maintain the minimum safe distance from the leading vehicle. If the leading vehicle is further slowing down, the following vehicle will decelerate further and reach a stationary stage to avoid the collision (4).



Car following model (according to: Wiedemann 1974)

Legend

Axes: **d**: Distance, **Δv**: Change in speed	**3**: Approaching state
1: "Free flow" state	**4**: Braking state
2: Following state	**5**: Collision state

Figure 2.2: Wiedemann car following model
(34)

2.4.4 The Intelligent Driver Model (IDM)

The Intelligent Driver Model is suitable for mixed traffic modes that include both CAVs and HDVs (4). The IDM is a deterministic time-continuous model that focuses on the dynamics of leader vehicle (40). Acceleration is defined as a function of the gap denoted by $S_\alpha(t)$, the speed denoted by $v_a(t)$, and the speed difference denoted by $\Delta v_a(t)$ between the leader and the following vehicle with the help of expressions (4):

$$\frac{d}{dt}\, v_\alpha(t) = \alpha(1 - (\frac{v_\alpha}{v_0})^\delta - (\frac{S^* v_\alpha \Delta v_\alpha}{S_\alpha})^2)$$

where δ is the acceleration component and the desired gap S^* can be derived as :

$$S^*(v_\alpha, \Delta v_\alpha) = S_o + S_1 * \sqrt{\frac{v_\alpha}{v_0}} + T * v_\alpha + \frac{v_\alpha \Delta v_\alpha}{2\sqrt{ab}}$$

in which a is the maximum acceleration, b is the maximum deceleration, T is the minimum time headway, and v0 is the free speed. Based on the above equations it is evident that the IDM models used tailored maximum acceleration along with minimum headway to achieve minimum safety distance between the leader and the following vehicle with the desired velocity. IDM is used as the based model for several other models such as Adaptive Cruise Control (ACC), and Cooperative Adaptive Cruise Control (CACC). Although this model is widely used for multi-lane simulations, it has the following limitations (5):

- The vehicle velocity can become negative which might impact the overall vehicle modeling
- The vehicle velocity can tend towards negative infinity There are many extensions to the IDM model such as Enhanced IDM (24), Foresighted Driver Model (10), Stochastic IDM (21) that overcome these limitations

2.4.5 Extended Intelligent Driver Model

As we consider real-life traffic situations where lane changes play an important role, the IDM model starts falling apart due to its limitations. Initially, IDM was developed as a car following model for single-lane traffic. As lane changes are introduced to the IDM model, the input parameters change in a non-continuous way which further results in a decrease in leader and follower vehicles below the equilibrium distance. The Enhanced IDM model is an extension of the IDM model along with the constant-acceleration heuristic (CAH). This improves the reaction to cut-in maneuvers maintaining the collision-free property of the IDM model. E-IDM introduces an upper threshold for safe acceleration based on the constant-acceleration heuristic (CAH). Here the driver assumes that the acceleration of the leader vehicle will not change for a few seconds. CAH is developed based on the following assumptions:

- Acceleration of leader and follower vehicle will not change in the next few seconds
- Zero reaction time
- No safe minimum distance is required at any time

The maximum acceleration is given by :

$$a_CAH(s, v, v_l, a_l) = \begin{cases} \frac{v^2 min(a_l,a)}{v_l^2 - 2s min(a_l,a)} & v_l(v - v_l) \leq -2s * min(a_l, a) \\ min(a_l, a) - \frac{(v-v_l)^2 - (v-v_l)}{2s} & \text{otherwise} \end{cases} \quad (1)$$

where s is the gap between leader and follower vehicle, v is the velocity of follower vehicle, v_l, and a_l are velocity and acceleration of leader vehicle respectively (24).

2.4.6 Lane changing model

As the name suggests, the Lane Changing Model handles the movement of a vehicle from one lane to another lane on a multi-lane highway network. The lane changing decision can be configured based on several factors such as speed gain after changing the lane, the critical gap between the leading vehicle of the new lane, minimum gap required for safe maneuvering. A lane-changing model well suited for urban driving was introduced by Gipps in 1986. This model covered the maneuvering of the vehicle with the impact of traffic signals, heavy vehicles, and road obstructions. The models Gipps models analyze the risk of vehicle-to-vehicle collisions, vehicle-to-obstacle collisions, and other logical driving patterns (4).

2.5 Simulation platforms for microscopic simulation

Many licensed and open-source traffic simulators have been developed over the years which provide a platform for real-world traffic simulation. These platforms also allow network configurations, vehicle and traffic dynamics configuration, and traffic monitoring as built-in features or with help of plug-ins. Some of the commonly used simulators are Aimsun: Advanced Interactive Microscopic Simulator, Simulation of Urban Mobility: SUMO, Verkehr In Städten – SIMulationsmodell: PTV VISSIM, Corridor Simulation: CORSIM.

The AIMSUN [1] (Advanced Interactive Microscopic Simulator) is a software company that provides licensed simulation platforms such as Aimsun Live, and Aimsun next. Aimsun deals with a large portfolio that involves services such as Mobility planning, Real-time transport management, and design and validation algorithms for CAVs. Aimsun was founded in 1997 in Barcelona, Spain, and was used to design some of the largest and most complex transportation models in cities such as Paris, London, New York, and Abu Dhabi. The tool uses the Gipps' safety distance models and is widely used for dynamic traffic assignment, incident management, and vehicle guidance systems (4). Aimsun supports the simulation of urban streets, freeways, interchanges, and roundabouts. It also supports 3-D animation. Aimsun provides software with a price based on the level of usage. The free version of some of the software is available with restricted usage and allowance limits.

The CORSIM is a licensed microscopic traffic simulation integrated platform developed by combining micro-simulation tools such as NETSIM (tool to simulate traffic patterns) and FRESIM (FREeway Simulation, tool to simulate freeway networks). This tool allows users to model surface roads, freeways, and integrated networks, including

[1] AIMSUN `https://www.aimsun.com/`

segments, frames, merges, detours, and intersections, traffic lights. It can also simulate traffic and traffic control systems using established driver and vehicle behavior models. The car-following logic used in this tool is designed in such a way that the lead vehicle moves to a new position with one time-step of the simulation time. The follower vehicle is then moved to a new location based on the leader vehicle's movement, such as if the lead vehicle decelerates at the maximum deceleration limit, the following vehicle will come to halt to avoid collision. FRESIM uses a stimulus-response model which is similar to the GM-type model (4). This ensures that the following vehicle always has a safe lead. [2]

VISSIM [3] is developed by PVT vision in 1992. With this software, users can modify the parameters of the factors controlling driving behavior such as lane-change, gap-acceptance, and car-following models. The benefits of VISSIM include:

- Support for Connected Autonomous Vehicles (CAVs)
- User can modify the vehicle behavior
- Built-in traffic capacity and safety evaluation measures
- Integration with external driving models

Due to these benefits, VISSIM is one of the most widely used platforms for micro-simulation. VISSIM also provides two Wiedemann car-following models for different application conditions, including the Wiedemann 74 and 99. The Wiedemann 74 model can be used for urban traffic and merging areas. (4)

SUMO (Simulation of Urban Mobility) is another free and open-source traffic simulation platform developed in 2001. This platform facilitates the modeling of multi-model traffic systems which can consist of different types of vehicles and public transport. It also supports the creation of complex road networks. SUMO comes with built-in tools which allow network creation using external network files, automate route creation and calculations, and traffic evaluations. It is also possible to extend the usability of SUMO with the help of APIs. Simulations can also be controlled using custom python scripts with the help of built-in libraries such as sumolib, Traci, etc. SUMO supports various car following and lane changing models. Customer models can also be configured using SUMO APIs.

[2] CORSIM, `https://mctrans-wordpress-prd-app.azurewebsites.net/tsis-corsim/`
[3] PTV VISSIM, `https://www.myptv.com/en/mobility-software/ptv-vissim`

3 Related work

This chapter describes the related work in the traffic management area and assesses the work based on requirements such as CAVs Market Penetration Rate, Complexity of highway network, Traffic Levels, and Type of study. The majority of the existing works, discuss how traffic flow management is achieved using methods such as Ad-hoc routing, Lane detections, etc but only a few of them have considered the need of increasing the proportion of CAVs in a single lane or areas to create autonomous vehicle zones. This would not only help utilize the CAVs' capabilities up to a large extent but also increase traffic efficiency as CAVs travel with lower headway. With the lower headway, a single lane can accommodate more CAVs and the CAVs can share information. The Sections below 3.1 and 3.2 explains the various techniques proposed to improve traffic efficiency.

3.1 Traffic Management Strategies

This section describes various strategies proposed to improve traffic efficiency without using lane management strategies. The description of these strategies is focused on the implementation and outcome of the strategies.

Peng et al., (32) propose a solution to improve traffic efficiency in in-signalized intersections using the vehicle to vehicle communication in CAVs and deep reinforcement learning. The approach considers a congestion situation caused by Human Driven Vehicles at the double-lane intersection. Here each lane consists of a fleet of one CAV and multiple HDVs. Each CAV leads the multiple HDVs in the respective lane. This approach assumes that the two CAVs can communicate with each other and share information about their location and speed. The behavior of CAVs is controlled by the Deep Reinforcement Learning model. CAVs coordinate with each other to avoid queuing at the intersection. To achieve this one CAV adjusts its velocity to maintain a time gap between itself and the other CAV to cross the intersection and avoid congestion. With their adaptive capability, CAVs control the flow of HDVs in the lane and maintain a steady flow to improve traffic efficiency. The solution is implemented on lanes with No CAV, 1 CAV, and 2 CAVs. The results show decreases in the number of waiting or stopped vehicles before the intersection with an increase in the number of CAVs in the lane. The application of this solution remains limited to an intersection and considers a non-general traffic situation. The study also does not consider the situations such as lane-changing, variable number of HDVs, and CAVs (32).

Subraveti et el., (29) propose multiple strategies to improve traffic flow at bottlenecks using lane assignment for CAVs. The approach focuses on reducing the unnecessary lane changes by both HDVs and CAVs. The strategies are based on the assumption that the destination of the traveling vehicle is known and accordingly CAV lane assignment is performed for existing and through vehicles. The strategies are proposed for bottleneck scenarios such as Diverges, Merges, and Weaves. For diverges, a setup with a single deceleration lane is considered. The lane change conflicts at the bottlenecks are proposed to be minimized by assigning left lanes to the furthest traveling vehicles and right lanes to the exiting vehicles. Overall, the roadway is divided into 3 zones, with zone 3 closest to the exit lane. Zone 1 and zone 2 are further upstream to the exit location. CAV lane assignment and accordingly the lane changes take place in zone 1. Based on the CAVs movement, HDVs adjust lanes in zone 2. In such a way zone 3 is established where minimum lane changes are expected. Similarly, strategies for weave sections with merge and diverge at a single exit location are proposed to minimize the lane changes in the auxiliary lane. Factors such as CAV penetration rate, Vehicle density, and exit rate are considered while assessing the feasibility of CAV lane assignment in any of the scenarios. For diverges, an increase in throughput was observed at a low CAV penetration rate and high exit flow. For weaves, a very minor improvement in throughput was observed for low merge and diverge flow. With an increase in CAV penetration rate, an increase in throughput was observed (29).

3.2 Lane Management Strategies

This section describes the techniques which are based on lane management strategies. Section 3.2.1 states the techniques that follow analytical or numerical based approach for the evaluation of stated scenario. Section 3.2.2 states the techniques that follow simulation based approach for the evaluation of stated scenario.

3.2.1 Analytical or Numerical based approaches

Ghiasi et el., (12) propose an analytical capacity model for highway mixed traffic based on Markov chain representation. This model is further used to build a lane management model to determine the required number of dedicated lanes for CAVs considering various traffic levels, CAV penetration rates, and CAV platooning intensities (12). The overall traffic pattern is characterized by the percentage of CAVs in mixed traffic and CAV platooning intensity. The simulation considers a setup with real-world stochasticity and driving uncertainties in a section of the highway without any inflow or outflow ramps. The highway section is divided into two parts: Managed lanes which are occupied only by CAVs and Non-managed lanes which are occupied by both HDVs and CAVs. The model allocated dedicated lanes for CAVs such that the total highway throughput is maximized. The numerical analysis considers five lanes and different CAV technologies such as aggressive, moderate, and conservative. These scenarios are simulated using relevant headways settings. The analysis shows that when the traffic is unsaturated, the lane management strategy is not required as the road capacity is sufficient to maintain the throughput. Similarly, when the CAV penetration rate of very less or very high, the lane management strategy does not show any improvement in highway efficiency, hence is not required. In a saturated traffic situation with CAV headways less than mixed traffic, CAVs shall be segregated in dedicated CAV lanes and the number of dedicated lanes should be increased to accommodate all CAVs in traffic. The experiments show that under certain CAV technologies and traffic demands, the lane management solution can increase highway efficiency. This model is based on the assumption that the traffic flow is stationary and may not work in case traffic is very dynamic. The author postulates that the number of dedicated lanes for CAVs can be revised based on real-time traffic observations (12).

Ghaiasi et et., (13) further enhances the above solution by considering the width of CAV lanes. The approach assumes that based on the CAV width, exclusive lanes for CAVs can accommodate more than designated CAVs in such a lane. Similar to that of the previous approach, this approach also takes varying mixed-traffic demand levels, CAV market penetration rates, platooning intensities (13) (12), and CAV technology scenarios into account. In mixed traffic mode along with HDVs and CAVs, this solution also considers human-driven heavy-duty vehicles. The experiments show improvement in traffic efficiency with a smaller width of dedicated lanes (13).

The study conducted by Xuedong et el., (22) investigates the impact of different dedicated lanes policies on mixed traffic modes for varying traffic demands and CAV penetration rates. The lanes are classified into three categories: CAV exclusive lane, MV exclusive lane, and General Lane. Strategies for two-lane and three-lane highways are proposed with the combination of the aforementioned three-lane categories. Based on these combinations, a total of four lane strategies were proposed for two-lane highways and twelve lane policies were proposed for three-lane highway. The results show that the road capacity increases with an increase in CAV exclusive lanes when the CAV penetration rate of more than 50 percent. For two-lane highways, when the CAV penetration is low, the assignment of an exclusive lane doesn't show any improvement in highway capacity. If the CAV penetration rate is between 30 to 70 percent, CAV and MV exclusive lane strategy shows the best results, whereas, for CAV penetration rates higher than 70 percent, General Lane and CAV exclusive lane policy show the best results. For three-lane highways, when the CAV penetration rate is more than 50 percent, two exclusive lanes for CAV and either one exclusive lane for MV or a general lane show improvement in highway capacity. The study also concludes that setting up exclusive lanes also reduces the probability of CAV reducing to AV with an increase in CAV penetration (22).

Lanhang Ye and Toshiyuki Yamamoto (47) analyzed the impact of dedicated lanes on traffic flow throughput. To compare the traffic throughput, the study considers a different number of CAV dedicated lanes with a three-lane highway model. Three dedicated lane policies with 0,1 and 2 dedicated CAV lanes are considered with two-lane changing policies. Lane changing policies include lane-changing between identical lane policies and lane-changing between different lane policies. Initially impact of CAV dedicated lane is studied with a CAV penetration rate of 60 percent, vehicle density of 60 veh/km/lane constant desired net time gap of CAV with respect to the preceding vehicle. The results show that the flow rate is similar for all the lanes with no dedicated lane in place. With CAV dedicated lane, the flow rate increases in the dedicated lane but a decrease in flow rate is also observed in other lanes. To further analyze this result, simulations with a different time gap between CAV and preceding vehicle and CAV penetration rates were performed. The results show that with an increase in vehicle density for any penetration rate, the effect of a dedicated lane becomes prominent. As the penetration rate reaches 50 percent the negative effect of setting up one dedicated lane vanishes. Increasing the penetrations rate further up to 80 percent shows the merits of setting up two dedicated lanes. The performance of dedicated lanes also varies with CAV penetration rates (47).

3.2.2 Simulation based approaches

Vranken and Schreckenberg (42) proposed a multi-lane model to improve traffic efficiency and highway capacity for the heterogeneous model by introducing different lane-changing rules for HDVs and CAVs. This allowed HDVs to behave aggressively as compared to CAV to create and simulate complex HDV and CAV interactions. For human-driven vehicles, the lane changing agent was configured to first check if the change in the lane would increase the speed of the vehicle. Once this is analyzed, the agent will check if the change lane is feasible and safe. It also checks if the distance between the following and the leading vehicle in the new lane is sufficient enough to avoid any collision. Along with these two new rules were introduced where lane change was allowed to take place once a second to reproduce realistic lane changes. If the lane change was successful, the agent was not allowed to move back to the previous lane for the next 5 seconds to avoid unnecessary back-and-forth lane changes. HDVs would not change in the lane for small improvements in the situation due to the defined rules, CAVs agents on the other hand are configured to switch to other lanes even for marginal improvements. The CAV agent also makes sure that lane change is performed in such a way that the preceding vehicle in the new lane does not need to deaccelerate. With all the mentioned rules, different simulations for traffic scenarios such as only HDVs, only CAVs, and both HDVs and CAVs were simulated. Traffic containing CAVs shows that there is no need for lane changes as CAVs for a coordinated network and traffic in both lanes work in a synchronized fashion. Heterogeneous traffic simulation observes an increase in traffic efficiency and road capacity for more than one lane traffic. CAV lane changes help create large platoons through lane changing which further reduces the vehicle following time. Based on the observations, the author also concludes that the traffic state in heterogeneous traffic depends on and can be dominated by the distribution of CAVs VRANKEN2022126629.

Xiao et el., (44) proposed a lane management model based on a Differentiated Per-Lane Speed Limit Policy on a two-way eight-lane highway. The model consists of passenger cars and heavy vehicles. For these vehicle types, both CACC-equipped and Non-CACC-equipped versions are considered to establish mixed mode traffic. The study focuses on the DPLSL policy where the maximum and minimum speed limits in each lane can be different. This helps in creating more complex highway traffic scenarios as the different speed limits can influence the lane-changing pattern. The study proposes 4 lane model where the inner lanes are dedicated to CACC vehicles. The distribution of the vehicles is done in such a way that the proportion of different vehicles on lanes with the same road management measure is identical. Simulations are performed to validate the traffic throughput for 3 different scenarios:

- Varying market penetrations rates of CACC cars from 0 percent to 100 percent with step size of 20 percent and keeping the heavy vehicle penetration constant at 10 percent
- Varying market penetration rates of both CACC cars [60 and 80 percent] and Heavy vehicles [0,5,10 percent]

For the first scenario, the results show that the traffic throughput for inner lanes [CACC dedicated lanes] is larger than that of outer lanes for every CACC penetration rate. An increase in throughput with an increase in CACC penetration rate is also observed for all four lanes. Although the increase in throughput was marginal when the CACC penetration rate is below 40 percent. As the CACC market penetration rate increases beyond 60 percent, the results of the CACC dedicated lane can be observed very prominently. For the second scenario, the CACC penetration rate is fixed at 60 and 80 percent as in the first scenario it was observed that the CACC dedicated lane impact was prominent at these penetration rates. The results show that the throughput of each lane reduces with an increase in heavy vehicle penetration rate. Overall higher reduction is observed in outer lanes where heavy vehicles are allowed as compared to inner lanes or CACC dedicated lanes. .

Zijja Zhong et. al (49), investigates the impact of different dedicated lane strategies on traffic flow at lane and vehicle level, Headway distribution, communication density, communication success rate, and fuel consumption by the CAVs. This study uses Wiedemann car-following model and the enhanced intelligent driver model (E-IDM) for HDVs and CAVs simulation respectively. The simulations are performed on a 9.3 km 4-lane hypothetical highway with two interchanges using Vissim. The author proposed three managed lane strategies:

- No Managed Lane: Here there is no dedicated CAV lane allocated. HDVs and CAVs simulated in mixed traffic
- One CAV lane: Left most lane of the highway is allocated to CAVs
- Two CAV lanes: leftmost and second left most lanes are allocated to CAVs

Experiments are conducted for one CAV lane strategy where the CAV penetration rate varied from 30%-100%, whereas the penetration rate varied from 40%-100% for two CAV lanes. The network also considers two interchanges with different entry and exit flows. The results show improvements in roadway capacity due to the introduction of CAV dedicated lanes. A CAV lane, with an MPR as low as 40%, can accommodate more traffic compared to a GP lane. The analysis of related work described in this section is summarized in the Table 3.1 with parameters such as Vehicle Type, Study Type, Traffic Level, CAV MPR and Network considered for the work.

Reference	Vehicle Type	Study Type	Traffic Level	MPR	Scenario
Bile Peng (32)	HDV CAV	Simulation	NA	NA	Unsignalized intersection
Tim Vranken (42)	HDV AV CAV	Simulation	Free flow	0-100% with step 10%	10 km highway section
Amir Ghiasi (12)	HDV CAV	Analytical	Free flow Moderate Saturated Over Saturated	NA	Highway without inflow, outflow ramps
Amir Ghiasi (13)	HDV CAV HV	Analytical	Free flow Moderate Saturated Over Saturated	NA	Highway without inflow, outflow ramps and variable lane width
Subraveti (29)	HDV CAV	Analytical	Moderate Saturated with low and high exit rate	0-100% with step 10%	3 lane highway Diverge Weave
Xuedong Hua (22)	HDV CAV	Analytical	Free flow	0-100% with step 20%	2,3 lane highway
Zhe Xiao (44)	CACC Non CACC Passanger HV	Simulation	Moderate	CACC [0%-100% with step 20%] HDV [0%-10% with step 5%]	Four lane highway with DPSL
Lanhang Ye (47)	HDV CAV	Analytical	Free flow Moderate Saturated	10%-90% with 10% step	3 lane highway
Zijia Zhong (49)	HDV CAV	Simulation	Freeflow	1 dedicated lane 30% - 100% 2 dedicated lanes: 40% - 100%	9.3 km highway with two interchanges

Table 3.1: Summary of related work for traffic and lane management strategies

3.3 Research Question

Based on the comparison in Table 3.1, it is evident that the majority of the approaches suggested for dedicated lane methodology are based on an analytical or mathematical simulation. These analytical models are based on macroscopic traffic flow models and may experience difficulty in faithfully capturing the complex phenomena in transportation networks and CAV behavior. Existing work which is based on vehicular simulation has been performed for hypothetical scenarios or highway setups. This also fails to capture the various complex structures in highway networks.

Traffic flow is one of the major factors contributing to the overall highway and traffic efficiency. Over the years the impact of the dedicated lane is studied by varying the traffic flow from free flow to over-saturated situations. Although in real life we do not expect the traffic flow to be constant and pre-deterministic. Hence this work focuses on analyzing whether traffic efficiency can be improved using dedicated lanes in realistic conditions:

- Realistic highway network
- Realistic and dynamic traffic flow with freeflow, saturated and congested traffic scenarios
- CAV penetration rate 0-100% range
- Different number of dedicated lanes
- Position of dedicated lane

In addition, this work investigates whether a rule-based and learning-based approach could improve traffic efficiency by dynamically deploying and removing the dedicated lane(s) based on the traffic level and CAV MPR.

4 Methodology

This chapter focuses on the methodology used to investigate the research question stated in the above Section 3.3. Simulation of mixed traffic composed of both CAV and HDV along with the dedicated lane setup would involve network configuration, vehicular simulation, and traffic simulation. All these three aspects are equally important to conduct the experiments successfully. Vehicular simulation heavily depends on vehicle modeling which involves various factors such as car following model, lane changing model, vehicle dimensions, maximum speed, etc. To conduct the experiments, a simulator is needed which can accommodate all of the aforementioned configurations. Section 4.1 explains the experiment design for this work in detail. Section 4.2 states the selection criteria for simulator selection. Section 4.3 explains the experiment setup in detail which includes simulator architecture, network modeling, vehicle and traffic demand modeling, and evaluation techniques used in this work.

4.1 Experiment Design

As stated in the research question in Section 3.3, focus of this work is to evaluate the effectiveness of dedicated lanes to improve highway efficiency on realistic road networks. Two different road networks were used for this work. An 8.5km one-way highway without inflow-outflow ramps was created as a dummy network to validate the observations from existing dedicated lane work. The M50 motorway network created by Gueriau and Dusparic (17) was further used as a real-time highway network as stated in the research question in Section 3.3. The traffic data used is generated from real data by averaging several months of data to generate workday traffic load. The traffic data for the M50 motorway was generated using the data from induction loop sensors data from the open dataset provided by the Transport Infrastructure Ireland [1]. The data consists of traffic flow per lane and direction for 346,278 vehicles aggregated every 5 minutes up to the year 2019. As per the existing work described in Section 3.2, highway efficiency depends on factors such as the number of dedicated lanes, CAV penetration rate, and speed limit policies. The experiments in this study are designed to cover all the possible combinations of several aspects mentioned in the research question. At a high level, the scenarios can be divided into four categories:

- No dedicated lane or Baseline
- One dedicated lane
- Two dedicated lanes

[1] https://www.nratrafficdata.ie/

- Three dedicated lanes

The first scenario, No dedicated lane, also referred to as the Baseline scenario is considered to ensure that the dedicated lane-related experiments in this work are easily comparable to the original work. The number of dedicated lanes is varied from one to three as the M50 motorway is a 4-lane highway. To analyze the impact of the dedicated lane on the variety of mixed traffic compositions, the CAV penetration rate varied from 0% to 100%. This enables us to understand the effect of dedicated lanes with pure HDV, pure CAV, and mixed traffic modes. Table 4.1 states the HDV and CAV distribution for the aforementioned scenarios. Each of these scenarios is executed for several configurations to validate the best-suited configuration for dedicated deployment. The Table 4.2 summarizes these configurations. The significance of each of the configurations is explained further in Section 4.3. Thus a total of 170 scenarios were simulated for both validation and real highway network. Figure 4.1 shows the high-level experiment execution workflow. Based on the analysis of these experiments using the evaluation metrics explained in Section 4.3.7, a rule-based adaptive approach is suggested and implemented. The rule-based approach will adapt the deployment or removal of dedicated lanes based on the traffic situation and CAV MPR. The experiments are executed for three different traffic scenarios for three-time windows: Free-flow [1PM-2PM], Saturated [3PM-4PM] and Congested [7AM-8AM]. The code for this study can be found here.

Lane Strategies	Scenario	HDV	CAV
• No Dedicated Lane • One Dedicated Lane • Two Dedicated Lanes • Three Dedicated Lanes	I	100%	0%
	II	90%	10%
	III	70%	30%
	IV	50%	50%
	V	30%	70%
	VI	10%	90%
	VII	0%	100%

Table 4.1: Simulation scenarios with CAV and HDV deployment

Configuration	**Dedicated lane position**	**HDV-CAV speed policy**	**Traffic Scenario**
I	Left	Constant	Free-flow, Saturated, Congested
II	Right	Constant	Free-flow, Saturated, Congested

Table 4.2: The M50 motorway Configurations based on dedicated lane position, speed policies, and traffic scenarios

4.2 Simulation Platforms

The simulation platforms considered for this work have been mentioned and briefly described in section . These platforms were reviewed and evaluated based on the following requirement criteria:

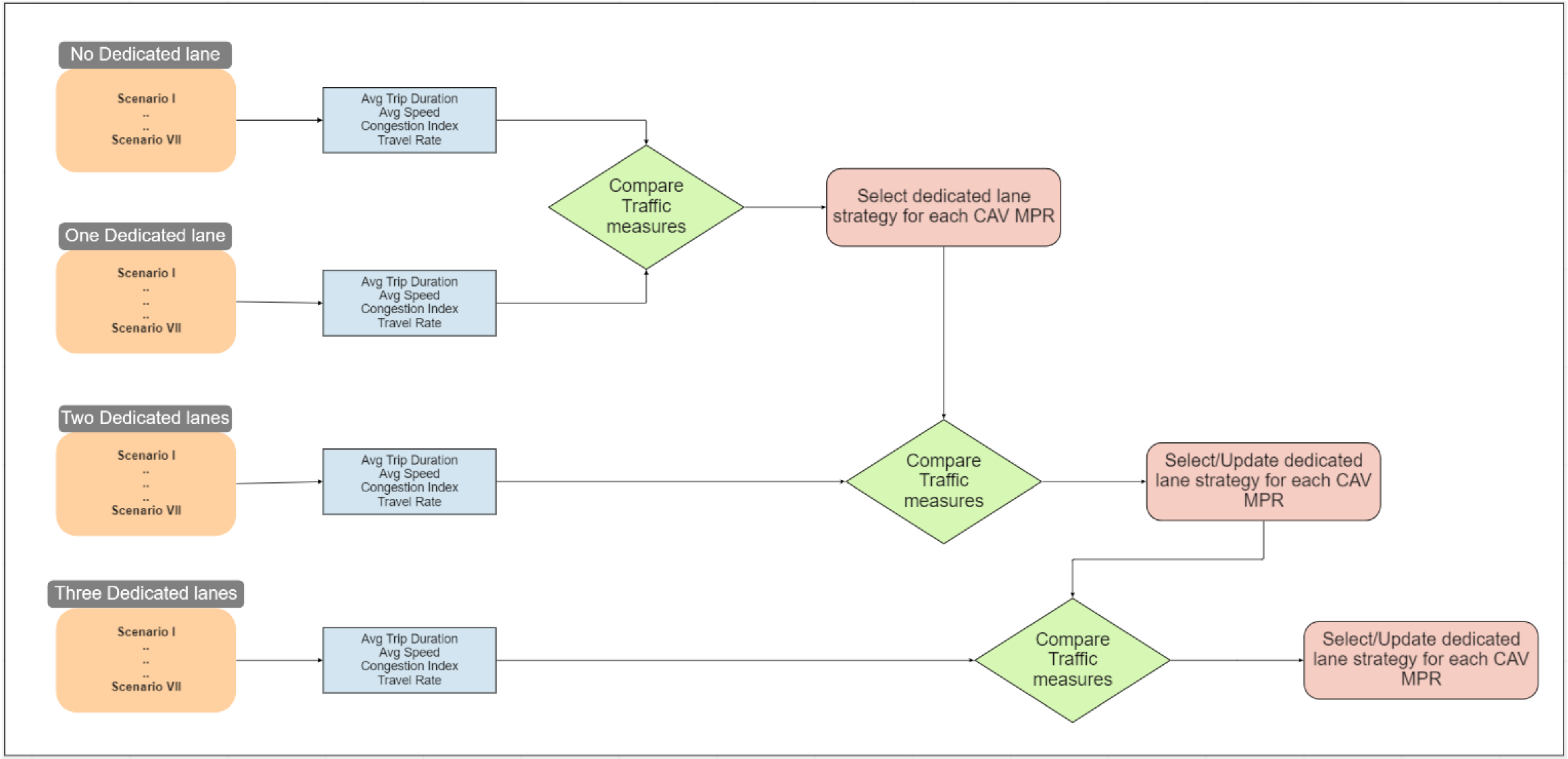


Figure 4.1: High level design for simulation experiment execution workflow

- Open source: The platform must be open source and the source code should be publicly available for any kind of modifications required
- Software License: All the essential features of the platform should be at no charge
- Reliability and Robustness: The platform should perform required functions stably and should work under stressful environmental conditions
- Ongoing: The platform must be well maintained and under active development
- Suitability: The platform should have built-in or external components to satisfy the requirements mentioned in the research question in the section
- Extensibility: The platform should support integration with other tools for additional features.

Based on the above criteria, the SUMO simulator is selected for this work. SUMO provides the below components which are used during the experiment design:

- NetConvert: Command application to import road networks from various sources and create SUMO-compatible road networks. It supports input files from sources such as OpenStreetMap, VISUM, Vissim, OpenDRIVE, MATsim, and Plain XML. It also generated road networks by combining multiple network files. This tool also handles the network components such as junctions, connections, ramps, etc.
- NETEDIT [2]: Graphical User Interface network editor to create networks from the start and modify existing road networks. It is also a powerful editor which can be used to debug the network with the select and highlight features. Users can also create additional road infrastructure elements such as Induction Loop Detectors, Lane Area Detectors, Multi-Entry Multi-Exit Detectors, Parking stops, and Re-routers, NETEDIT also allows specific lane and edge level configurations. Along with the networks, it is also a useful tool to define and generate traffic demands and relevant elements such as routes, vehicle types, etc.
- dfrouter: dfrouter is one of the SUMO tools to generate traffic demand and routes based on real-time data. The dfrouter uses edge-based data from induction loops to generate the routes and traffic demand.
- TraCI [3]: The Traffic Control Interface is an online interactive tool provided by SUMO. It allows users to gain access to the in-progress simulations, retrieves values and observations from the simulation objects, and modifies network and traffic elements. TraCI can be used with different programming languages such as Python, C++, .NET, and Java which allows the user the flexibility to choose a language of his or her comfort.

4.3 Experiment Setup

This section states the experimental setup and its various components in detail. Section 4.3.1 details the overall architecture of SUMO and its components used for this work. Section 4.3.2 , 4.3.3 and 4.3.4 details the network, vehicle level design and traffic

[2]NETEDIT,https://sumo.dlr.de/docs/Netedit/index.html

[3]TraCI,https://sumo.dlr.de/docs/TraCI.html

demand modelling required for in this work. Section 4.3.7 states the evaluation metrics used to analyze the traffic performance across various experiments.

4.3.1 Architecture

SUMO Simulator Architecture for microscopic simulation

(33)

- Graphical User Interface: Component that consists of various classes that encompass the entire graphical user interface model that controls the micro-simulation parameters and their deployment (33)
- MSNet: The orchestrator that handles the simulation with provided highway network and stores all the micro-simulation entities (33)
- MSVehicleControl: The class that deals with build, insert, and deletion of vehicles during the simulation. It contains the vehicle type [vtype] and vehicle statistics data until a vehicle is removed. (33)
- MSEdgeControl: This class is responsible for storing edge data, lane data for respective lanes and lane movements of the vehicles. This class also stores the active lanes which have at least one vehicle on the network during the simulation (33).
- MSEdge: Edge is a road connecting two junctions. This class stores lanes belonging to the respective edge. The class contains methods that handle functions such as retrieving current travel time for an edge, retrieving mean speed for an edge, retrieving and set speed limit for an edge, etc (33).
- MSLane: This class acts as a representation for a single lane storing all the required information and performing some of the critical functions such as maximum lane speed, allowed/disallowed vehicles on the lane, shape/ width/length of the lane, allow/disallow left/right lane changes, etc (33).
- MSLaneChange: This class deals with lane changes of the vehicles.
- MSSubLaneChange: This class inherits the MSLaneChange class and handles the lane changes at the sub-lane level. SL2015 is a sub-lane level lane change model supported by SUMO.
- MSVehicle: This class acts as a representation of a vehicle in the micro-simulation. It allows users to define several vehicle configurations such as vehicle type, speed, color, length, acceleration, vehicle devices, etc. This class is very useful when simulation contains vehicles belonging to different categories and needs to be distinguished accordingly (33).
- MSVehicleType: This class stores the details about the type of the vehicle. Vehicle types in SUMO can be custom defined and can have any of the SUMO-supported vehicle classes. SUMO has several built-in vehicle classes such as passenger, private, taxi, evehicle, bus, coach, delivery, truck, trailer, emergency, motorcycle, rail, tram, etc. Users can generate vehicles with similar vehicle types but different vehicle performance configurations. Similarly, different types of vehicles can also

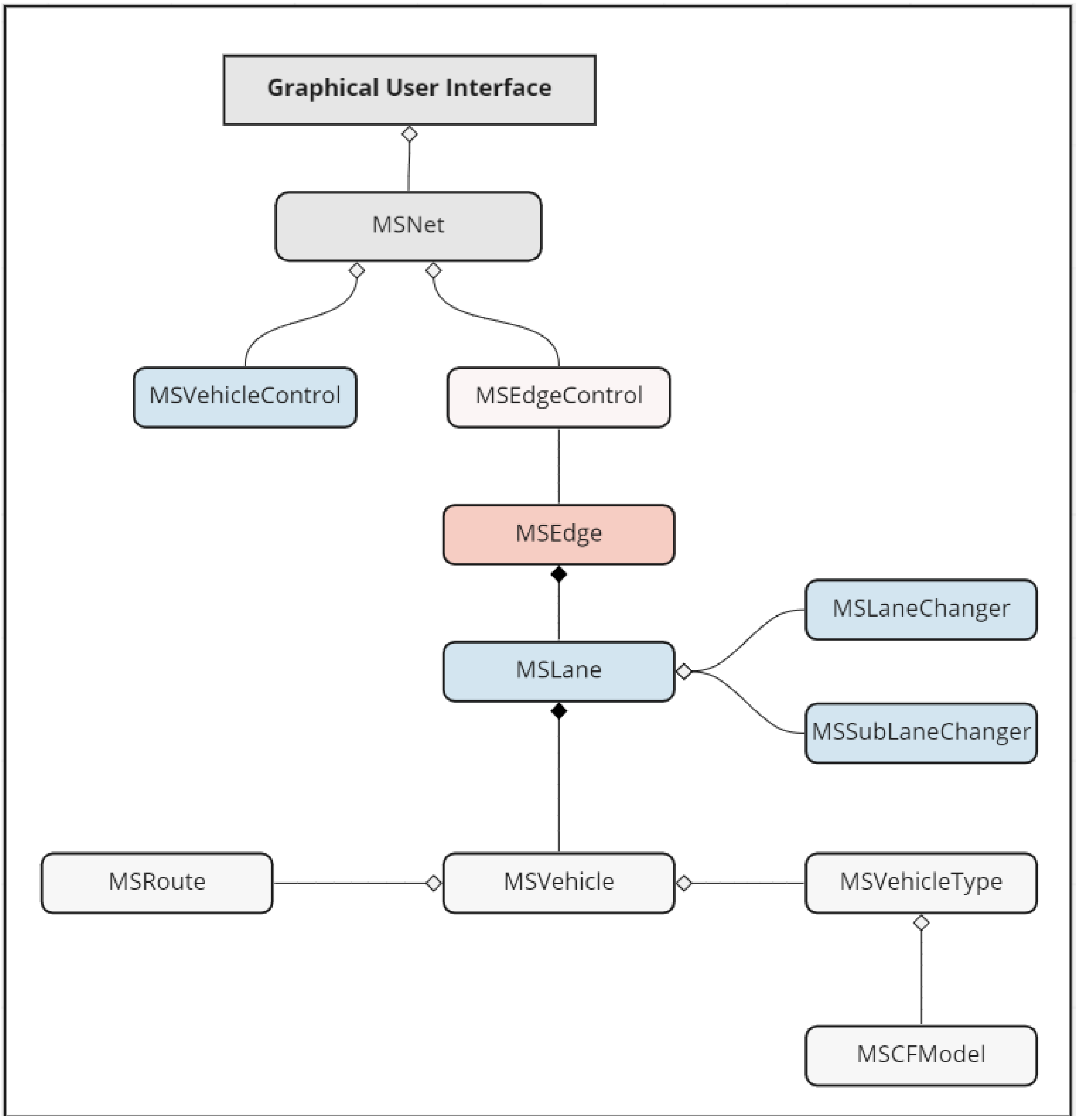


Figure 4.2: Overview of SUMO microscopic simulation module components (33)

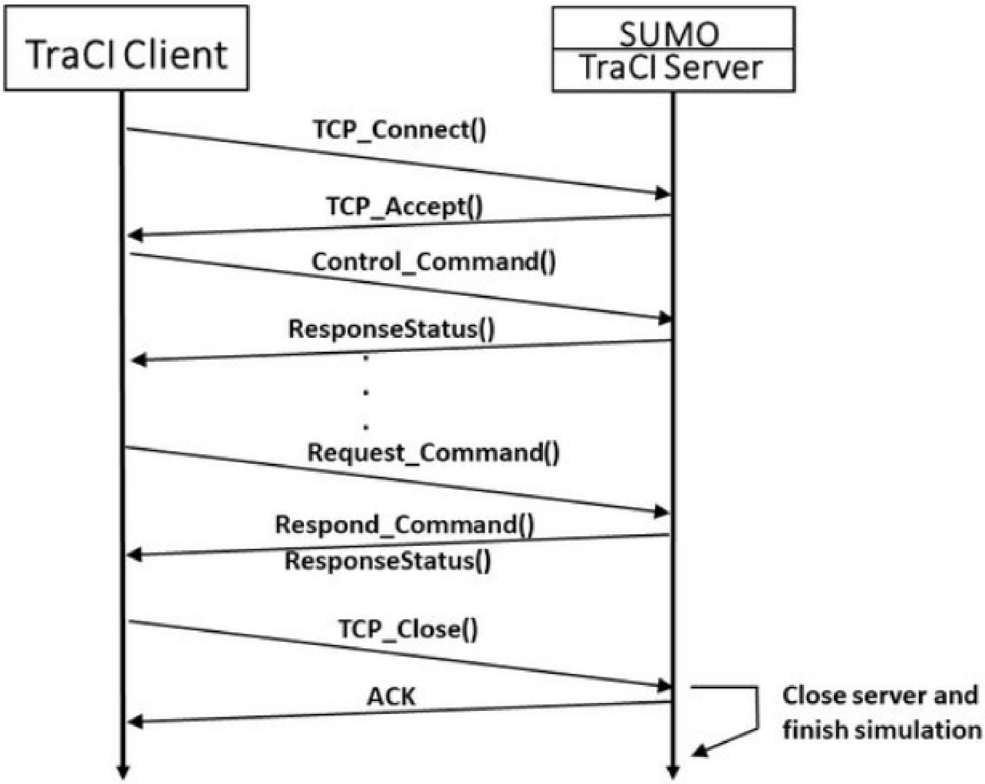


Figure 4.3: Communication between SUMO and TraCI client
(31)

be created. This class also stores the functions that use the vehicle type parameters for generating the car following actions. The emission class of the vehicle can also be defined at the vehicle type level.

- MSCFModel: This is an interface for several state-of-the-art car following models supported by SUMO. Some of the car following models supported by SUMO are ACC, CACC, Krauss, Intelligent Driving Model (IDM), Enhanced Intelligent Driving Model (EIDM), W99, Wiedermann, etc.

SUMO-TraCI communication

Figure 4.3 shows the communication protocol between SUMO and a TraCI client. The TCP protocol is used by TraCI client to communicate with the simulation during runtime. This interface is used to implement an adaptive or rule-based dedicated lane deployment approach [explained in Section 4.1]. As shown in the image, once the initial handshake is established, TraCI can start sending requests to the SUMO simulation. The Traci commands can be of two types:

- Control command: Command to modify the vehicle behavior such as change vehicle speed, forced lane change, vehicle insertion/deletion, or modify the highway network such as block a lane, change allowed vehicle classes for a lane.
- Request command: Command to retrieve values from the simulation such as get mean travel time, number of vehicles inserted, number of vehicles completed, etc.

Below are versions of the software/tools used:

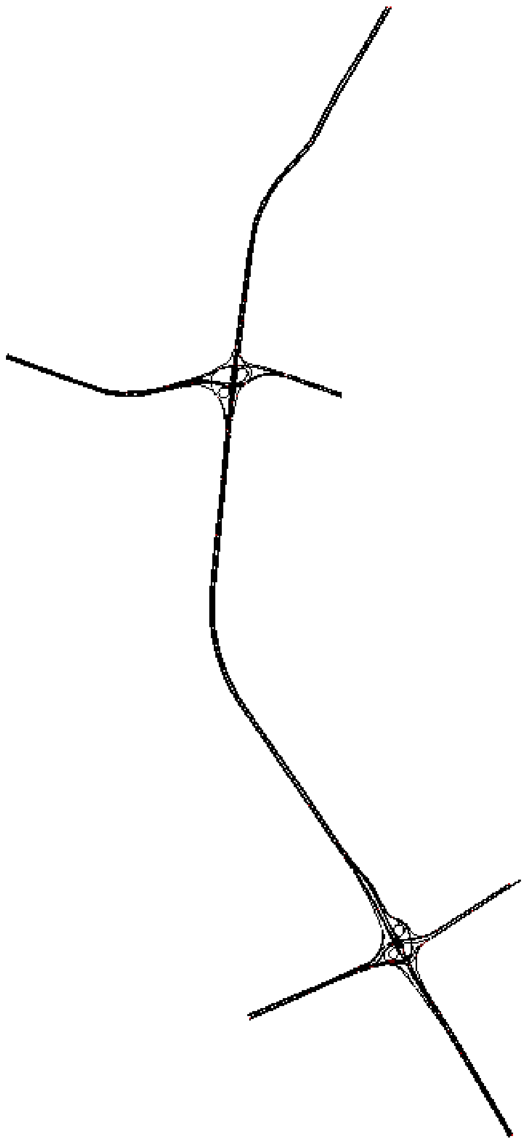


Figure 4.4: The M50 motorway

- SUMO: 1.13.0
- TraCI: 1.14.1
- Python: 3.9

4.3.2 Network modelling

As stated in Section 4.1, two different road networks were used for this work and different strategies for the deployment of dedicated lanes were adopted. Figure 4.4 shows the M50 motorway which is a 7km 4-lane highway with two interchanges. The dummy 8.5km highway consists of 29 edges with each edge having 4 lanes and was created using NETEDIT editor manually. This section explains in detail the how dedicated lane is configured, and the factors considered during the dedicated lane configuration.

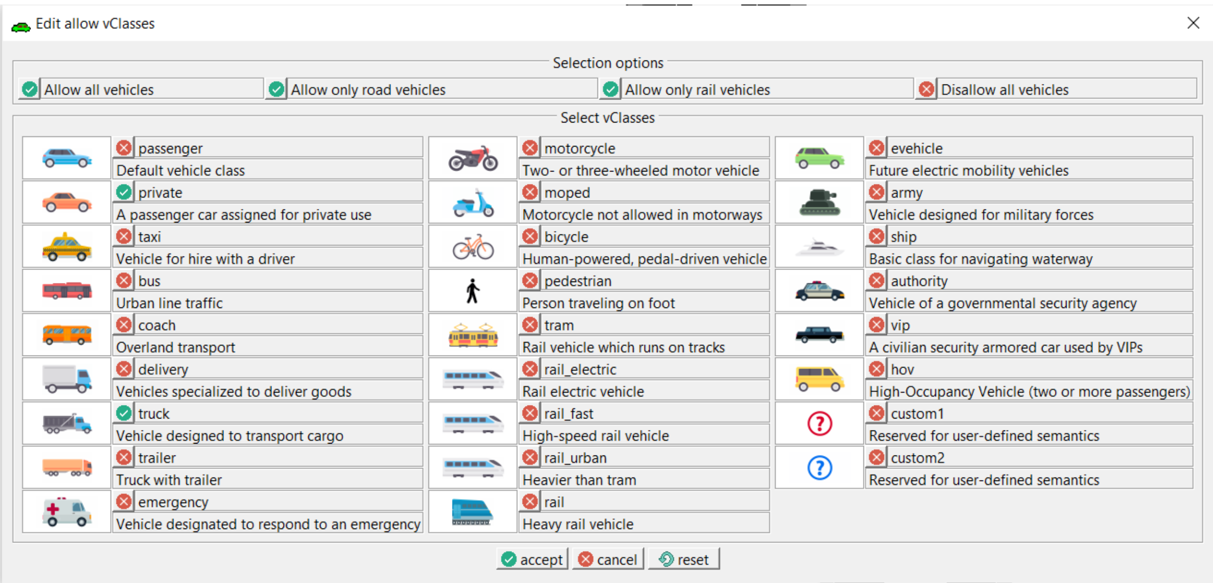


Figure 4.5: Selection of allowed vehicle classes for dedicated lane

Dedicated lane deployment

The dedicated lane is the reserved lane that can only be used by CAVs. However, these may not be the only lanes CAVs can use. CAVs can travel using other lanes which are also called shared lanes. These lanes are used by both CAVs and HDVs. In SUMO, the dedicated lane is configured using NETEDIT by allowing or restricting the vehicle classes for any existing lane. This can be achieved by using the network mode and allowing or disallowing options from the left panel. It can also be defined using the setAllowed() or setDisallowed() method of MSLane class states in Section 4.3.1. This restricts the usage of that lane by the allowed vehicle class. The figure 4.5 shows the selection of a certain class of vehicles to be allowed on a lane. CAV and HDV modeling is discussed in detail in Section 4.3.3. Figure 4.6 shows that the left-most lane is converted to a dedicated lane and only CAVs [Green colored vehicles] are traveling via this lane.

Position of dedicated lane

When the highway network under consideration has more than two lanes, which lanes should be converted into the dedicated lane is subject to debate. Some of the existing work suggests that (9) if the traffic is following Right Hand Side or driving to the right mode the dedicated lane should be the left-most lane of the network. Hence the left-most lane results in the fastest lane. However, for a real highway network, the position of the dedicated lane depends on the overall highway network under the consideration. This can be illustrated with the comparison between the validation and actual roadway network considered for this work. The 8.5km validation network has 4 lanes throughout and allows one-directional travel. It is evident that the structure of this network is simple and has a consistent pattern. Whereas the M50 motorway has a complex structure and does not a have consistent pattern. Referring to the figure 4.4, the M50 motorway allows bi-directional traffic. It has two major interchanges with inflow and outflow traffic. At some instances, the motorway has more than 4 lanes with additional ramps whereas at the interchanges and roundabouts the number of lanes varies. Deploying a dedicated lane on the validation network is fairly simple and

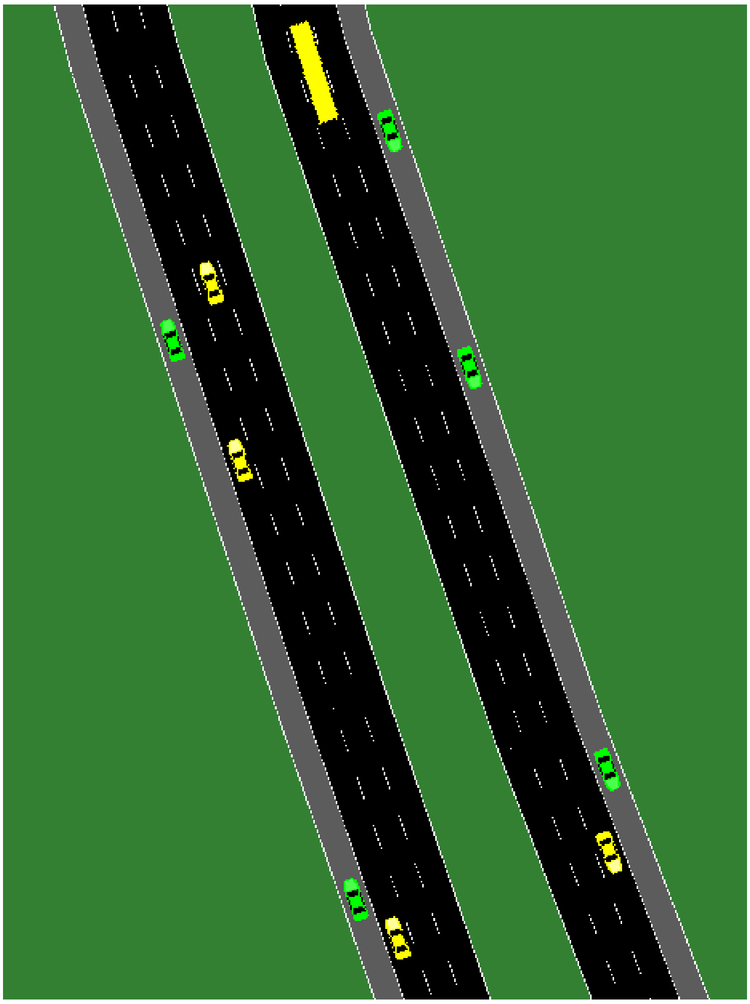


Figure 4.6: Deployment of one dedicated lane

does not involve microscopic analysis of the network. Hence, the assignment of the dedicated lane on this network was done from the left-most lane. In one dedicated lane scenario, the left-most lane is configured as a dedicated lane for CAVs. In two dedicated lane scenarios, the second left-most lane is configured as a dedicated lane. On the other hand, the M50 network possesses challenges to follow this approach. It can be seen that on the northbound side of the highway the outward movement of the vehicles at the interchanges originates from the left-most lane. Also, the inflow at the interchanges merges into the left-most lane. A similar structure is observed on the southbound side of the highway network. Hence the configuration of the dedicated lane from the left side lanes might result in congestion at the interchanges if the majority of CAVs traveling through these lanes need to travel straight. This would result in heavy lane changes just before the interchanges and will result in a decrease in mean speed, increase in mean trip duration, and total travel time. Hence the experiments are designed with the deployment of the dedicated lane from both left and right most lanes. This would help understand the impact of the position of the dedicated lane on the highway.

Location of dedicated lane

Along with the position of the dedicated lane, the location of the dedicated lane also plays a critical role in improving traffic efficiency. Location in this context is referred to the part of the highway where dedicated lanes are deployed. In terms of SUMO, it can be referred to as the edge ids and respective lane ids which are configured as dedicated lanes for CAVs. Similar to that of the previous position, the significance of the location of the dedicated lane can also be easily explained using validation and a real highway network. The structure of the validation network allows configuring the dedicated lane from the start of the highway to the end of the highway. Hence the placement of dedicated lanes is not affected by the complexity of the highway network. On contrary, it is difficult to configure the varying number of dedicated lanes from start to end on the M50 highway due to the interchanges and additional network elements such as inflow, and outflow ramps. Hence the start and end of the dedicated lane had to be analyzed. To achieve realistic outcomes, the dedicated lane was started at a certain distance from the start of the network so that the CAVs are not directly placed on the dedicated lane. Various aspects considered during the configuration of the dedicated lane can be illustrated below scenarios:

- Scenario I - Deadlock at the start of the dedicated lane: During the simulation, vehicles are inserted randomly into any lane. This could result in HDVs traveling through prospective dedicated lanes. Hence it is required to shift such HDVs towards shared lanes to avoid deadlock situations at the start of the dedicated lane. A deadlock situation occurs as the dedicated lane is strictly allowed for CAVs, hence HDVs will perform emergency breaks and will come to halt. The start of the dedicated lane is configured in such a way that the simulator has enough time for all the necessary lane changes required to move HDVs toward the shared lane.

- Scenario II - Deadlock at the end of dedicated lane: The start and end of the dedicated lane also depend on the inflow and outflow at the interchanges. It is required to end the dedicated lane to allow the required lane changes for both

HDVs and CAVs to continue travel using the vehicle routes.

- Scenario III - Deadlock at interchanges [inflow]: At the interchanges, the traffic inflow merges into the main network. Here if the left-most lane is set up as a dedicated lane at the start of the conjunction, then it will create a deadlock situation. If the vehicle traveling on the inflow link is an HDV then it will be forced to perform an emergency stop which will result in congestion. Hence the starting of the dedicated lane at such instance should be configured to allow successful merging and required lane changes.

The start and end of the dedicated for an edge are strategically placed to allow the simulator sufficient time to perform all the required lane changes.

4.3.3 CAV-HDV modelling

The mixed traffic mode consists of both Connected Autonomous Vehicles (CAVs) and Human Driven Vehicles (HDVs). For these types, Light Motor Vehicles (passenger cars) and Heavy Motor vehicles (truck, bus) were considered to simulate realistic traffic components. SUMO allows users to define vehicles with custom types. Once a vehicle type is defined multiple vehicles belonging to that type can be created. This vehicle includes both physical and behavioral parameters of a vehicle. The physical parameters include length, color, speed, etc. The behavioral parameters include car following model, lane changing model, speed factor, acceleration, deceleration, etc. The vehicle type is defined using one of the existing vehicle classes mentioned in Section 4.3.1. For this work, four different types of vehicles is created using four different vehicle classes. As shown in figure 4.5, the dedicated lane is configured based on vehicle class. Hence to distinguish CAVs and HDVs different classes are used for modeling purposes. Table 4.3 shows the CAV and HDV configuration and parameters considered.

The SUMO documentation provides the explanation for the car following and lane change model parameters. [4] [5]. These parameters are explained briefly in context of this work in consequent sub-sections.

Car Following Model Parameters

- tau is the minimum time headway desired by the driver. Since CAVs can travel with minimum headway, the value is less compared to that of HDVs.
- Sigma is the driver's imperfection factor. Higher the value, the more imperfect the driving. Since CAVs are expected to have lower imperfection as compared to the HDVs, the value is set to 0.05. 0 denoted perfect driving.
- Speed Deviation is the factor that defines the deviation in the vehicle per-lane speed limits
- Minimum gap defines the desired gap (empty distance) between a leader and the following vehicle

[4]Car Following Models, `https://sumo.dlr.de/docs/Definition_of_Vehicles%2C_Vehicle_Types%2C_and_Routes.html#car-following_models`

[5]Lane Changing Models,`https://sumo.dlr.de/docs/Definition_of_Vehicles%2C_Vehicle_Types%2C_and_Routes.html#lane-changing_models`

Parameters	Vehicle Category			
	HDV	HDV	CAV	CAV
Type	Passenger	Long	Passenger	Long
Vehicle Class	Passenger	Bus	Private	Truck
Car Following Model	Krauss	Krauss	EIDM	EIDM
Tau	1.2	1.2	0.5	0.5
Sigma	0.5	0.5	0.05	0.05
Speed Dev.	0.1	0.1	0.05	0.05
Min. Gap	2.5	2.5	1	1
Lane Change Model	LC2013	LC2013	LC2013	LC2013
lcStrategic	0.5	0.5	0.5	0.5
lcSpeedGain	1	1	10	10
lcCooperative	1	1	0	0

Table 4.3: CAV and HDV modelling parameters

Lane Change Model Parameters

- lcStrategic is the factor that defines the eagerness of the following vehicle for performing strategic lane changes.
- lcSpeedGain is the factor that defines the willingness of a vehicle to change lanes for speed gain. Value for this parameter is higher in CAVs as compared to that of HDVs.
- lcCooperative is the factor that defines the eagerness of a vehicle to perform cooperative lane changes. A value set to 0 means that lane changing is performed if the target lane provides a higher speed. Lane change model parameters were changed to make CAVs travel through the dedicated lane as it is the fastest lane in the network.

4.3.4 Traffic Demand modelling

The aggregated traffic data used in the original work was converted into SUMO-compatible traffic demand using dfrouter tool provided by SUMO. This same traffic data was used for both validation and the M50 motorway networks. The dfrouter take the network file, detector file (location and type of induction loop detectors), and traffic flow measure files as input. The same traffic flow measure file used for the original work was used for this work. The parameters which control the insertion of vehicles during the simulation were also defined at this stage. Below are these parameters:

- departLane: Vehicle departure lane on which the vehicle should enter the network during the simulation

- departPos: Position at which the vehicle should enter the network
- departSpeed: Vehicle speed when the vehicle is entering the network
- arrivalPos: Position at which the vehicle should leave the network

dfrouter generates feasible routes based on the input network file and vehicle data. As mentioned in Section 4.1, the CAV MPR is varied from 0% to 100%. Here the same vehicle file generated by the dfrouter is used for different scenarios and the CAV MPR is handled by the probability parameter while defining the vehicle type. The probability of 0.3 for CAVs and 0.7 for HDVs means that 30% of vehicles inserted during the simulation will be CAVs and 70% HDVs.

Before using dfrouter, several methods were used to generate traffic demand. However, none of these methods could fulfill the required realistic and dynamic traffic flow. One of the methods used was randomTrips.py. RandomTrips generates a number of random trips based on the input network files. While generating the routes and trips, it considers the source and destination edge information uniformly at random or based on a distribution. The arrival rate or traffic volume was defined using both insertion rate and insertion density parameters. To create randomness in the traffic flow between different simulations, a randomization factor was also configured. The tool generated the traffic data based on the given configurations. However, the traffic was not uniformly distributed on both southbound and northbound roads. Since the tool generates trips randomly, the distribution of CAV MPR was not similar in all the traffic directions.

4.3.5 Rule based adaptive approach

Based on the analysis of the experiments described in the Section 4.1, a rule-based adaptive approach is proposed and implemented. This implementation handles the dynamic conversion of the shared lane to a dedicated lane and vice versa based on the CAV MPR and traffic situation. These rules are created based on the observations derived from the simulation experiments. The algorithm 1 states the pseudocode for the dynamic dedicated lane assignment.

Algorithm 1 Rule based assignment pseudocode

```
Parse network XML file and retrieve edge ids
Start simulation
Retrieve number of vehicles running on every edge for each after every 900 simulation steps [15 minutes interval]
Calculated total number of vehicles in the network
Classify traffic scenario based on number of vehicles in the network
Move HDVs to shared lane from probable dedicated lanes before deployment
Assign or remove dedicated lane based on the rules
End simulation
```

The dynamic assignment is handled by changing the allowed vehicle classes for the eligible dedicated lanes. In this case, vehicle classes for CAV vehicle types are only allowed to travel using these lanes. First, all the candidate lanes are parsed using the XML network file for all lane strategies, and the lane permissions are changed accordingly using *setAllowed* method under the Lane module in Traci. Before dynamically deploying the dedicated lane, all the HDVs traveling on the probably dedicated lane have to move towards the shared lane to avoid the emergency stopping of such vehicles. The algorithm 2 states the steps taken to move the HDVs towards the shared lane. However, additional steps are taken to move the halted HDVs (if any) towards the shared lane. The vehicle ids of the running vehicles on every edge of the dedicated lanes are retrieved at every simulation step. Further vehicle ids with vehicles speed equal to zero are only considered. Once these halted vehicle ids are retrieved, the best lane for these vehicles is identified based on the dedicated lane strategy deployed at that moment. The vehicles are then forced to change the lane to the newly identified lane and the simulation proceeds. In case this part of the algorithm fails to capture the halted vehicles, the next attempt is made using *traci.simulation.getEmergencyStoppingVehiclesIDList* method. Lane ids of vehicles retrieved by this method are retrieved and the best possible lane is identified. Similar to the previous approach, the vehicles are forced to change lanes. If any other vehicles are halted and are not processed in these two stages, such vehicles are then teleported after 1 second.

Algorithm 2 Algorithm to move HDVs towards shared lanes

1: Parse network XML file and retrieve probable candidates for dedicated lane
2: Retrieve HDVs with probable dedicated lanes as future lanes using traci.vehicle.getVehicleClass()
3: Force lane change for such HDVs to shared lane using traci.vehicle.changeLane()
4: Deploy dedicated lane
5: For the next 10 simulation steps:
6: Retrieve stopped vehicles by checking the condition traci.vehicle.getSpeed==0.0
7: Retrieve emergency stopped vehicles using traci.simulation.getEmergencyStoppingVehiclesIDList()
8: Move the vehicles from the above two steps to the shared lane
9: Teleport all other stopped vehicles

4.3.6 Learning based adaptive approach

As a further extension to the rule-based approach discussed in the previous Section 4.3.5, a learning-based approach is proposed to handle the dynamic assignment of a dedicated lane. The figure 4.7 describes the high-level design of this approach. The learning-based approach involves two stages:

- Future traffic Prediction using existing traffic data
- No. of dedicated lane required prediction based on the traffic level

Future Traffic flow Prediction

Traffic prediction is the technique of forecasting traffic flow for traffic management. This technique is widely used to prevent traffic congestion using techniques such as time series forecast models, Long Short Term Memory models (1) (26), regression models (18), (38) and Deep Leaning networks (27) (45). In this study, traffic prediction using the stacked LSTM technique is proposed. The traffic data used for this study is a 24hrs

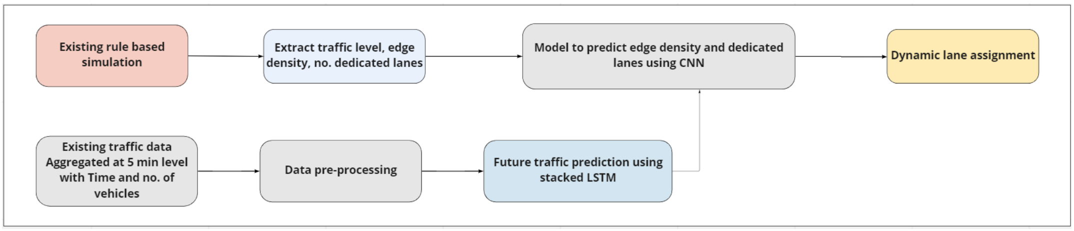


Figure 4.7: High level design for learning based approach

data aggregated at 5 minutes intervals with a number of vehicles to be inserted into the network. The M50 motorway traffic data with a similar format but for a longer period [more than 3 months for higher accuracy] can be used for training and testing the stacked LSTM models. Evaluation metrics such as Root Mean Square Error [RMSE] can be used to evaluate the performance of these models. The output of these models would be the number of vehicles that will be inserted into the network in the future time. This output can be passed to the next component of this approach that deals with the prediction of the number of dedicated lanes required.

Number dedicated lane to be used

Based on the existing rule-based simulations, a dataset can be created with the number of vehicles in the network and the number of dedicated lanes configured. This dataset further can be used to train the Convolutional Neural Network [CNN] model. The prediction obtained from the previous component will act as input to this model and it will predict the number of dedicated lanes required. Once the number of dedicated lanes required has been obtained, the dynamic deployment can be handled using the algorithm 1 implemented in this study.

4.3.7 Evaluation Metrics

To answer the research question postulated in Section 3.3, multiple scenarios were simulated on both the validation and the real network with mixed traffic. The hypothesis is prone to rejection if the traffic efficiency is not improved for the dedicated lane scenarios compared to the baseline (no dedicated lane) scenarios. To compare the traffic efficiency, the below metrics were taken into consideration:

- Average trip duration: How much time on average a vehicle takes to complete a trip. This would help understand if the time taken for a vehicle to complete a trip is reduced due to the dedicated lane.
- Travel Rate: How much time does it take for vehicles to travel per km.
- Congestion Index: How much congestion is reported at the edge level in the entire network. This would help understand if the congestion is reduced or increased due to the deployment of a dedicated lane.

To compare the traffic efficiency based on the above metrics, several types of outputs were generated. Below output files were generated for each simulation:

- statistics output gives the overall statistics of the simulation which includes vehicles, teleports, safety, persons, vehicleTripStatistics. Measures such as average

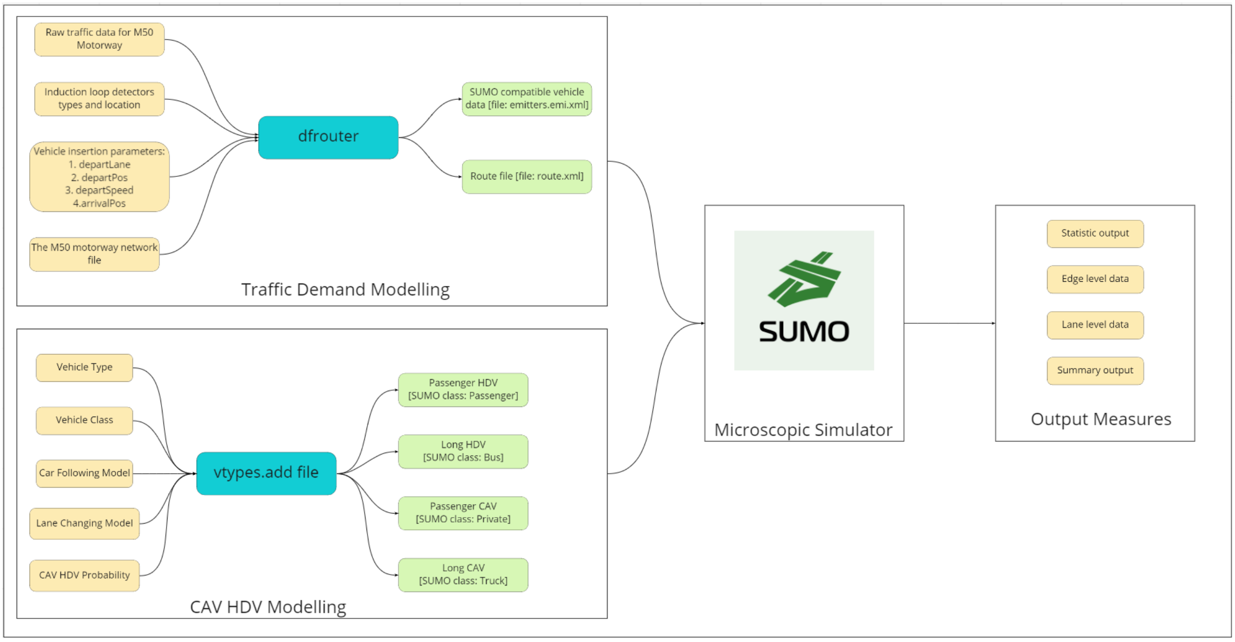


Figure 4.8: Low level design for Network and Vehicle modelling and its integration with SUMO

trip duration, and average trip speed generated as a part of vehicleTripStatistics are relevant to the evaluation metrics for this work

- summary output contains simulation step-wise extract of the number of vehicles loaded, inserted, running, waiting to be inserted, completed the simulation, mean travel time, and mean speed for the completed vehicles.
- lane-based measures are the aggregated lane level outputs that consist of measures such as lane id, travel time, lane density, occupancy, speed, etc. These outputs are generated as per the specified simulation time interval.
- edge-based measures are similar to that of lane-based measures aggregated on edge level
- trip info is the aggregated output for each vehicle's trip from start to end of the simulation

some of these files contain a large amount of data and hence further data processing is required to extract the required information. An xmlparse.py script was created to parse the network XML and generate travel rate and congestion index output files at the edge level. The algorithm 3 shows the pseudocode for the calculation of congestion index and travel rate. The figure 4.8 shows the low-level design for various components involved in this work and their integration with the SUMO simulator.

To represent the significance of the change in travel rate and congestion index, heatmaps are generated using these modified edge-based data files. The heatmaps are generated using plot_net_dumps.py tool provided by SUMO. Further plots were created using Tableau.

Algorithm 3 Calculation of Congestion index and travel rate pseudocode

Parse input XML network file and store edge_id, lane_id, lane_index, speed, length and allowed_vehicle_classes
Convert edge_level_data.xml to csv file
Parse edge_level_data.csv file and retrieve edge level data for required simulation interval time
For every edge calculate:
$travel\_rate \leftarrow 1/speed * 16.667$
$actual\_travel\_time \leftarrow edge\_length/speed$
$expected\_travel\_time \leftarrow edge\_length/edge_{s}peed$
$congestion\_index \leftarrow (actual\_travel\_time - expected\_travel\_time)/actual\_travel\_time$
Export edge level XML data file with new calculated fields

5 Results and Analysis

Previous studies have suggested that CAVs at a higher penetration rate lead to an improvement in traffic efficiency (11, 17). Thus in this study, we first analyzed if the CAVs show signs of improvement in traffic efficiency on a validation network without any dedicated lane. Later the impact of dedicated lanes is analyzed on the same network. Also with a dedicated lane setup, the traffic efficiency is expected to improve at higher CAV market penetration rates (12, 44, 47). This was also verified on the validation network. All these experiments were then performed on the M50 motorway. During the analysis, three different traffic scenarios were considered: Free-flow, Saturated, and Congested. In this chapter, the results of the simulation scenarios stated in Section 4.1 are presented in detail. Section 5.1 presents the analysis of results for the validation network. Section 5.2 presents the results for the M50 motorway. The Section 5.3 states how results from Section 5.1 and 5.2 used to implement the rule bases approach.

5.1 The 8.5km one-way validation network

As discussed in Section 4.1, the experiments are first executed on the validation network. This section describes the results of the experiments conducted on the validation network.

5.1.1 Congested traffic scenario

Results from the simulation of baseline, one dedicated lane, two dedicated lanes, and three dedicated lanes experiment described in Table 4.1 are discussed in this section. Table 5.1 shows the results for each of these scenarios in terms of trip duration and average speed. The No Dedicated Lane strategy section of the table shows the effect of introducing CAVs in the mixed traffic mode. The average trip duration decreases and the average speed increases as the CAV MPR increased from 0% to 100%. A similar observation is observed for other lane strategies. This validates the conclusion from the original work that the introduction of CAVs improves traffic efficiency in mixed traffic mode. When the CAV MPR is either 0% or 10% the no dedicated lane strategy yields the lowest trip duration and highest average speed. For these CAV MPRs, the traffic efficiency decreases as the number of dedicated lanes increases. These results are as expected and in line with the existing work since when the CAV MPR is 0% and dedicated lane(s) are configured, the number of lanes for HDVs to travel in is reduced, which in turn increases the time required to travel the entire network. Hence the traffic efficiency decreases. Similarly, for scenario II where the CAV MPR is 10%, there are very few CAVs in the traffic that could use the dedicated lane. Hence in this case also the traffic efficiency is less than that of the baseline scenario with the same CAV MPR. The improvement in traffic performance with dedicated lane configuration can be seen as the CAV MPR is increased beyond 30%. It can be seen that one dedicated lane strategy shows improvement in traffic efficiency when the CAV MPR is between 30% and 90%. All the dedicated lane strategies show similar performance when the traffic is purely CAV dominated (CAV MPR 100%). The results from this section validate the results of the dedicated lane on the validation network. Thus the dedicated lane configuration can further be evaluated with realistic traffic conditions on the M50 motorway.

Lane Strategies	Scenario	CAV MPR	Trip Duration
• No Dedicated Lane	I	0%	360.37
	II	10%	356.91
	III	30%	351.39
	IV	50%	346.29
	V	70%	341.94
	VI	90%	338.77
	VII	100%	337.48
• One Dedicated Lane	I	0%	391.44
	II	10%	365.42
	III	30%	344.74
	IV	50%	333.33
	V	70%	328.00
	VI	90%	323.80
	VII	100%	322.45
• Two Dedicated Lanes	I	0%	524.29
	II	10%	496.14
	III	30%	395.41
	IV	50%	343.72
	V	70%	331.21
	VI	90%	324.31
	VII	100%	322.45
• Three Dedicated Lanes	I	0%	605.81
	II	10%	588.55
	III	30%	523.31
	IV	50%	446.02
	V	70%	344.31
	VI	90%	326.64
	VII	100%	322.45

Table 5.1: Average trip duration for the validation network for all dedicated lane strategies

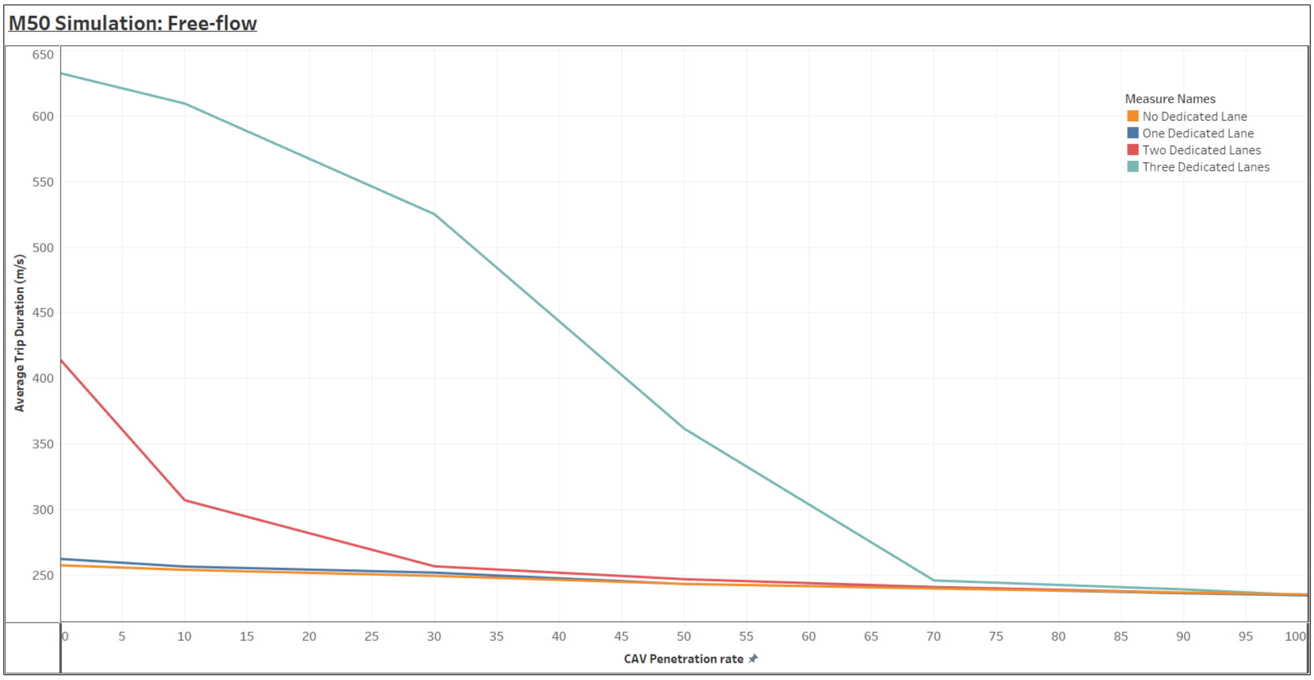


Figure 5.1: Average trip duration for M50 free-flow

5.2 The M50 Motorway

As stated in the previous section, the impact of a dedicated lane was validated on the toy network before implementing it on the realistic highway network. As discussed in Sections 4.1 and 4.3.2, two different approaches based on the position of the dedicated lane for the M50 motorway were followed. Section 5.2.1 presents the results from experiments where dedicated lanes were configured starting from the left-most lane for three traffic scenarios: Free-flow, saturated and congested. Section 5.2.2 presents the results from experiments where dedicated lanes were configured starting from the right-most lane for the same traffic scenarios.

5.2.1 Dedicated lane configuration: Starting from Left most lane

Free-flow traffic scenario

The figure 5.1 shows that there is no difference in average trip duration for no dedicated and one dedicated lane strategy. For two and three dedicated lanes, the average trip duration has increased significantly for lower MPRs. This suggests that at lower MPRs, two and three dedicated lanes are creating congestion, and hence the traffic efficiency is reduced. Increased congestion especially at interchanges with two and three dedicated lanes can be seen in figure 5.2. These results are as expected, as there is not enough CAVs to warrant several dedicated lanes. Similarly, the figure 5.3 shows an increase in travel rate. Similarly, at higher CAV MPR there is no difference in average trip duration is observed. This shows that one, two and three dedicated lane strategies achieve similar results as that of the baseline scenario with no dedicated lane. These results are expected as during the free-flow traffic scenario the number of vehicles traveling through the network is low. Based on these results, it is evident that the dedicated lane strategies for the M50 free-flow traffic scenario do not improve the traffic efficiency

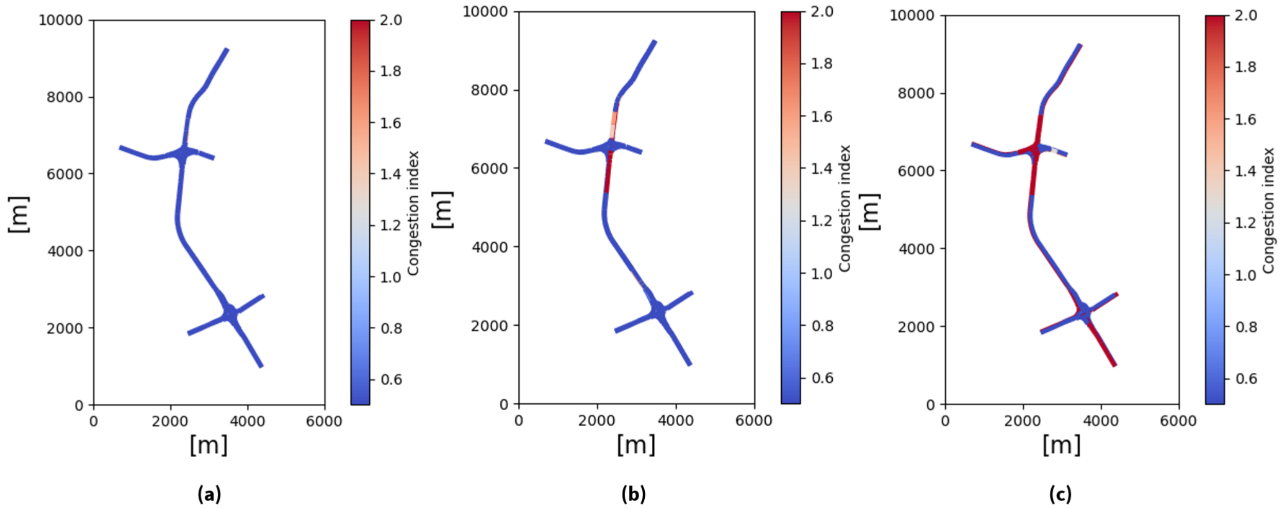


Figure 5.2: Congestion Index for M50 Free-flow for CAV MPR 10% with (a) No dedicated lane (b) Two dedicated lane (c) Three dedicated lane

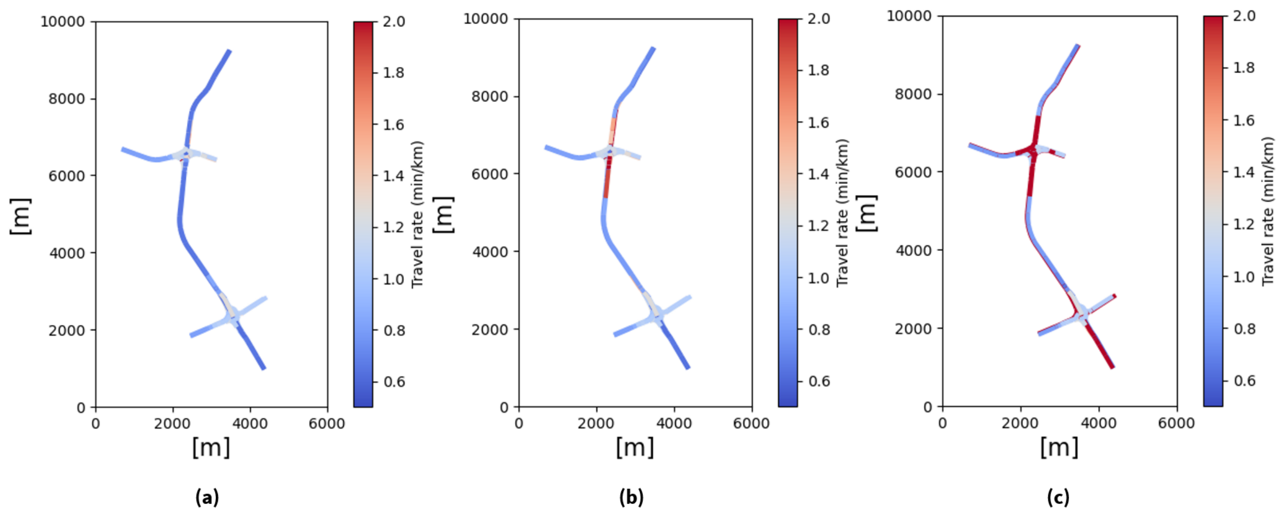


Figure 5.3: Travel rate for M50 Free-flow for CAV MPR 10% with (a) No dedicated lane (b) Two dedicated lane (c) Three dedicated lane

compared to the no dedicated lane strategy.

Saturated traffic scenario

Figure 5.4 shows the results from all the four lane strategies. For the two dedicated lane settings, the average trip duration are higher than that of no dedicated lane for CAV MPR 0% to 30%. Whereas for three dedicated lanes setting, this is observed until CAV MPR 50%. No significant difference is observed for higher CAV MPRs for these two settings compared to baseline. There is no significant difference in these two traffic measures for no dedicated lane and one dedicated lane strategy. However, for CAV MPR 70% and 90%, traffic efficiency with one dedicated lane shows a slight improvement in traffic efficiency. In terms of congestion index and travel rate, one dedicated lane configuration shows marginal improvement. Figure 5.5 and 5.6 shows the congestion index and travel rate for CAV MPR 70% and 90% for no dedicated lane and one dedicated lane strategies. Table 5.2 states the mean congestion index and

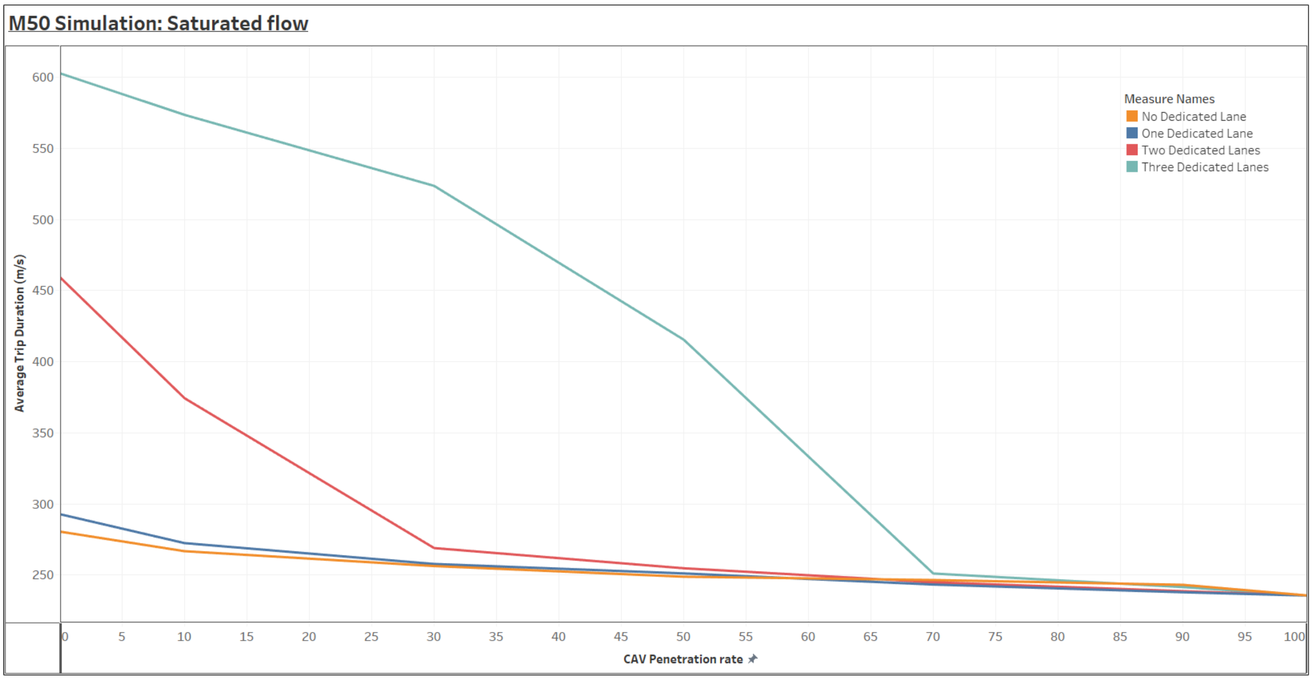


Figure 5.4: Average. trip duration for M50 saturated flow

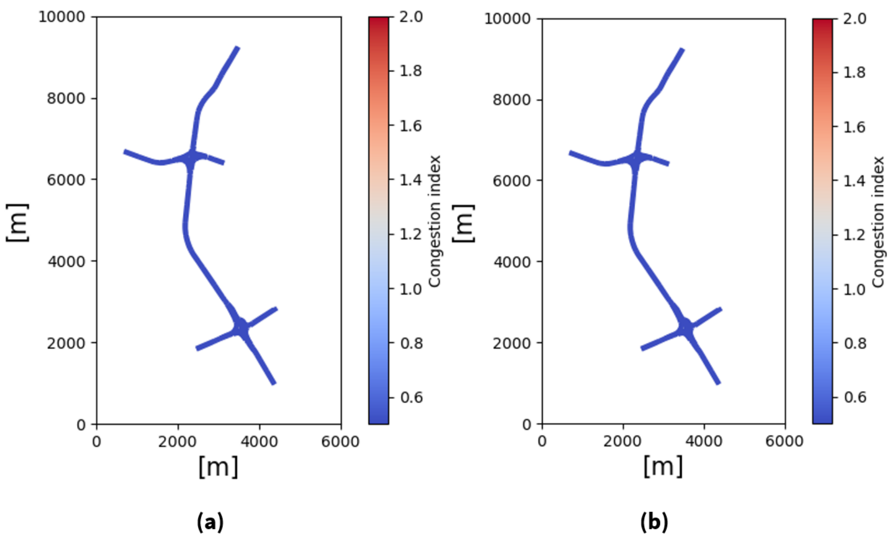


Figure 5.5: Congestion Index for M50 Saturated flow for CAV MPR 90% with (a) No dedicated lane (b) One dedicated lane

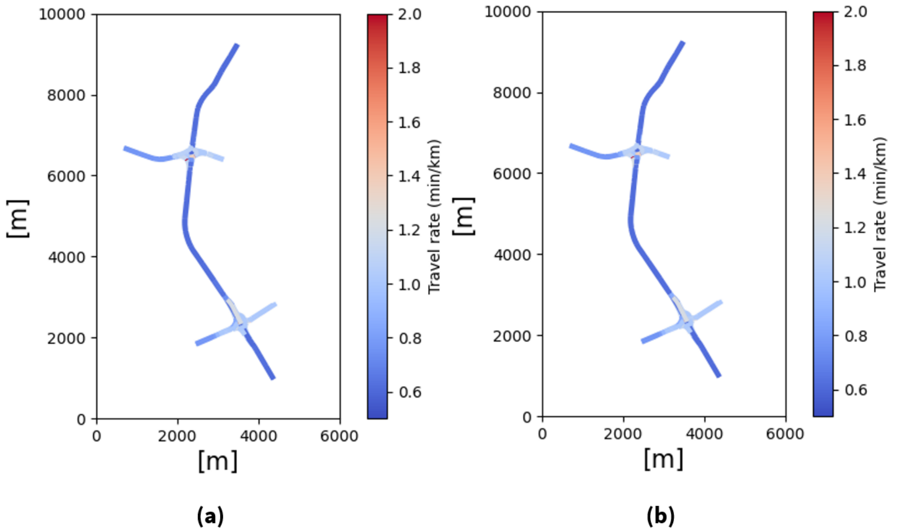


Figure 5.6: Travel rate for M50 Saturated flow for CAV MPR 90% with (a) No dedicated lane (b) One dedicated lane

travel rate for the above configuration. Based on these results, for CAV MPR 70% and 90% one dedicated lane improves the traffic efficiency and when the CAV MPR is below 70% there is no need to set up a dedicated lane in a saturated traffic situation as there is no significant improvement in traffic efficiency.

CAV MPR	No Dedicated Lane		One Dedicated Lane	
	TR	CI	TR	CI
0%	1.0000	0.2375	1.011	0.2633
10%	0.9728	0.1977	0.9774	0.2104
30%	0.9480	0.1638	0.9480	0.1661
50%	0.9263	0.1337	0.9331	0.1462
70%	0.9143	0.1193	0.9089	0.1105
90%	0.9011	0.1035	0.8975	0.1015
100%	0.8948	0.0960	0.8948	0.0960

Table 5.2: Mean Congestion Index (CI) and Travel Rate (TR) for No Dedicated Lane and One Dedicated Lane for Saturated traffic flow

Congested traffic scenario

Figure 5.7 shows the results from all four lane strategies. It can be seen that for lower CAV MPR, as the number of dedicated lanes is increased the average trip duration increases, and average vehicle speed decreases. For lower CAV MPRs [0% and 10%] the average trip increases up to 650 seconds as compared to that of 380 seconds with no dedicated lane. This is expected because at lower CAV MPRs majority of traffic

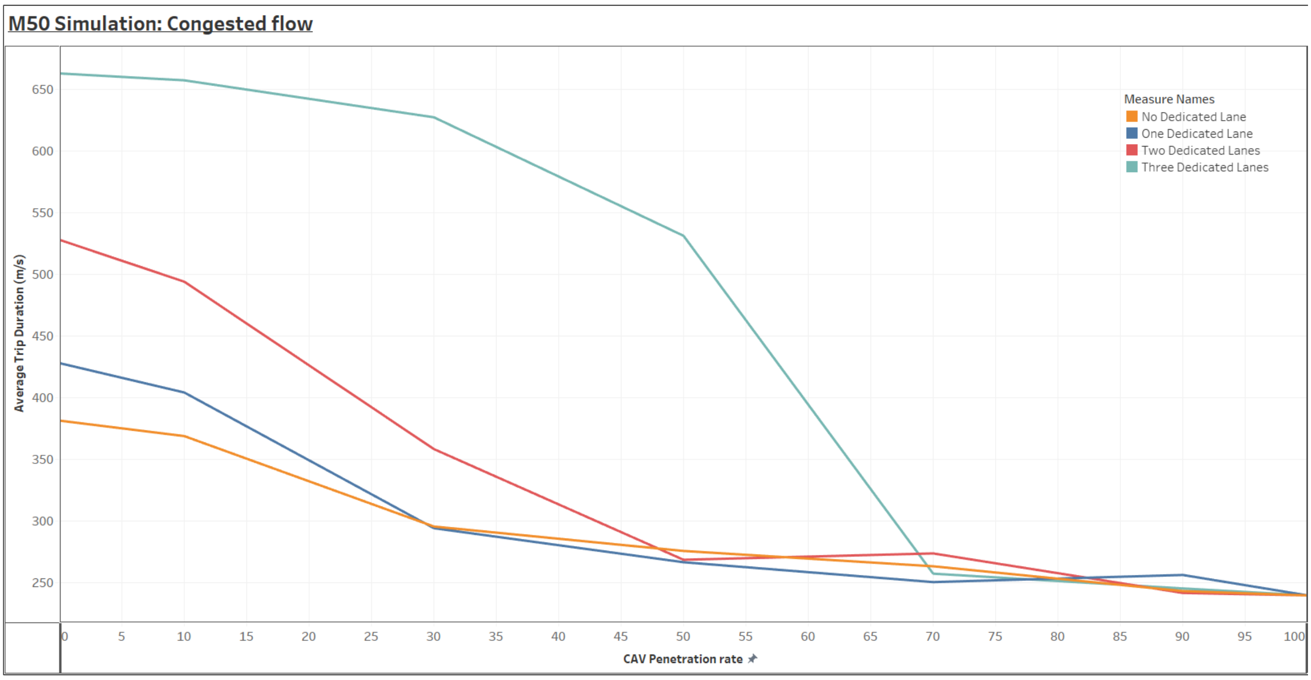


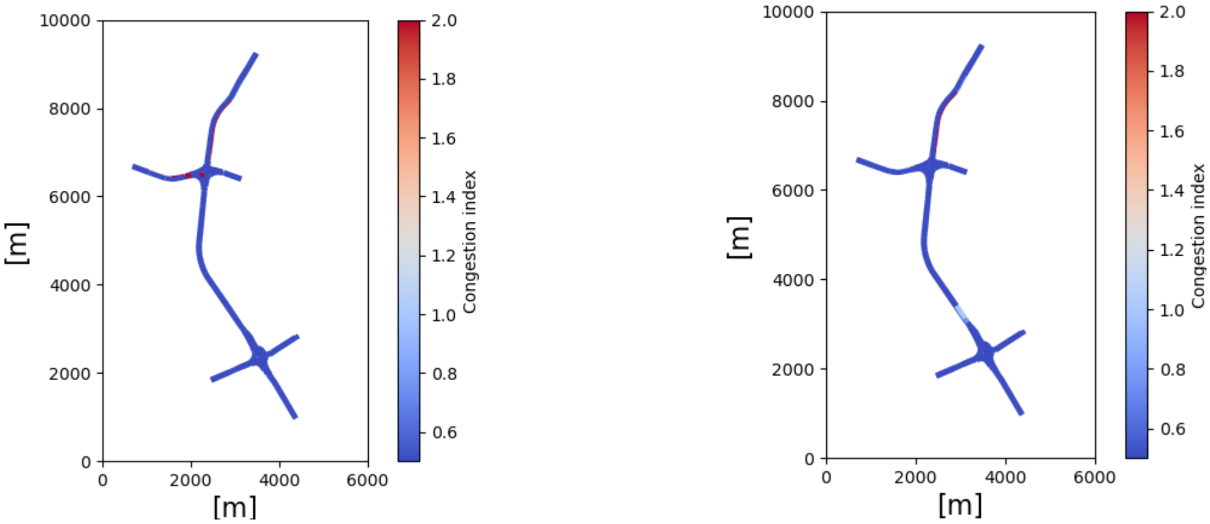
Figure 5.7: Average trip duration for M50 congested flow

consist of HDVs and with no dedicated lane setting all vehicles can utilize all 4 lanes of the highway network. Due to the increase in a number of dedicated lanes, the number of lanes for HDVs is reduced. This creates congestion and long vehicle queues at the interchanges. For CAV MPR 30% to 70%, the one dedicated lane configuration show improvement in traffic efficiency. Average trip duration decreases as compared to that of the baseline scenario. For CAV MPR 90%, a motorway with two dedicated lanes show improvements in these traffic measures.

The figures 5.8, 5.9 and 5.10 show the congestion index heat-map for CAV MPR 30%, 50% and 70% respectively for no dedicated lane and one dedicated lane. The figures 5.12, 5.13, 5.14 shows the travel rate heat-map for CAV MPR 30%, 50% and 70% respectively for no dedicated lane and one dedicated lane. Improvement in both congestion index and travel rate can be seen from no dedicated lane to one dedicated lane. The figures 5.11, 5.15 show the congestion index and travel heat-map for CAV MPR 90% for one dedicated lane and two dedicated lanes. The effect of improvement in the average trip duration can be seen in both the congestion index and travel rate. These changes are more significantly observed at the interchanges, and inflow and outflow links at the interchanges. For fully CAV traffic [CAV MPR 100%], the dedicated lane setting does not show any improvement in traffic efficiency.

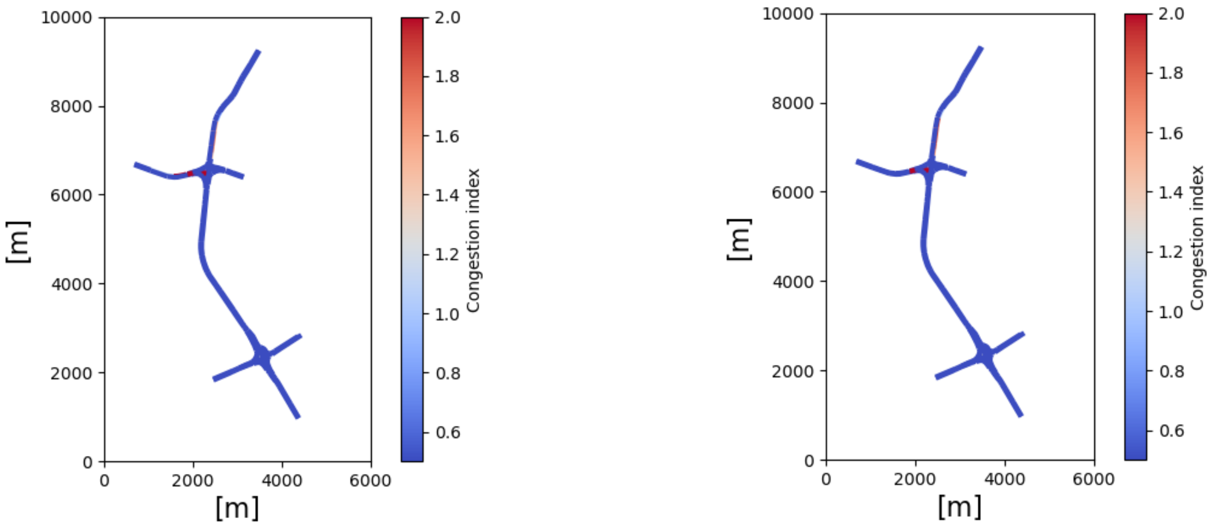
5.2.2 Dedicated lane configuration: Right most lane

This section states the results from the experiments where the dedicated lane assignment is started from right-most lane for all three traffic scenarios.



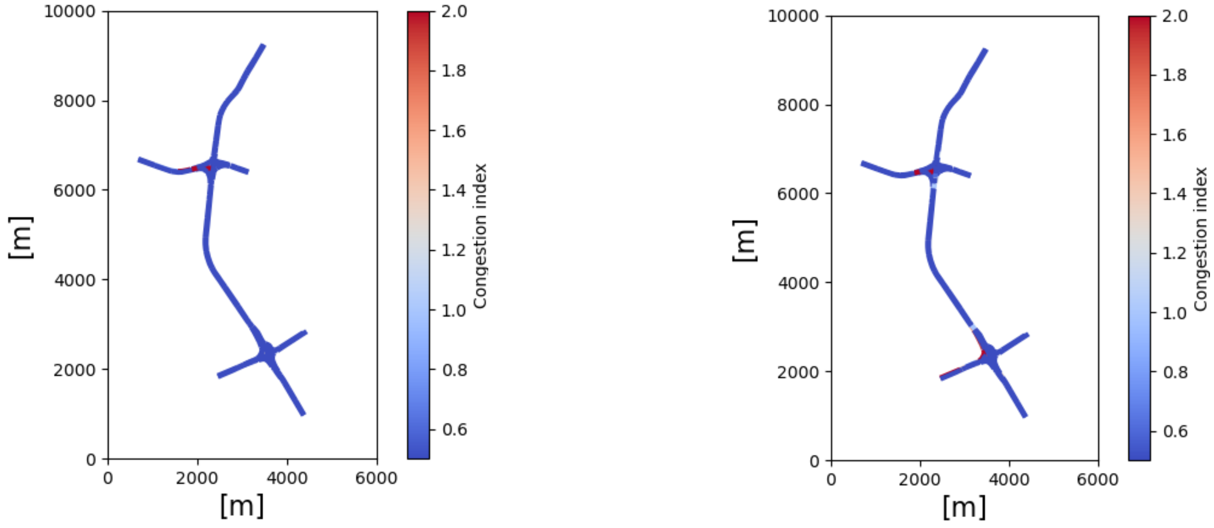
(a) (b)

Figure 5.8: Congestion index for M50 congested flow for CAV MPR 30% with (a) No dedicated lane (b) One dedicated lane



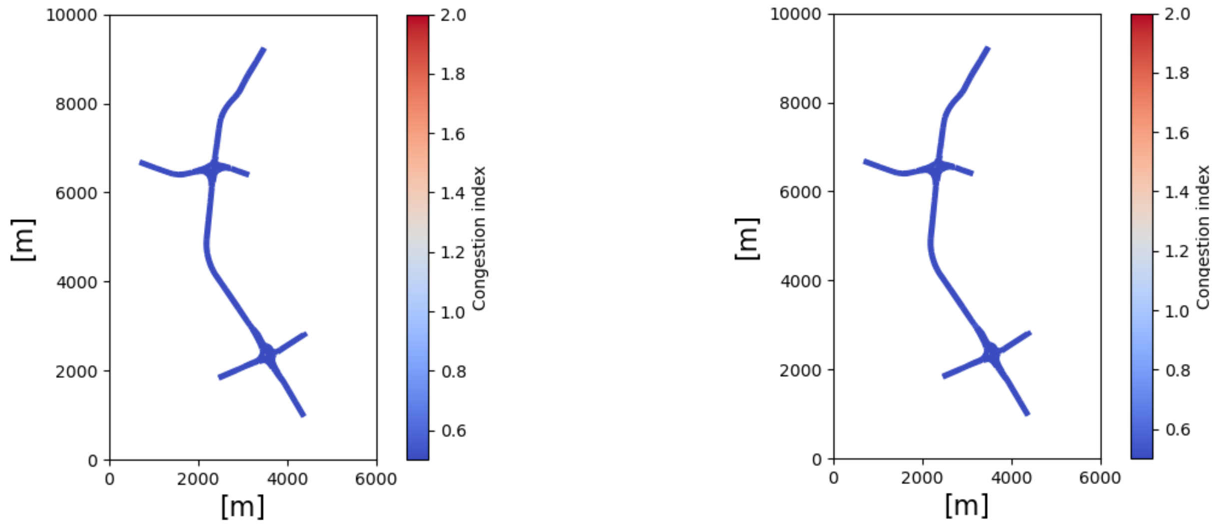
(a) (b)

Figure 5.9: Congestion index for M50 congested flow for CAV MPR 50% with (a) No dedicated lane (b) One dedicated lane



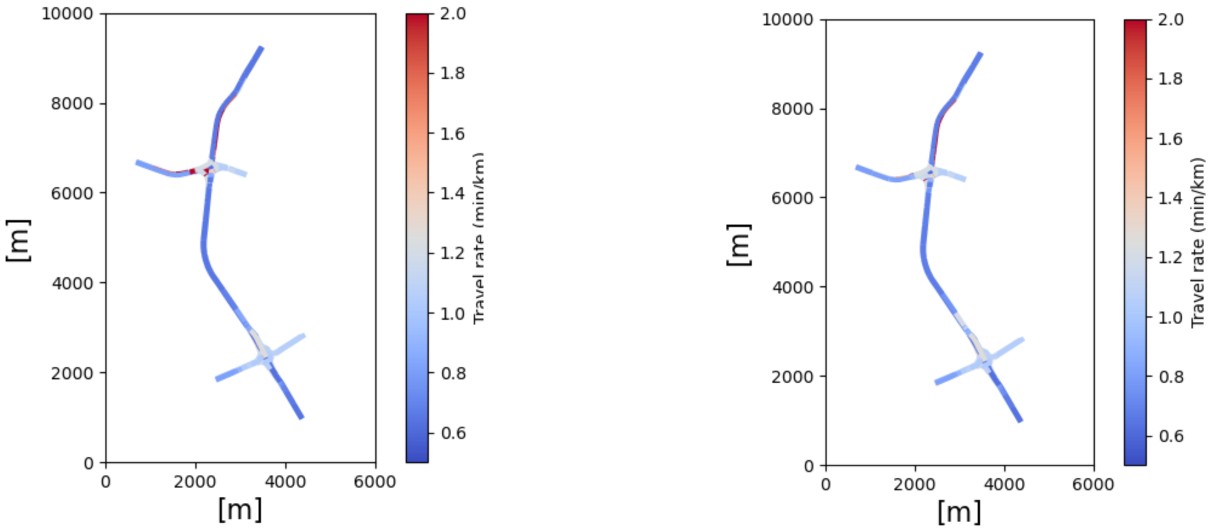
(a) (b)

Figure 5.10: Congestion index for M50 congested flow for CAV MPR 70% with (a) No dedicated lane (b) One dedicated lane



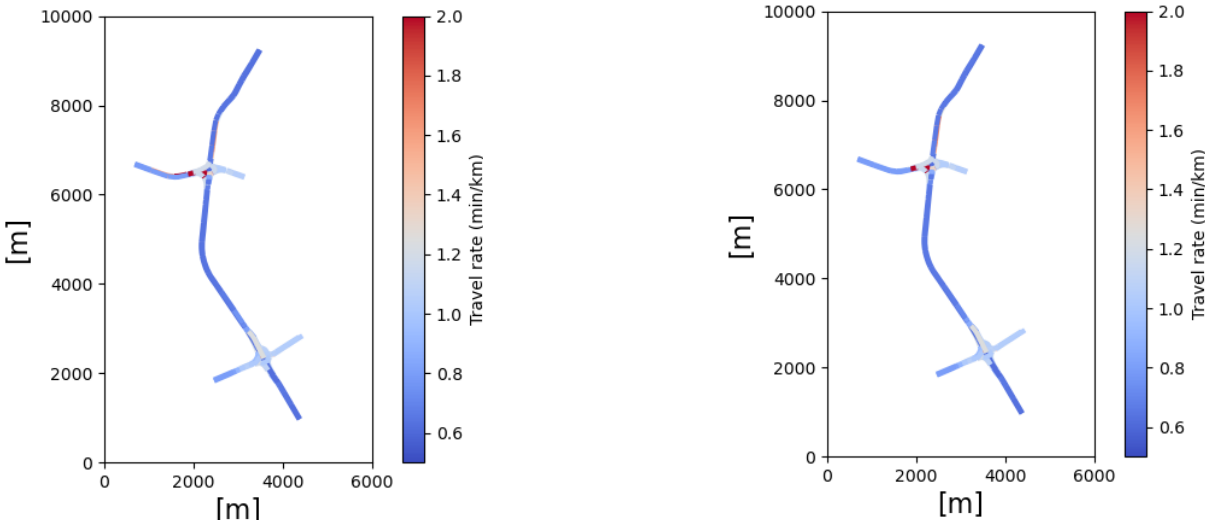
(a) (b)

Figure 5.11: Congestion index for M50 congested flow for CAV MPR 90% with (a) One dedicated lane (b) Two dedicated lanes



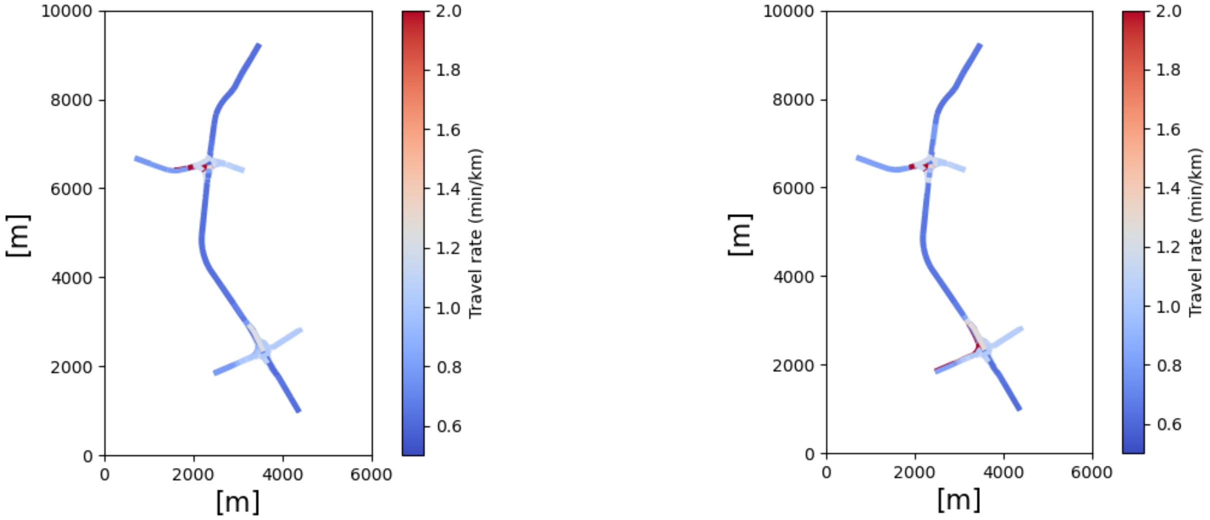
(a) (b)

Figure 5.12: Travel Rate for M50 congested flow for CAV MPR 30% with (a) No dedicated lane (b) One dedicated lane



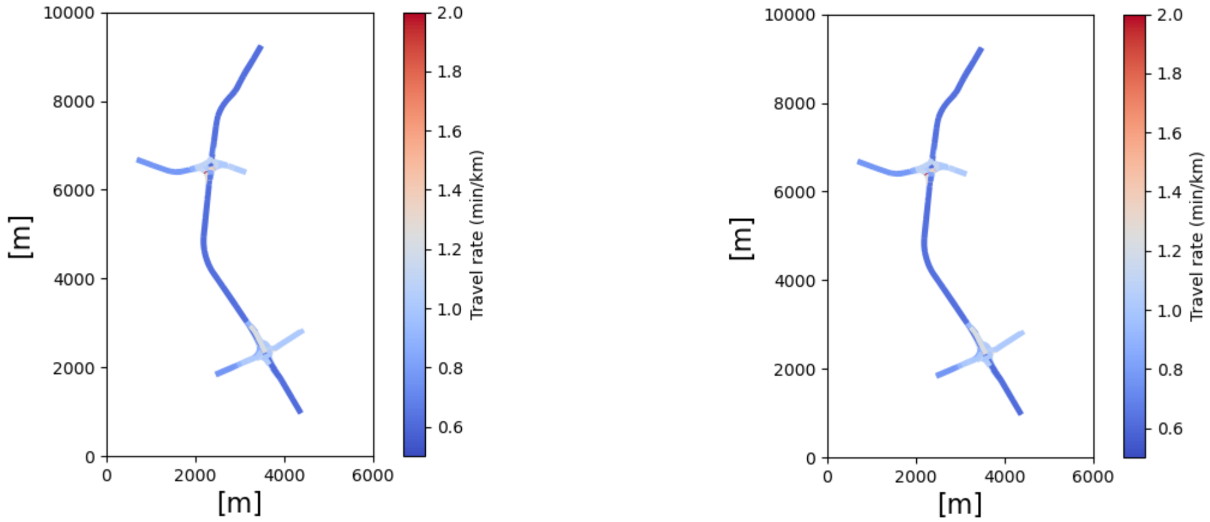
(a) (b)

Figure 5.13: Travel Rate for M50 congested flow for CAV MPR 50% with (a) No dedicated lane (b) One dedicated lane



(a) (b)

Figure 5.14: Travel Rate for M50 congested flow for CAV MPR 70% with (a) No dedicated lane (b) One dedicated lane



(a) (b)

Figure 5.15: Travel Rate for M50 congested flow for CAV MPR 90% with (a) One dedicated lane (b) Two dedicated lanes

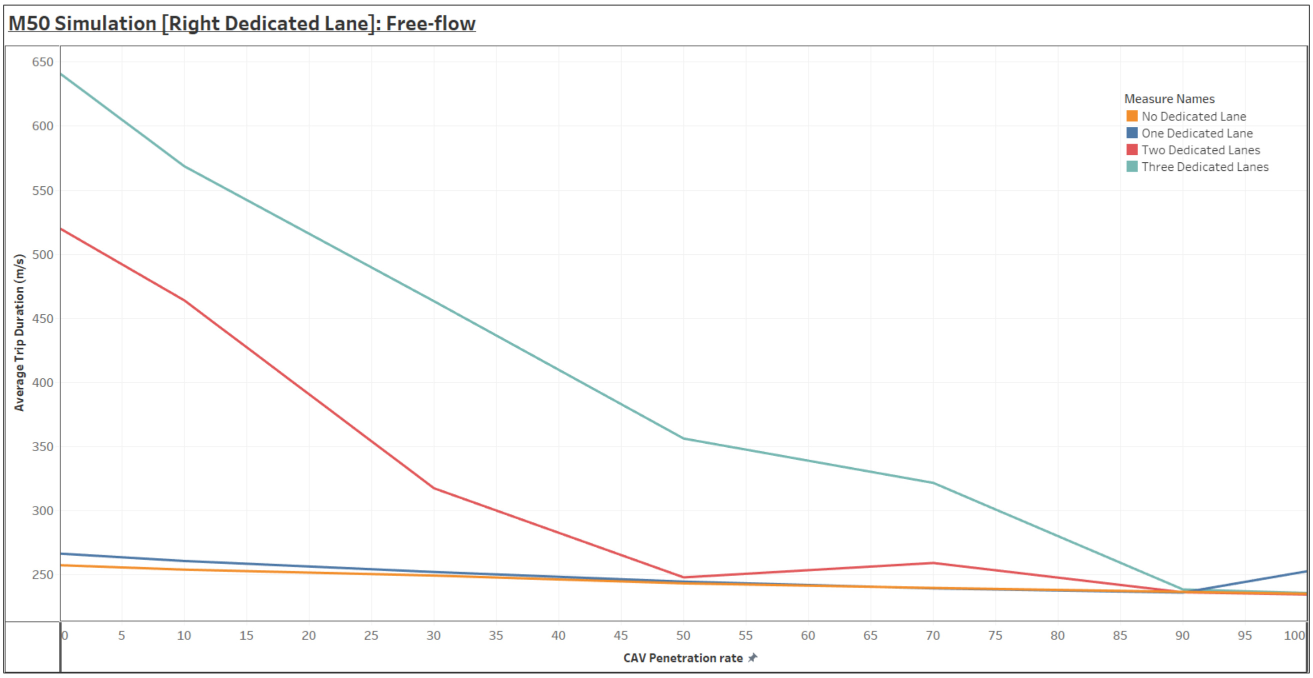


Figure 5.16: Average trip duration for M50 free-flow with right dedicated lane

Free-flow traffic scenario

Based on figure 5.1 and 5.16, it can be seen that the traffic performance is very much similar to that of left side dedicated lane configuration and does not show any improvement in the considered traffic measures with the introduction of dedicated lanes. Overall, the average speed has decreased and the average trip duration has increased for every scenario as compared to that of the left-side dedicated lane configuration. Due to these results, the congestion index and travel rate for this scenario are not discussed further in this section.

Saturated traffic scenario

Similar to that of the left side dedicated lane configuration, this configuration shows improvement in traffic efficiency with one dedicated lane when the CAV MPR is 70% and 90%. When the CAV MPR is below 70% traffic performance is higher with no dedicated lane. For CAV MPR 100% all the lane strategies yield similar performance. However, based on 5.4 and 5.17 it can be seen that the traffic performance with left side dedicated lane configuration is better than that of right side dedicated lane.

Congested traffic scenario

Similar to that of the left side dedicated lane configuration, this configuration shows improvement in traffic efficiency with one dedicated lane when the CAV MPR is between 30% and 70%. For CAV MPR between 70% and 90% setting up two dedicated lanes improved the traffic efficiency as compared to that of other lane strategies. When the CAV MPR is below 30% traffic performance is higher with no dedicated lane. For CAV MPR 100% all the lane strategies yield similar performance. However, based on 5.7 and 5.18 it can be seen that the traffic performance with left side dedicated lane configuration is better than that of right side dedicated lane.

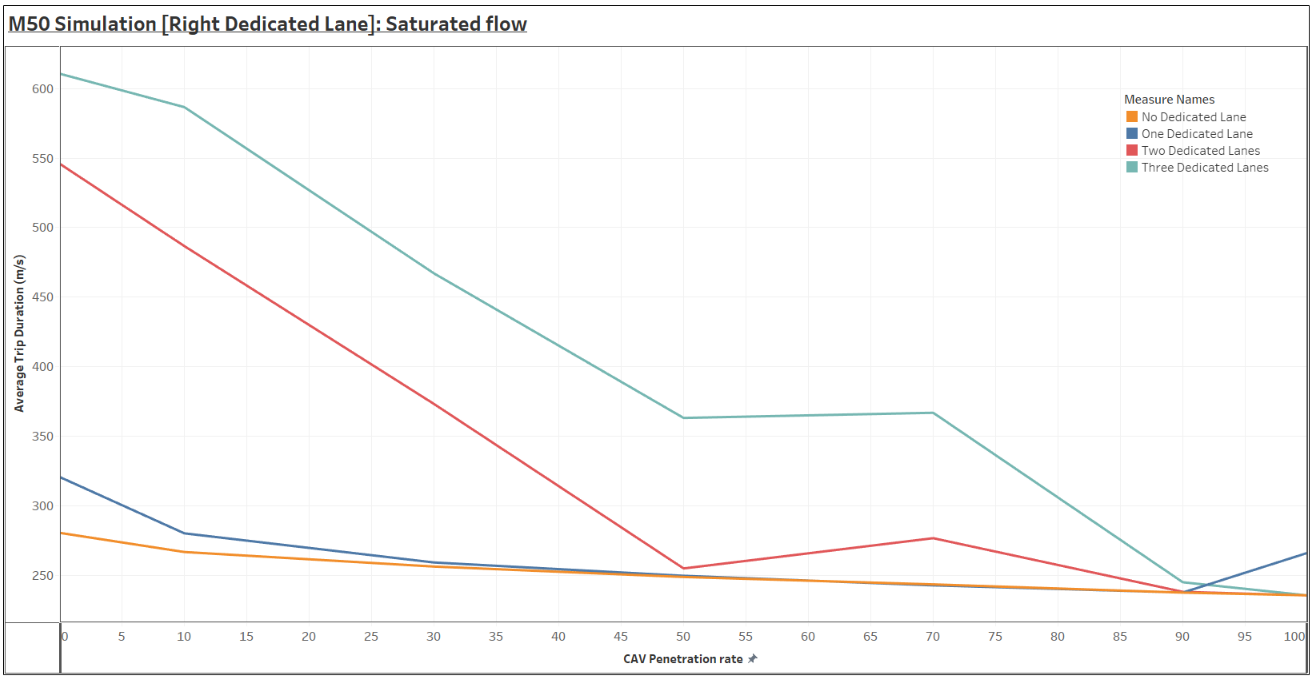


Figure 5.17: Average trip duration for M50 saturated flow with right dedicated lane

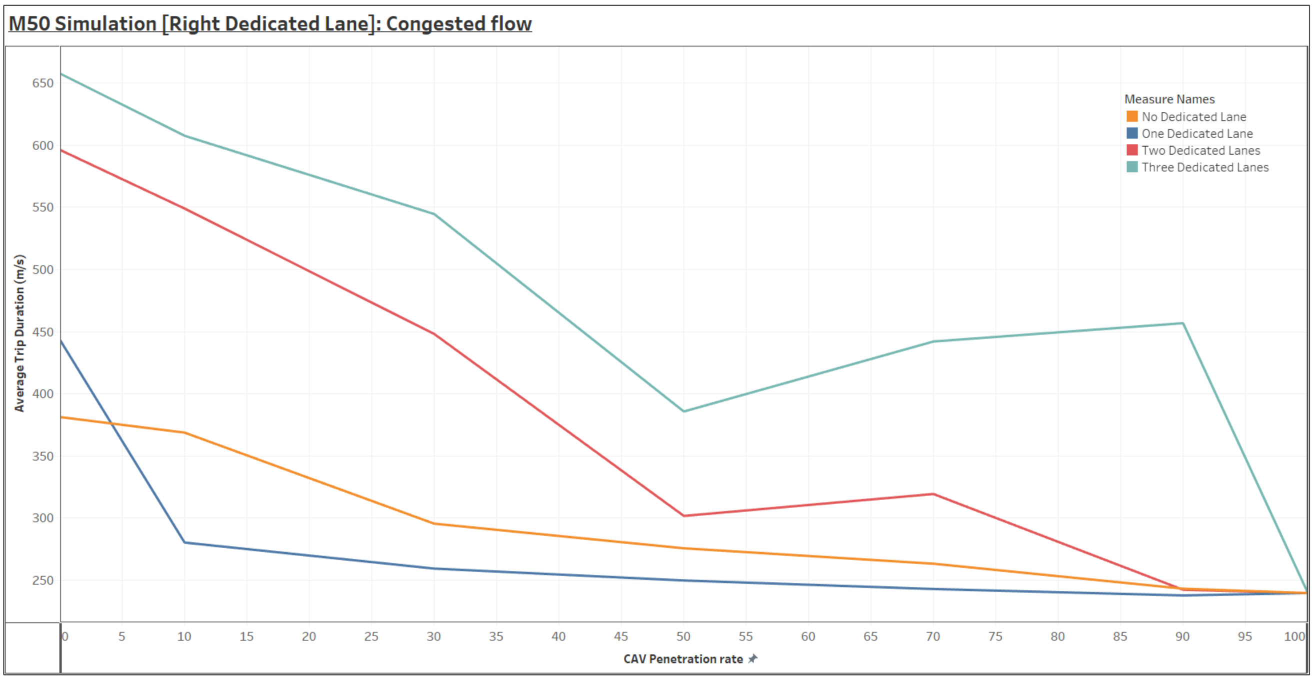


Figure 5.18: Average. trip duration for M50 congested flow with right dedicated lane

5.3 Rule-Based adaptive approach

As discussed in Section 4.1, a rule based approach is designed to dynamically convert a shared lane to a dedicated lane and vice versa based on the traffic level and CAV MPR. The Table 5.3 states the dedicated lane deployment configuration suggested based on this study.

Traffic Scenario	CAV MPR	Dedicated Lane Strategy
Free-flow	0% to 100%	No Dedicated Lane
Saturated	0% to 70%	No Dedicated Lane
	70% to 90%	One Dedicated Lane
	100%	No Dedicated Lane
Congested	0% to 30%	No Dedicated Lane
	30% to 70%	One Dedicated Lane
	70% to 90%	Two Dedicated Lanes
	100%	No Dedicated Lane

Table 5.3: Suggested dedicated lane deployment based on the experiment results

The algorithm 4 describes the steps and parameters using which the algorithm is designed. The rule based approach was executed over 24 hour realistic traffic data for

Algorithm 4 Rule based dedicated lane assignment algorithm

$TrafficScenario \leftarrow Freeflow, Saturated, Congested$
$CAVMPR \leftarrow 0\%, 10\%, 30\%, 50\%, 70\%, 90\%, 100\%$
$noDedicatedLanes \leftarrow 0$
if $TrafficScenario = Freeflow$ **then**
  $noDedicatedLanes \leftarrow 0$
else if $TrafficScenario = Saturated$ **then**
  if $CAVMPR \leq 70$ **then**
    $noDedicatedLanes \leftarrow 0$
  else
    $noDedicatedLanes \leftarrow 1$
  end if
else if $TrafficScenario = Congested$ **then**
  if $CAVMPR \leq 30$ **then**
    $noDedicatedLanes \leftarrow 0$
  else if $CAVMPR \geq 30 \ \& \ CAVMPR \leq 70$ **then**
    $noDedicatedLanes \leftarrow 1$
  else if $CAVMPR \geq 70 \ \& \ CAVMPR \leq 90$ **then**
    $noDedicatedLanes \leftarrow 2$
  end if
end if

MPR 50% and 70%. The performance of rule based approach is compared with baseline and all three dedicated lane strategies. Table 5.4 shows the comparison of average trip duration for these strategies.

CAV MPR	Lane Strategy	Average Trip Duration
50%	No Dedicated lane	255.20
	One Dedicated Lane	255.69
	Two Dedicated Lanes	261.72
	Three Dedicated Lanes	271.56
	Rule Based dynamic assignment	252.33
70%	No Dedicated lane	247.81
	One Dedicated Lane	245.24
	Two Dedicated Lanes	246.87
	Three Dedicated Lanes	252.06
	Rule Based dynamic assignment	243.79

Table 5.4: Average trip duration for 24 hour simulation for all dedicated lane strategies

Based on the Table 5.4, it can be seen that the rule-based dynamic assignment strategy achieves the lowest average trip duration amongst all the strategies. Hence it shows that the dynamic assignment approach slightly outperforms all other strategies.

5.4 Discussion

Based on the results and analysis in the previous Sections 5.1, 5.2, it can be said the dedicated lane strategy shows improvement in the traffic efficiency but is dependent on the factors such as traffic level and CAV MPR. This is observed for both scenarios where a dedicated lane is configured starting from the left-most most and right-most lane. The dedicated lane configuration from the left-most lane yields better traffic performance in terms of average trip duration, congestion index, and travel rate for all traffic levels and CAV penetration rates. Overall irrespective of the traffic flow for low MPRs (0% - 10%) it is observed the average trip duration and congestion index significantly increase with two and three dedicated lane strategies. This is due to the imbalance between lanes reserved for CAVs and the number of CAVs in the traffic. Due to the low volume of CAVs, the dedicated lanes are not utilized to their full capacity. On the other hand, due to the high volume of HDVs and fewer shared lanes, shared lanes fail to accommodate the HDVs and result in congestion. For free-flow traffic level, no dedicated lane strategy outperforms the baseline scenario with no dedicated lane. This is expected as the overall vehicle volume during the free flow is low and all the vehicles can travel without any reports of congestion. For saturated traffic flow, one dedicated lane strategy shows the improvement in traffic efficiency when the CAV MPR is between 70% to 90%. Two and three dedicated lane strategies yield almost similar traffic performance as compared to that of one dedicated lane at higher MPR but do not outperform one dedicated lane strategy. When the CAV MPR is between 0% to 70%, the baseline strategy with no dedicated lane performs better as compared to all other dedicated lane strategies. When the traffic flow is purely CAV with MPR 100%, all the lane strategies yield similar traffic efficiency.

For congested traffic flow, the one dedicated lane strategy improves traffic efficiency when the CAV MPR is between 30% and 70%. When the CAV MPR is below 30%, the baseline strategy outperforms all other strategies. Here the two dedicated lane strategy shows improvement in traffic efficiency when the CAV MPR is between 70% and 90%. Similar to that of saturated flow, for purely CAV traffic all the lane strategies yield similar traffic performance. Based on these results, it is evident that no single dedicated lane strategy outperforms the traffic performance for all traffic levels and CAV penetration rates as compared to that of the baseline strategy with no dedicated lane. Hence deploying a uniform dedicated lane strategy to the M50 motorway network will not yield the desired result in terms of traffic efficiency. As the traffic scenario and CAV MPR vary, the number of dedicated lanes required to improve traffic efficiency also changes.

The experiment results are in line with the trend observed in the existing work where the impact of the dedicated lane is significantly observed with increasing CAV MPR. However, the results of the experiments are not generic in terms of the number of dedicated lanes required for improvement in traffic efficiency. Thus, these results may not be applied to other networks. The number of dedicated lanes can change with the complexity of the highway network, traffic levels, CAV penetration rate, types of vehicles in traffic, and modeling of Human Driven and Connected Autonomous vehicles. As the complexity of the highway network changes, the location of the dedicated can change. In a simple highway network with no interchanges, the dedicated lane can be configured throughout the highway. The same may not be possible on a complex highway with one or more interchanges. The consistency of the highway network also impacts the decision on the number of dedicated lanes required. The traffic flow at different sections on the highway will be different for highways with a consistent number of lanes and highways with a varying number of lanes. The modeling of HDVs and CAVs controls their behavior in terms of vehicle speed, the minimum distance between vehicles, lane changing behavior, etc. Hence, a change in these parameters may change the required number of dedicated lanes.

6 Conclusion

This chapter encapsulates the findings of the study undertaken in Section 6.1, challenges faced during the implementation and execution of the simulation experiments in Section 6.2 and possible extensions to this study in Section 6.3.

6.1 Summary

As a part of this work, observations from previous studies of the impact of CAVs to improve traffic efficiency were evaluated with different CAV penetration rates on both validation and realistic highway networks. The realistic M50 motorway traffic data were considered for this study. The dedicated lane experiments designed under this study focused on analyzing the impact of dedicated lanes by considering factors such as the number of dedicated lanes, traffic scenarios, position and location of the dedicated lane, and CAV penetration rate. Further, a rule-based approach is implemented to accommodate the dynamic dedicated lane deployment based on the experimental observations. Traffic efficiency was measured in terms of average trip duration, average speed, congestion index, and travel rate.

The experiments showed that the configuration of the dedicated lane for CAVs improves traffic performance. However, the number of dedicated lanes required varies per the traffic situation and CAV penetration rate. On the M50 network, one dedicated lane shows improvement in traffic efficiency in saturated and congested traffic scenarios for CAV MPR between 70%-90% and 30%-70% respectively. Two dedicated lanes show improvement in traffic efficiency only for congested traffic scenarios for CAV MPR between 70% - 90%. The rest of the scenarios do not show any requirement for a dedicated lane. Hence a uniform dedicated lane strategy would not be a plausible solution to improve traffic efficiency. The rule-based approach to dynamically assign dedicated lanes implemented in this study slightly outperforms the baseline and all three dedicated lane strategies. The evaluation of the assignment of a dedicated lane from the left-most lane and right-most lane shows that the location of the dedicated lane has equal importance along with other parameters.

Based on the experiment design, it can be said that a thorough analysis of the highway under consideration is required for dedicated lane deployment. Also, the decisive factors for the number of dedicated lanes required can vary with the complexity of the highway network. The number of dedicated lanes can also change based on CAV penetration rate, traffic levels, parameters used for Connected Autonomous Vehicle and

Human Driven Vehicle modelling. Hence generic rules for the deployment of a number of dedicated lanes can not be applied to every network. The rule based approach implemented in this work to dynamically allocate the dedicated lane outperforms the other lane strategies. During the experiment setup, several issues were identified which are included in the future scope of this work 6.3.

6.2 Challenges

- Due to the complexity of the M50 motorway, thorough analysis, and multiple simulation attempts were required to identify the location of the dedicated lane on the network.
- The HDV and CAV modeling involves a large number of parameters that if not carefully chosen can result in adverse behavior. The documentation of some of the parameters is also limited and required source code analysis to understand the significance.
- The documentation lacks the support for custom scenarios and thus required analysis of related archive queries raised by SUMO users posted on the forum. The forum also did not resolve the issue directly. Thus several simulation attempts were made to understand the exact behavior due to the attempted configuration.
- The experiments designed for the M50 network were enormously resource extensive. The integration of SUMO with Traci further slowed the execution due to a number of commands executed during one simulation step. Execution of rule-based scenario for CAV MPR 50% took approximately 10 hours to complete.
- A total of 170 scenarios were executed multiple times which increased the amount of time required for execution. Also, a large amount of data was generated for every scenario which had to be processed and analyzed to obtain insights. Analyzing such a high amount of data is a time-consuming and error-prone process.
- The documentation for Traci lacks the technical description required by a beginner and thus requires the analysis of source code. Not all required values can be obtained with existing methods and thus requires a custom function to be implemented, The execution of such functions is time-consuming and thus increases the simulation time.
- The lack of simulation-based studies and implementation methodology in the published work made the implementation difficult during the initial phase of the study.

6.3 Future Scope

Due to time constraint, some part of the research question was not implemented and is identified as possible extension of this work:

- The impact of the dedicated lane in current work is validated under the constant speed policy for both lanes and vehicles. This can further be extended to see if the application of different speed limit policies such as Differential Speed Limit Policy, and Variable Speed Limit Policy further improves traffic efficiency.

- The location of deployment of a dedicated lane in this work was decided by manual analysis of the network. A more technical approach can be adopted to decide the location of a dedicated lane over a series of edges by analyzing the impact of a dedicated lane in terms of traffic efficiency. This would also provide a comprehensive approach to deciding the location of a dedicated lane on a complex highway network.
- Three lane strategies are implemented in the current study: One, two, and three dedicated lanes. In all of these strategies, a constant number of dedicated lanes are configured throughout the network. However, based on the traffic flow and diversity of the network, a flexible number of dedicated lanes can be set up to analyze the impact on traffic efficiency.
- This work evaluates the research question from a traffic efficiency perspective. This can further be extended by evaluating the application of a dedicated lane with the help of safety measures.
- The learning-based approach proposed in this study can be implemented for the dynamic assignment of dedicated lanes. The suggested approach can further be improved by using more advanced time series forecast models to predict short-term future traffic.

Bibliography

[1] Abduljabbar, R., Dia, H., and Tsai, P.-W. (2021). Unidirectional and bidirectional lstm models for short-term traffic prediction. *Journal of Advanced Transportation*, 2021:1–16.

[2] Administration, F. H. (2022). Managed lanes: A primer.

[3] Aftabuzzaman, M. (2007). Measuring traffic congestion- a critical review. *30th Australasian Transport Research Forum*.

[4] Ahmed, H. U., Huang, Y., and Lu, P. (2021). A review of car-following models and modeling tools for human and autonomous-ready driving behaviors in micro-simulation. *Smart Cities*, 4(1):314–335.

[5] Albeaik, S., Bayen, A., Chiri, M. T., Gong, X., Hayat, A., Kardous, N., Keimer, A., McQuade, S. T., Piccoli, B., and You, Y. (2021).

[6] Anderson, J., Kalra, N., Stanley, K., Sorensen, P., Samaras, C., and Oluwatola, T. (2014). *Autonomous Vehicle Technology: A Guide for Policymakers*. RAND Corporation.

[7] Azlan, N. N. N. and Rohani, M. M. (2018). Overview of application of traffic simulation model.

[8] Chao, Q., Bi, H., Li, W., Mao, T., Wang, Z., Lin, M. C., and Deng, Z. (2020). A survey on visual traffic simulation: Models, evaluations, and applications in autonomous driving. *Computer Graphics Forum*, 39(1):287–308.

[9] Chen, Z., He, F., Zhang, L., and Yin, Y. (2016). Optimal deployment of autonomous vehicle lanes with endogenous market penetration. *Transportation Research Part C: Emerging Technologies*, 72:143–156.

[10] Eggert, J., Damerow, F., and Klingelschmitt, S. (2015). The foresighted driver model. *2015 IEEE Intelligent Vehicles Symposium (IV)*, pages 322–329.

[11] Garg, M., Johnston, C., and Bouroche, M. (2021). Can connected autonomous vehicles really improve mixed traffic efficiency in realistic scenarios? In *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, pages 2011–2018.

[12] Ghiasi, A., Hussain, O., Qian, Z. S., and Li, X. (2017). A mixed traffic capacity analysis and lane management model for connected automated vehicles: A markov chain method. *Transportation Research Part B: Methodological*, 106:266–292.

[13] Ghiasi, A., Hussain, O., Qian, Z. S., and Li, X. (2020). Lane management with variable lane width and model calibration for connected automated vehicles. *Journal of Transportation Engineering, Part A: Systems*, 146:04019075.

[14] Gipps, P. (1981). A behavioural car-following model for computer simulation. *Transportation Research Part B: Methodological*, 15(2):105–111.

[15] Gong, S. and Du, L. (2018). Cooperative platoon control for a mixed traffic flow including human drive vehicles and connected and autonomous vehicles. *Transportation Research Part B: Methodological*, 116:25–61.

[16] Gora, P., Katrakazas, C., Drabicki, A., Islam, F., and Ostaszewski, P. (2020). Microscopic traffic simulation models for connected and automated vehicles (cavs) – state-of-the-art. *Procedia Computer Science*, 170:474–481. The 11th International Conference on Ambient Systems, Networks and Technologies (ANT) / The 3rd International Conference on Emerging Data and Industry 4.0 (EDI40) / Affiliated Workshops.

[17] Guériau, M. and Dusparic, I. (2020). Quantifying the impact of connected and autonomous vehicles on traffic efficiency and safety in mixed traffic. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–8.

[18] H R, D., Madhav, A., and Tyagi, A. (2022). *Traffic Prediction Using Machine Learning*, pages 969–983. Springer Singapore.

[19] Higgs, B., Abbas, M. M., and Medina, A. (2011). Analysis of the wiedemann car–following model over different speeds using naturalistic data.

[20] Hoogendoorn, S. P. and Bovy, P. H. L. (2001). State-of-the-art of vehicular traffic flow modelling. *Proceedings of the Institution of Mechanical Engineers, Part I: Journal of Systems and Control Engineering*, 215(4):283–303.

[21] Hörmann, S., Stumper, D., and Dietmayer, K. C. J. (2017). Probabilistic long-term prediction for autonomous vehicles. *2017 IEEE Intelligent Vehicles Symposium (IV)*, pages 237–243.

[22] Hua, X., Yu, W., Wang, W., and Xie, W. (2020). Influence of lane policies on freeway traffic mixed with manual and connected and autonomous vehicles. *Journal of Advanced Transportation*, 2020:1–20.

[23] International, S. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles j3016-202104.

[24] Kesting, A., Treiber, M., and Helbing, D. (2010). Enhanced intelligent driver model to access the impact of driving strategies on traffic capacity. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 368(1928):4585–4605.

[25] Koutsopoulos, H. N. and Farah, H. (2012). Latent class model for car following behavior. *Transportation Research Part B: Methodological*, 46(5):563–578.

[26] Li, J., Guo, F., Sivakumar, A., Dong, Y., and Krishnan, R. (2021). Transferability improvement in short-term traffic prediction using stacked lstm network. *Transportation Research Part C: Emerging Technologies*, 124:102977.

[27] Mehdi, M. Z., Kammoun, H. M., Benayed, N. G., Sellami, D., and Masmoudi, A. D. (2022). Entropy-based traffic flow labeling for cnn-based traffic congestion prediction from meta-parameters. *IEEE Access*, 10:16123–16133.

[28] Musarat, M. A., Altaf, M., Rabbani, M. B. A., Alaloul, W. S., Alzubi, K. M., and Al Salaheen, M. (2021). Automation in traffic engineering to prevent road accidents: A review. In *2021 Third International Sustainability and Resilience Conference: Climate Change*, pages 388–393.

[29] Nagalur Subraveti, H. H. S., Srivastava, A., Ahn, S., Knoop, V. L., and van Arem, B. (2021). On lane assignment of connected automated vehicles: strategies to improve traffic flow at diverge and weave bottlenecks. *Transportation Research Part C: Emerging Technologies*, 127:103126.

[30] of Idaho, U. (2003). Traffic flow theory: Theory concepts.

[31] Olaverri Monreal, C., Errea-Moreno, J., Díaz, A., Biurrun Quel, C., Serrano, L., and Kuba, M. (2018). Connection of the sumo microscopic traffic simulator and the unity 3d game engine to evaluate v2x communication-based systems. *Sensors*, 18.

[32] Peng, B., Keskin, M. F., Kulcsár, B., and Wymeersch, H. (2021). Connected autonomous vehicles for improving mixed traffic efficiency in unsignalized intersections with deep reinforcement learning. *Communications in Transportation Research*, 1:100017.

[33] Pereira, J. L. F. (2012). An integrated architecture for autonomous vehicles simulation.

[34] PTV AG, Karlsruhe, G. (2020). Ptv vissim 10 user manual.

[35] Schrank, D., Eisele, B., Lomax, T., and Bak, J. (2015). 2015 urban mobility scorecard.

[36] Sengupta, R., Rezaei, S., Shladover, S., Cody, D., Dickey, S., and Krishnan, H. (2007). Cooperative collision warning systems: Concept definition and experimental implementation. *Journal of Intelligent Transportation Systems - J INTELL TRANSPORT SYST*, 11:143–155.

[37] Shladover, S. (2017). Connected and automated vehicle systems: Introduction and overview. *Journal of Intelligent Transportation Systems*, 22:00–00.

[38] Sun, H., Liu, H. X., Xiao, H., He, R. R., and Ran, B. (2003). Use of local linear regression model for short-term traffic forecasting. *Transportation Research Record*, 1836(1):143–150.

[39] Thrun, S. (2010). Toward robotic cars. *Commun. ACM*, 53(4):99–106.

[40] Treiber, M., Hennecke, A., and Helbing, D. (2000). Congested traffic states in empirical observations and microscopic simulations. *Physical Review E*, 62(2):1805–1824.

[41] van Arem, B., van Driel, C., and Visser, R. (2006). The impact of cooperative adaptive cruise control on traffic- flow characteristics. *IEEE transactions on intelligent transportation systems*, 7(4):429–436.

[42] Vranken, T. and Schreckenberg, M. (2022). Modelling multi-lane heterogeneous traffic flow with human-driven, automated, and communicating automated vehicles. *Physica A: Statistical Mechanics and its Applications*, 589:126629.

[43] Wang, J., Li, S., Zheng, Y., and Lu, X.-Y. (2015). Longitudinal collision mitigation via coordinated braking of multiple vehicles using model predictive control. *Integrated Computer-Aided Engineering*, 22:171–185.

[44] Xiao, Z., Guo, X., Guo, X., and Li, Y. (2021). Impact of cooperative adaptive cruise control on a multilane highway under a differentiated per-lane speed limit policy. *Transportation Research Record: Journal of the Transportation Research Board*, 2675:036119812110114.

[45] Xu, L., Kun, W., Pengfei, L., and Miaoyu, X. (2020). Deep learning short-term traffic flow prediction based on lane changing behavior recognition. In *2020 2nd International Conference on Information Technology and Computer Application (ITCA)*, pages 760–763.

[46] Yao, Z., Hu, R., Jiang, Y., and Xu, T. (2020). Stability and safety evaluation of mixed traffic flow with connected automated vehicles on expressways. *Journal of Safety Research*, 75:262–274.

[47] Ye, L. and Yamamoto, T. (2018). Impact of dedicated lanes for connected and autonomous vehicle on traffic flow throughput. *Physica A: Statistical Mechanics and its Applications*, 512:588–597.

[48] Ye, L. and Yamamoto, T. (2019). Evaluating the impact of connected and autonomous vehicles on traffic safety. *Physica A: Statistical Mechanics and its Applications*, 526:121009.

[49] Zhong, Z., Lee, J., and Zhao, L. (2021). Traffic flow characteristics and lane use strategies for connected and automated vehicles in mixed traffic conditions. *Journal of Advanced Transportation*, 2021:1–19.