

**Investigation and Utilization of Autonomous Vehicles Impacts
on Signalized Intersection Performance under Mixed Traffic
Environment with Regular Vehicles**

BY

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A Dissertation Presented to the
FACULTY OF THE COLLEGE OF GRADUATE STUDIES
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

DOCTOR OF PHILOSOPHY

In

CIVIL ENGINEERING

February, 2023

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN- 31261, SAUDI ARABIA
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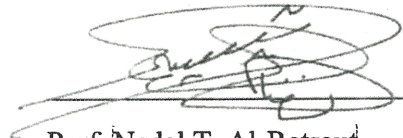


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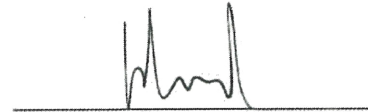


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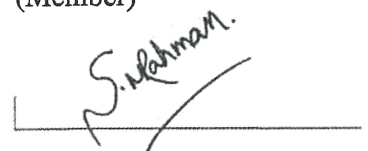
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I would like to dedicate this work to my darling family members
And to all of my colleagues and friends |

ACKNOWLEDGMENTS

First of all, I express my humble, sincere thanks to ALLAH Almighty for blessing me in so many ways and helping me in achieving the doctoral degree. Secondly, I am highly appreciative to my family members, especially my mother, wife and daughters, for all the support they provided to me during my doctoral program, mainly at difficult times.

I would like to state my honest appreciation and deepest thanks to my advisor, Prof. Nedal T. Al-Ratrout for his limitless hours of encouragement, support, guidance and constructive criticism during the whole dissertation work and for mentoring and teaching me in my graduate studies. Also, I have a desire for paying special gratitude to my thesis committee members: Dr.Syed Masiur Rahman, Dr. Khaled J. Assi, Prof.Shakhawat Chowdhury and Dr.Salah Al-Dulaijan.

Finally, I am highly thankful to King Fahd University of Petroleum and Minerals for allowing me to conduct my research works utilizing its research facilities.

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LIST OF ABBREVIATIONS

AV	:	Autonomous Vehicle
ADAS	:	Advanced Driver-Assistance System
AI	:	Artificial Intelligence
AUC	:	Areas Under Curve
ACC	:	Adaptive Cruise Control
ANN	:	Artificial Neural Network
AIM	:	Autonomous Intersection Management
CACC	:	Cooperative Adaptive Cruise Control
CAV	:	Connected Autonomous Vehicle
CV	:	Connected Vehicle
C	:	Cycle Length
DL	:	Deep Learning
DNN	:	Deep Neural Network
DE	:	Differential Evolution
DSRC	:	Dedicated Short-Range Communication
EIDM	:	Enhanced Intelligent Driver Model

EPO	:	Emperor Penguin Optimization
GWO	:	Grey Wolf Optimization
GPS	:	Global Positioning System
GA	:	Genetic Algorithms
HCM	:	Highway Capacity Manual
I-V	:	Infrastructure-to-Vehicle
IDM	:	Intelligent Driver Model
LOS	:	Level of Service
LR	:	Linear Regression
ML	:	Machine Learning
MPE	:	Mean Percentage Error
MAE	:	Mean Absolute Error
PSO	:	Particle Swarm Optimization
RV	:	Regular Vehicle
RL	:	Reinforcement Learning
RF	:	Random Forest
RMSE	:	Root Mean Square Error

REC	:	Regression Error Characteristics
SHAP	:	SHapley Additive exPlanations
Shapley	:	SHAP Value
STCA	:	Symmetric Two-Lane Cellular Automaton
TSC	:	Traffic Signal Control
TRL	:	Transport Research Laboratory
V-V	:	Vehicle-to-Vehicle
V-I	:	Vehicle-to-Infrastructure
VSL	:	Variable Speed Limits
XGBoost	:	Extreme Gradient Boosting

ABSTRACT

Full Name : [MOHAMMED KHALID MOHAMMED ALTURKI]
Thesis Title : [Investigation and Utilization of Autonomous Vehicles Impacts on Signalized Intersection Performance under Mixed Traffic Environment with Regular Vehicles]
Major Field : [CIVIL ENGINEERING]
Date of Degree : [February, 2023]

Recent advancements in industrial revolution have offered novel approaches that have considerable potential for increasing the efficiency of road networks. Emerging concepts of autonomous driving and machine learning can be incorporated intelligently for improving traffic flow efficiency. Effective implementation of autonomous vehicles (AVs) could overcome different problems of stochastic human driving behavior. However, in the coming years, traffic composition can vary in terms of AV implementation rate, which can lead to a dynamic and mixed traffic environment comprising regular vehicles (RVs) and AVs with different characteristics. As a result, the gradual implementation of the AVs will definitely cause unique impacts on traffic system. The first part of this research focuses on reviewing and investigating impacts of the AV implementation under mixed AV-traffic environment considering different related aspects. Findings from the review indicated that the AV implementation has positive impacts on the traffic flow, such as improved traffic capacity and stability. However, the impact depends on some factors including implementation rate of the AVs, characteristics and operational settings of the AVs, traffic volume level, and human driving behaviour. Results obtained from the simulation-based investigation indicated that even partial AV implementation could improve the operational efficiency of a signalized intersection compared to full RV traffic.

AV implementation reduces the vehicle delay, stopped delay, and queue length. The expected improvements are primarily based on the implementation rate, and are higher at higher rates ($\geq 50\%$). Considering the different AV models employed in this research, connected autonomous vehicle (CAV) model exhibited the best performance. The second part of this research focuses on signalized intersection control under mixed AV-traffic environment. The different proposed methods in the literature are based on different assumptions, requirements, and constraints related to the network environment. To overcome these limitations, the application of adaptive traffic signal control (TSC) can effectively optimize traffic signal plans for variations of AV traffic environments. However, artificial intelligence (AI) approaches should be considered to better utilization of the improved AV characteristics. The effective application of machine learning (ML) based methods may be used to develop a real adaptive TSC which are able to respond effectively to the dynamic varying conditions of traffic system using their intelligent continuing learning and adaptation. Based on these concepts, a future TSC problem of AV-based traffic is solved by proposing and developing a novel intelligent-based optimization framework. The proposed framework improves intersection performance under congested traffic conditions compared with that of the traditional optimization methods. Compared to full RV-based traffic, the implementation rates of 25%, 50%, and 100% can decrease optimized cycle lengths by 26%, 39%, and 53%, respectively, which can result in delay reductions of approximately 18%, 31%, and 56%, respectively. The proposed framework when applied in an adaptive-based manner can help in the generalization of controlling existing signalized intersections with the gradual implementation of AVs without the extra infrastructure or specific operational and connectivity capabilities of the involved vehicles. |

ملخص الرسالة

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تاريخ الدرجة العلمية: فبراير 2023

قدمت التطورات الحديثة في مجال الثورة الصناعية مناهج جديدة لديها إمكانات كبيرة لزيادة كفاءة شبكات الطرق. يمكن دمج المفاهيم الناشئة للقيادة الذاتية والتعلم الآلي بذكاء لتحسين كفاءة تدفق حركة المرور. يمكن أن يتغلب التطبيق الفعال للمركبات ذاتية القيادة (AVS) على المشاكل المختلفة الناتجة من سلوك القيادة البشرية العشوائية. ولكن ، في السنوات القادمة يمكن أن يختلف تكوين حركة المرور من حيث معدل تطبيق السيارات ذاتية القيادة مما قد يؤدي إلى حركة مرور ديناميكية ومختلطة تشمل مركبات عادية (RVs) ومركبات ذاتية القيادة ذات الخصائص المختلفة. نتيجة لذلك ، سيؤدي التطبيق التدريجي للمركبات ذاتية القيادة إلى تأثيرات فريدة على نظام المرور. يركز الجزء الأول من هذا البحث على مراجعة واستقصاء تأثيرات تطبيق السيارات ذاتية القيادة على خصائص التدفق المروري في ظل بيئة مرور مختلطة مع مراعاة الجوانب المختلفة ذات الصلة. أشارت النتائج المستخلصة من المراجعة إلى أن تطبيق المركبات ذاتية القيادة له تأثيرات إيجابية على تدفق حركة المرور مثل تحسين سعة الطريق واستقرار حركة المرور. ولكن، هذه التأثيرات تعتمد على بعض العوامل بما في ذلك معدل تطبيق المركبات ذاتية القيادة، الخصائص والإعدادات التشغيلية للمركبات، مستوى حجم حركة المرور، وسلوك القيادة البشرية. وأشارت النتائج التي تم الحصول عليها في هذا البحث بناء على الاستقصاء القائم على المحاكاة إلى أنه حتى التطبيق الجزئي للمركبات ذاتية القيادة يمكن أن يحسن الكفاءة التشغيلية للتقاطعات المرورية ذات الإشارات الضوئية مقارنة بحركة مرور مكونة من مركبات عادية بشكل كامل. يقلل تطبيق المركبات ذاتية القيادة من تأخير المركبة والتأخير المتوقف وطول قائمة الانتظار عند التقاطعات. و تعتمد التحسينات المتوقعة بشكل أساسي على معدل التطبيق وهي أعلى عند معدلات تطبيق عالية ($\leq 50\%$). بالنظر إلى النماذج المختلفة للمركبات ذاتية القيادة المستخدمة في هذا البحث، أظهر نموذج المركبة ذاتية القيادة المتصلة أفضل أداء. يركز الجزء الثاني من هذا البحث على التحكم في التقاطعات ذات الإشارات الضوئية في ظل بيئة مرور مختلطة. تعتمد الطرق المقترحة المختلفة في الأدبيات على افتراضات ومتطلبات وقيود مختلفة تتعلق ببيئة الشبكة المرورية. للتغلب على هذه المحددات ، يمكن لتطبيق التحكم التكيفي لإشارة المرور (TSC) من تحسين خطط

إشارات المرور بشكل فعال مع التغيرات في بيئة حركة المرور المختلطة. ومع ذلك، ينبغي استخدام أساليب و مناهج الذكاء الاصطناعي (AI) لتحسين الاستفادة من الخصائص المحسنة للمركبات ذاتية القيادة. يمكن للتطبيق الفعال للطرق القائمة على التعلم الآلي (ML) على تطوير نظام إشارة مرور متكيف قادر على الاستجابة بفعالية للظروف الديناميكية المتغيرة لنظام المرور باستخدام التعلم والتكيف المستمر الذكي. بناءً على هذه المفاهيم ، تم في هذا البحث حل مشكلة مستقبلية للتحكم بالتقاطعات المرورية لحركة المرور المختلطة من خلال اقتراح وتطوير نظام تحسين ذكي. يعمل النظام المقترح على تحسين أداء التقاطع في ظل ظروف المرور المزدهمة مقارنة بأنظمة التحسين التقليدية. مقارنةً بالحركة المرورية المكونة من مركبات عادية بشكل كامل، يمكن أن تؤدي معدلات تطبيق المركبات ذاتية القيادة البالغة 25% و 50% و 100% إلى تقليل أطوال دورات الإشارات الضوئية بنسبة 26% و 39% و 53% على التوالي ، مما قد يؤدي إلى تقليل التأخير بحوالي 18% و 31% و 56% على التوالي. يمكن أن يساعد النظام المقترح عند تطبيقه بطريقة قائمة على التكيف على تعميم التحكم في التقاطعات الحالية ذات الإشارات الضوئية مع التطبيق التدريجي للمركبات ذاتية القيادة بدون الحاجة الى بنية تحتية إضافية أو قدرات تشغيلية وقدرات اتصالية للمركبات المعنية.

CHAPTER 1

INTRDUCTION

1.1 Background

The advancements of industrial, information and communication technologies have created new opportunities to improve driving environment. The emerging concept of automated driving and it's different applications is considered a promising approach for overcoming deficiencies in human driving behavior and therefore solve different traffic problems. Automated driving capabilities can range from partial automation to full automation ([1],[2],[3]). Partial automation may help improve human driving behavior using various advanced driver assistance systems [1]. In contrast, full automation can perform all driving tasks without the need for human intervention [4].

The conventional manner of human operating vehicles is being revolutionized using novel vehicle technology where computers and artificial intelligence (AI) take over some or all of the driving tasks instead of humans. Autonomous vehicle (AV)—a term commonly used to refer to vehicles that are capable of fully automated driving (level 5 automation)—can replace humans by handling all driving tasks [5]. So, with the full automation level of AVs, human behavior does not play any role in making the decisions related to driving actions or in response to traffic control systems. This can reduce human-related deficiencies and improve the response of vehicles to different control systems.

AVs can accurately sense, gather and share data related to the traffic environment around the vehicle using different technologies, such as radars, cameras, global positioning system (GPS) sensors and other applications of information and communication technologies [6] and also may

communicate with each other or with traffic control units [7]. Using various built-in software and different AI-based applications, AVs interpret the acquired data to plan the required driving actions, which are transferred to the control system as commands [6]. AVs with connectivity capabilities are commonly referred to as connected autonomous vehicles (CAVs) ([8],[5]). CAVs are capable of vehicle-to-vehicle (V-V), vehicle-to-infrastructure (V-I) and infrastructure-to-vehicle (I-V) interactions that enable them to communicate with other CAVs or the traffic control network [6]. The exchange of information through the V-V and V-I communications may help the AV to adjust their driving behaviors based on real-time traffic conditions. It should be highlighted that the connected vehicle technology and automatic driving are two different technologies that should be treated separately [9]. The term connected vehicle (CV) is referring to any type of vehicle, including regular vehicle (RV) (human-driven vehicle); with connectivity capabilities which may has the access to the information of their surrounding vehicles or the traffic infrastructure.

The AVs occupy the same amount of road space as the RVs, but have different operational characteristics. Utilizing these characteristics and other advanced capabilities, compared to the RV, AV maintains an improved driving behavior in terms of car following ([10],[11]), lane changing ([12],[13]), speed harmonization, and anticipation and response to traffic conditions ([10],[14],[15]). Moreover, AVs are systemic and behave accurately by assigned algorithms and rules, unlike RVs that behave stochastically due to the nature of human driving behavior [7]. RVs have complete freedom to change a control input at any time, while the AVs can only adjust control input at periodic discrete times [16].

The AV implementation may lead to several impacts on transportation planning, urban mobility and city design [17]. For example, AVs may lead to an increase in urban sprawl, resulting in

increased travel time, energy consumption, and air pollutants [17]. Also, AVs will have impacts on individual travel behavior such as trip generation, mode choice, vehicle ownership and travel time ([18],[19],[20]). Compared to the RVs, the implementation of AVs in the traffic networks can potentially change our mobility quality leading to different positive impacts on the traffic flow system [21]. These impacts result from its efficient driving and response behavior obtained by its improved operational characteristics and advanced connectivity capabilities. For example, the full implementation of AVs in traffic networks may increase road capacity, increase the efficiency of traffic control methods and improve traffic stability and safety ([6],[22],[23]).

Utilizing its characteristics and connectivity capabilities, the AVs could also have significant impacts on signalized intersection control's design and operational performance. As AVs have shorter perception and reaction times ([24],[25]), fewer speed variations, and smoother acceleration and deceleration rates [24], the time lost during the response of a vehicle to traffic signals can be reduced. Consequently, the required yellow change and red clearance intervals can be minimized. In fact, some studies showed that AVs have negligible reaction time delays as compared to RVs [12]. As AVs have improved following characteristics, including reduced headways and safe distances ([12],[25]), the road capacity and use of vehicle platooning at intersections can be increased [26]. Considering speed, AVs can maintain the desired design speeds, acceleration, and deceleration rates with low variations [27], which can serve to optimize the green phase durations of signal plans effectively. Different reports showed that the AV implementation in the traffic flow might harmonize and increase the mean speed in the traffic flow ([28],[12]) and decrease the speed variability ([10],[24]). AVs may also perform smarter and fewer lane-changing maneuvers in traffic, thereby improving the stability of the traffic flow

[12] as a result of fewer disturbances and less heterogeneity in the traffic leading to maximizing throughput in the traffic ([29],[11]).

1.2 Problem Statement

Traffic problems related to control, safety, and environmental issues are prevalent globally, especially in urban areas. These problems can be primarily attributed to the increased demand for vehicles [11], lack of road infrastructure, inefficient traffic control systems [30], and poor driving behavior [6]. The stochastic nature of the human driving behavior associated with the RVs is critical for determining traffic flow efficiency ([31],[32]). Examples of such behaviors include high fluctuations in terms of reaction time, desired speed, selected time headway, and safe distance in addition to their heterogeneous reactions to traffic disturbances, such as performing lane changes or applying sudden brakes ([32],[33]). Many psychological, environmental, and vehicle design factors influence human driving, such as driver perception and reaction time, driver age, and design speed. The interaction of these factors leads to significant variance in driving behavior and response to traffic control methods.

As indicated earlier, the development of the AVs in recent years has raised the prospect of improving the conventional control of vehicles. Although the full implementation of AVs may only occur after several decades, it is expected that traffic networks in the near future will involve various traffic compositions owing to the expected gradual implementation of AVs. By the year 2040, 75% of total vehicles would be AVs [34]. The 90% implementation rate of the CAVs would not occur before 2045 [35]. Therefore, in the coming transition period, road networks will be shared between RVs and AVs under different implementation rates, and this will lead to a mixed and dynamic traffic environment with two models of vehicles that maintain different driving behaviors and vehicle capabilities.

Although the main objective of AV implementation in traffic networks is to improve the comfort and safety of users, environmental benefits during their mobility, AVs role could be pivotal in improving traffic flow characteristics. The related literature indicates that many studies have investigated the impacts of the AV implementation on traffic flow systems. However, it appears that there are limited numbers of papers that reviewed these impacts on different related aspects. Most of the published papers focused on reviewing the impacts on traffic systems assuming a full AV environment. Also, the literature indicates that a large proportion of papers focused on the impacts of the partial automation level of AVs. However, it is expected that the implementation of different types of AVs, including full AV level, will occur gradually, and therefore, it will cause different impacts on the traffic system ([36],[23],[37]). None of the published reviews adequately focused on reviewing the impacts on the traffic flow characteristics under a mixed traffic environment with RVs.

To develop optimal policies for future development and achieve the effective implementation of AVs, it is essential to conduct reliable investigations considering various possible scenarios. The expected impacts of AV implementation may be influenced by the AV implementation rate, network-level, and AV characteristics [4]. The critical analysis of the literature indicates that there is an urgent need for further interpretations to overcome the limitations of the existing research on the expected impacts of AV implementation [38]. Considering the impacts of partial AV implementation, most studies have focused on highway networks and few studies have focused on urban network level. The quality of the traffic flow at signalized intersections may have significant impacts on the level of service across an entire traffic network. Evaluating these impacts on signalized intersection performance could provide valuable insights into the impacts of AVs on the traffic flow characteristics of urban traffic networks [2].

On the other hand, traffic management at intersections is a critical component of vehicular traffic systems that directly affect the quality of the entire urban traffic network. Due to complex traffic management, different researches have indicated that problems at signalized intersections are a major cause of traffic delays and accidents in urban networks, especially during rush hours [39]. For example, around 22% of traffic delays occur at signalized intersections [39]. The level of service (LOS) at signalized intersections can be controlled by different factors related to traffic volume ([40],[32]), traffic composition [9], traffic control design and operation [30], and driving behavior [41]. In addition to the human driving problems mentioned earlier, many studies have shown that the application of inefficient traffic control methods plays a critical role in different traffic problems mainly at signalized intersections ([42],[43]). The implementation of AVs is also expected to significantly impact the design and operation of signalized intersection control, which includes traffic signal control (TSC) [23]. Most of the significant positive impacts of AVs occur in a full AV traffic environment. As a result, different researchers have utilized these impacts in addition to the advanced connectivity capabilities of AVs for proposing autonomous-based TSC methods for full AV traffic ([44],[45]). However, the effective operation and control of mixed traffic of AVs and RVs are considered as a critical and complex challenge in AV development and implementation ([14],[16]). Considering both safety and acceptable LOS, the control of signalized intersections in the transition period to full AV traffic is a challenging task mainly in cases with high traffic demands [16]. The literature indicates that majority (almost 95%) of the proposed TSC methods consider full AV implementation, whereas few consider partial AV implementation [40]. A few researchers reviewed the proposed methods that considered the signalized intersection control under a mixed traffic environment ([46],[47]).

The real application of autonomous-based TSC methods cannot be employed without considering different limitations ([48],[37],[49]). Thus far, several studies have investigated the traffic signal optimization of adaptive-based TSC systems under RV-based traffic. These studies focused on solution quality with respect to the performance of the optimization method while considering different traffic flows and TSC information. The main assumption is that RVs maintain stochastic driving behavior for pure traffic involving only RVs. However, given the future implementation of AVs, the optimization problem should be designed for utilizing the deterministic and improved operational characteristics of the AVs and expected positive impacts of its implementation for improving optimization performance without compromising other control objectives [14]. The integration of this concept with signal optimization-based methods under mixed AV traffic has the potential to overcome the different limitations of autonomous-based TSC methods. Existing literature indicates that few studies have focused on the development of TSC methods that consider signal optimization under mixed AV traffic ([40],[48]).

1.3 Research Objectives

The motivation of this dissertation is focused on the development and realistic introduction of AVs in the near future. Basically, the research focuses on the investigation and effective utilization of the AV implementation impacts at signalized intersections under mixed traffic environment comprising RVs and AVs. Based on the different problems and research limitations discussed earlier, following are the main objectives aimed to be achieved from this research:

1. To conduct a comprehensive literature review to investigate the AV implementation impacts on the traffic flow characteristics under mixed AV traffic environment. It is also

aimed to provide a policy implication discussion on the interpretation of main obtained findings for the future actual practice and further research interests.

2. To investigate and analyze the impacts of AV implementation on the performance of an urban signalized intersection under mixed AV traffic environment through microscopic traffic simulations, considering different AV characteristics and gradual AV implementation rates, under different traffic volume conditions.
3. To conduct a comprehensive literature review of proposed methods for the signalized intersection control under mixed AV traffic environment. It is also aimed to discuss different limitations of the proposed methods and include a policy implication discussion intended to provide an alternative base solution of near future control of signalized intersection.
4. Based on the accomplished outcomes of the previous objectives, the research aimed to propose, develop and evaluate a novel machine-learning-based optimization framework for designing intelligent adaptive TSC systems under different conditions of mixed AV-based traffic.

1.4 Dissertation Organization

This dissertation is divided into six main chapters. The current section provides the organization of the remaining chapters of this dissertation. Chapter 2 presents a comprehensive literature review on the impacts of AVs implementation on traffic flow characteristics under mixed AV traffic environment. Chapter 2 also discusses the basic factors controlling the impacts of AVs and includes a policy implications discussion of the future perspectives. In Chapter 3, a simulation-based investigation study of the AV implementation impacts on the performance of signalized intersection is reported. It includes the details of the study methodology along with

detailed analysis of the obtained results. A comprehensive literature review on the signalized intersection control under mixed AV traffic environment is presented in Chapter 4. Limitations of the proposed methods of the signalized intersection control are discussed with supporting examples. This chapter includes the policy implications discussion of the future alternatives. Chapter 5 reports the different details of the proposed optimization framework. It describes the methodology of the framework, introduces the applied methods and discusses the different obtained results. Finally, Chapter 6 presents the main conclusions of this research and some recommendations.

CHAPTER 2

COMPREHENSIVE LITERATURE REVIEW ON IMPACTS OF AUTONOMOUS VEHICLES ON TRAFFIC FLOW CHARACTERISTICS UNDER MIXED TRAFFIC ENVIRONMENT

As mentioned earlier, there are different levels of vehicle automation range from partial automation to full automation level. Partial automation may help to improve human driving behavior by utilizing advanced driver-assistance systems (ADAS). The main rule of such systems is to improve driving comfort, reduce human driving errors, minimize the necessity for physical road signals and vehicle insurance and improve safety ([1],[50]). Most of these are based on adaptive cruise control (ACC) systems, which are available now in a wide range of the existing models of the RVs [51]. By automatically controlling the throttle or the brake, the ACC system can control the car following behavior, such as adjusting its speed and providing a specified distance, location and acceleration from the trajectory data by using on-board sensors ([1],[52],[29],[8]). These systems are considered partial (semi) automated vehicles that only offer autonomous longitudinal following control ([2],[5]). The cooperative adaptive cruise control (CACC) is an updated and improved driver assistance system built upon the ACC system. It uses more information collected from the advanced V2V communication technologies [38] to automatically adjust the longitudinal control depending on the behavior of its leading and following vehicles [53]. With both ACC and CACC systems, the drivers are still responsible for actively steering the vehicle, keeping lanes, and monitoring traffic conditions. However, unlike

ACC systems, CACC has direct communication with the vehicles ahead, using dedicated short-range communication (DSRC), which can enlarge the detection range of the distance sensors [9]. It can provide a range of 3000 ft in diameter with the possibility of an extended range using multiple transmitters [32]. As a result, compared to ACC, CACC can gather more information which enables more accurate and effective performance in faster manners ([54],[52],[8]).

The implementation of the AV will lead to different impacts on the traffic system. The adjusted characteristics of the AVs impact the traffic flow elements such as road capacity parameters and the components of the traffic stability. The road capacity is mainly affected by different factors such as traffic composition, road conditions, and driving behaviors of the vehicles. Traffic composition, including vehicle's type with their specific driving behavior and the implementation of each type, is a significant factor that may affect the capacity [9]. Capacity is highly dependent on the longitudinal time headways and the lateral movements of vehicles [24]. The traffic flow stability is also an important parameter that determines the efficiency of the traffic networks [28]. Traffic stability indicates maintaining the traffic capacity without a traffic breakdown incident. When traffic volume exceeds capacity, automobiles are compelled to perform cyclic acceleration-deceleration operations, resulting in unstable traffic flows influenced by the creation and spread of shockwaves ([33],[32]). One of the important factors in this regard is the speed and time gap distributions. With a smaller standard deviation, the flow will be more stable, and there will be fewer unexpected breakdowns. Traffic hysteresis and oscillations develop in the flow due to automobile lane-changing and car-following behavior [32]. Examples may include lane changes near merges and diverge section, lane drops, or changes of road geometrics.

Due to its improved operational characteristics, the implementation of the AV is expected to overcome the problems of stochastic human driving behavior and positively impact traffic flow efficiency. Several studies have investigated the possible impacts of AV implementation. Due to the lack of available observed traffic data, most of these studies focus on modeling and simulation. The literature indicates that limited numbers of papers that reviewed the impacts of AV implementation on different related aspects. In 2014, Hoogendoorn et al. reviewed the general impacts of AVs on traffic flow efficiency [10]. In 2020, Narayanan et al. reviewed the contributing factors affecting the impacts of AVs [5]. Most of the published papers focused on reviewing the impacts under full AV environment. None of the published reviews adequately focused on reviewing the impacts on the traffic flow characteristics under a mixed traffic environment with RVs.

To fill the critical research gap in the future development of AVs in urban networks, the main objective of the current chapter was to include and discuss a comprehensive review of the AV impacts on the traffic flow characteristics under partial AV implementation. The concepts of road capacity and traffic stability were considered to analyze the impacts of the AVs on the traffic flow characteristics. Unlike other reviews in the literature, this review discussed the impacts under different important aspects of the topic, such as different types of AVs representing different automation levels and connectivity capabilities and network types to enhance the analysis capacity for some meaningful findings. Based on the findings of the current review, a policy implication was included to significantly help the traffic community to maximize the benefits of AV implementation by developing effective policies for future traffic operation and control under a mixed traffic environment.

The sections of this chapter are organized as follows. Section 1 includes the research methodology of the review. Section 2 includes a brief discussion of the impacts of the full AV implementation. In section 3, a review of the partial AV implementation impacts is included considering different types of AVs. In section 4, the primary factors of the impacts of AVs implementation on mixed traffic environments are discussed in detail. Section 5 includes the policy implications discussion for the actual future practice and further research interests. Finally, section 6 includes a summary of the chapter.

2.1 Methodology

Despite covering an enormous body of literature, which is still growing, this study included a systematic review that aimed at finding the impacts of different types of AVs (e.g., ACC, CACC, AV, CAV) on the traffic capacity and stability under mixed traffic environment with the RVs (Figure 2-1). The planning part of this systematic review entails creating the study purpose and question, keywords, and a set of inclusion and exclusion criteria. Thus, 'autonomous vehicle', 'road capacity', 'traffic stability,' and 'mixed traffic environment' were selected to be the search keywords. The inclusion criteria were specified to peer-reviewed journal papers published in English and related to the research objective. However, this review has ignored the impacts of AVs on traffic safety, travel planning, including travel time and road choice, driver comfort, environmental issues, economic and social impacts. The impacts related to the application of the platooning concept or the use of dedicated AV lanes in the traffic network was not considered. The selected publications are mainly related to investigating the impacts of AVs on the traffic characteristics in mixed traffic environments sharing the same traffic network lanes with other different types of vehicles, including RVs. The search's first publishing date was not specified; however, April 2021 was chosen as the end date. Following limitations should be noted in this

review approach: (a) exclusion of non-peer-reviewed full-text papers that are freely available online, including conference proceedings, book chapters, and white papers, and (b) unintentional bias of the authors may influence how the review and findings are carried out and interpreted. The second phase entails the reviewing of pertinent articles. Throughout the extraction procedure, the complete contents of the publications were searched and read. At the beginning of this stage, according to differing levels of complexity, the AVs types are divided into three main categories. For each category, critical ideas about representative models are reviewed and explained. Furthermore, their impacts on the road capacity and traffic stability are critically reviewed along with their critical related factors. In general, the distinctions and links that connect traffic flow and AV driving behavior under a mixed traffic environment are extensively discussed in this research.

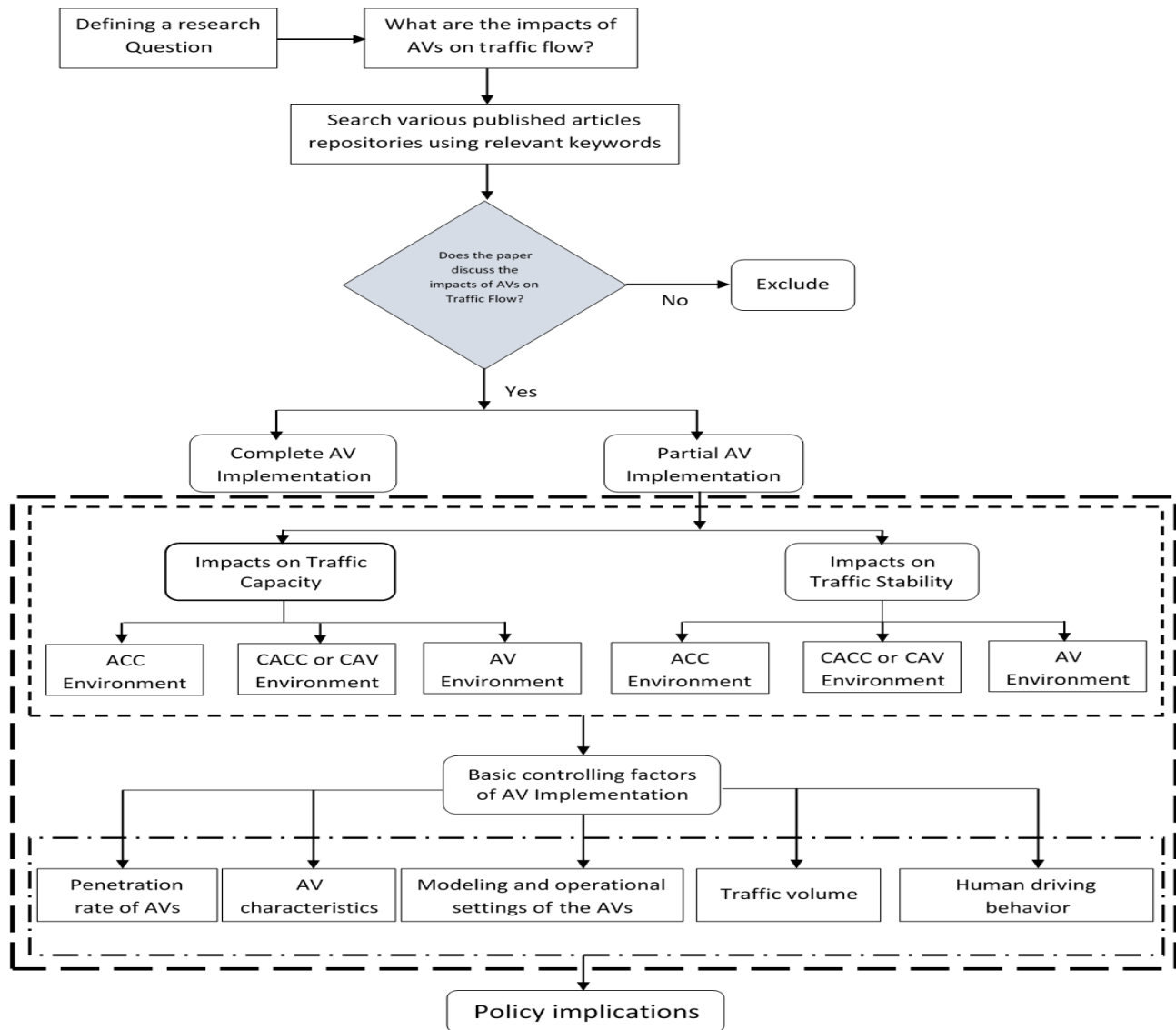


Figure 2-1 Methodology Flowchart

2.2 Impacts of the Full AV Implementation

Many related studies have been conducted to evaluate the impacts of full implementation of different types and models of AVs in traffic networks. In general, most of these studies have confirmed that the full implementation has positive impacts on the traffic flow characteristics mainly in terms of improved traffic capacity. For example, Van Arem et al. concluded that full

CACC implementation increase the traffic flow and capacity in highway system [55]. Tientrakool et al. concluded that compared to full RVs environment, full CACC environment in urban network increase the capacity by 273% [56]. However, full ACC environment increase the capacity by 43%. Shladover et al. concluded that the capacity of full CACC traffic is doubled compared to full RV environment [57]. Bohm and Häger concluded that when the traffic volume is high, the full AV (Level 3) traffic increase the capacity parameters compared to full environment of RVs [6]. The delay and number of stops decreased by 56 and 54% respectively while the speed increased with 34 %. However, in case of low volume, the full AV implementation did not showed any improvement, the delay increased by 1.3%, speed decreased by 0.38% and the number of stops increased by 2.9 %. B. Friedrich, using mathematical modeling, found that compared to full RVs, the capacity of full AV environment increased by 40% and 80% in urban network and highway respectively [58]. Liu et al., using improved symmetric two-lane cellular automaton (STCA) model, concluded that the capacity with full AVs increase from 2000 veh/h at 0% implementation rate of AVs to 3070 veh/h [12]. Mena-Oreja et al. also confirmed that based on the proper selection of the maximum platoon length and a desired gap, the traffic flow of the full CACC may increase by almost 39% compared to full RVs traffic [59]. Abdulsattar et al. concluded that full CAV environment may lead to improved capacity by 250% compared to RVs traffic in multi- lane highway systems [32]. In contrast to the above findings, Lu et al. contradicted the significant improved capacity of the full CAV implementation [11].

2.3 Impacts of the Partial AV Implementation

Different studies in the literature have investigated the possible impacts of partial implementation of AVs on traffic flow characteristics under a mixed traffic environment. This

literature included all of the related published studies during the period from 2003 up to April 2021. Tables 2-1, 2-2, and 2-3 summarized the main findings of these studies, respectfully, for the three categories: ACC environment, CACC and CAV environment, and AV environment, respectively. The variables of each study, including AV's type, network type, and the study type, are included. The following parts of this section will discuss these findings concerning the two main traffic characteristics: traffic capacity and stability for each AV type. The next section will include an extended discussion about the primary factors of the impacts of AVs implementation on a mixed traffic environment.

Table 2-1 Review of the Studies Related to the Impacts of ACC on the Traffic Flow Characteristics

Study [Reference No.]	Study variables			Main findings
	AV's type	Network type	Study type	
Bose et al., 2003 [29]	ACC	Highway	Macroscopic analysis	• ACC improved the stability and increased the flow
Kesting et al., 2010 [60]	ACC	Multi-lane highway	Simulation	• Flow increased by 3% per 10% increase of the implementation rate of ACC. • Outflow increased by 2.4% per 10% increase of the rate of ACC • Low rates of ACC (25%) can decrease congestions
Jerath and Brennan, 2012 [61]	ACC	Closed ring road	Meso-simulations	• Low rates of ACC increased the capacity • Capacity and flow increased as ACC rate increased • Increased rate of RVs caused high susceptibility of congestions
Ntousakis et al., 2015 [62]	ACC	Single lane and ring roads	Simulation	• With time gaps less than 1.1 seconds, capacity rose linearly with increasing ACC rate; however, with time gaps greater than 1.5 seconds, capacity declined as rates climbed • Higher rates of ACC led to more improved stability
Calvert et al., 2017 [24]	ACC	Multi-lane road	Simulation (Considered lane changing)	• ACC had negative impacts on the flow and capacity • The positive impacts were found at rates above 70% • Capacity drop was slightly higher with the ACC implementation and was increasing as the rate increasing • Decreased lane changes did not show significant impacts
Li et al., 2017 [63]	ACC	Multi-lane highway	Micro-simulation	• ACC performance was highly affected by the parameter settings. Inappropriate settings increased the collision risks and caused traffic disturbances • Optimal settings are expected to be different for different traffic conditions • Higher time gaps and deceleration rates improved stability and safety; but it decreased capacity

Kerner, 2020 [64]	ACC	Highway	Review	- Classical ACC increased the speed disturbance due to long time headway, however, the dynamic rules of modified ACC types decreased it and therefore that improved the flow - The likelihood of a traffic breakdown is determined by the ACC's dynamic parameters.
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Table 2-2 Review of the Studies Related to the Impacts CACC and CAV on the Traffic Flow Characteristics

Study [Reference No.]	Study variables			Main findings
	AV's type	Network type	Study type	
VanderWerf et al., 2004 [65]	CACC	Multi-lane highway	Simulation	- Partial CACC implementation increased the flow from 2,100 (with 100% RVs traffic) to 2,900 (with 20% RVs, 20% ACC, 60% CACC traffic) - A critical time gap of 1.4 sec was found is the limit between the deterioration and improvement
Van Arem et al., 2006 [55]	CACC	Highway	Simulation	- At low traffic volumes, no significant impacts of different rates of CACC - At high traffic volumes, increased CACC rates improved stability, increased throughput and speed, and decreased shockwave impacts - With rates less than 40%, the impacts was minimal
Schakel et al., 2010 [66]	CACC	Single lane highway	Simulation	- Increased headway variability, due to the mixed traffic, had minor impacts on the stability - CACC quickly damped shockwaves at low rates (50%) and that improved more with higher rates
Tientrakool et al., 2011 [56]	CACC	Urban signalized intersection	Capacity analysis	- Compared to full RVs, full ACC increased the capacity by 43%, while full CACC increased it by 273% - Capacity increased slightly until the CACC rate exceeded 85%
Shladover et al., 2012 [57]	CACC,ACC	Single lane highway	Micro-simulation	- ACC did not show improvement on the capacity, however, CACC significantly increased the capacity mainly with higher rates - Increased rates of CACC had significant impacts on traffic flow, but,

the rate of ACC had small impacts				
Jones and Philips, 2013 [54]	CACC		Review	The positive impacts of CACC on the stability and throughput were only found with CACC rates of more than 40%
Zhao and Sun, 2013 [52]	CACC,ACC	Three lane highway	Micro-simulation	- Platoon size had small impacts on the capacity - Capacity was increasing as the rate of CACC increasing
Arnaout and Arnaout, 2014 [67]	CACC	Four-lane highway	Simulation	- CACC implementation increased the capacity and improved the stability - At low traffic volume, no significant impacts of different implementations rates - At high traffic volume, increased CACC rates led to a significant increase of the flow. - Rates of less than 40% had small impacts
Milanes et al., 2014 [68]	CACC,ACC	Urban road	Field testing	CACC increased the capacity and improved the stability
Le Vine et al., 2015 [69]	CAV	Signalized intersection	Micro-simulation	CAVs with more smooth acceleration/deceleration profile had negative impacts on capacity
Nikolos et al., 2015 [62]	CACC,ACC	Highway	Numerical simulation	- Compared to ACC, CACC improved the stability - CACC increased the capacity and improved traffic dynamics mainly at on-ramp bottlenecks
Talebpour and Mahmassani, 2016 [29]	CAV,AV	Single lane highway	Micro-simulation	- CAV enabled more reliable driving experience than AV - CAV with shorter headway increased the capacity and improved stability even at low rates - CAV with longer headway decreased the capacity and increased delays, however, it improved the stability
Bailey and Kroll, 2016 [2]	CACC,ACC,AV	Urban signalized intersection	Simulation	- Different behavioral models and parameters of AVs had different impacts on traffic flow - AVs implementation rate had similar impacts in urban network and

		n		highways
				Capacity and flow were increasing and delay was decreasing as AV rate was increasing
Zhou et al., 2016 [5]	CAV	Highway	Simulation	- CAV with longer time gaps improved stability and safety; however it decreased the capacity - The level of the impacts was increasing with the increase in the rate of CAV
Ye and Yamamoto, 2018 [9]	CAV	Multi-lane highway	Simulation (Considered lane changing)	- CAV's capability to maintain shorter headways was negligible at lower rates - Capacity increased with an increase of CAV rate and that was more significant with rates of higher than 30% - Higher time gaps improved the stability and safety; however it decreased the capacity
Ye et al., 2018 [50]	CAV	Multi-lane highway	Simulation (Considered lane changing)	- As the rate of CAV increased, traffic flow became smoother owing to a reduction in excessive deceleration rates - When rates of CAV is between 40 and 50%, the proportion of stop-and-go traffic was decreased
Mena-Oreja et al., 2019 [59]	CACC	Multi-lanes road	Micro-simulation (Considered platooning)	- Compared to full RVs traffic, full CACC traffic, with maximum platoon length of 2 vehicles and desired gaps of 10, 5, 1m, increased the flow by 9.39, 26.09 and 39.21% respectively - With rates of less than 20%, capacity and flow decreased, however, with higher rates, capacity and flow increased - Desired gaps and maximum platoon length were important factors of the capacity improvement
Makridis Michail et al., 2018 [70]	AV, ACC,CAV	Ring road	Simulation (Considered lane - changing)	- The average speed decreased, while density and congestion increased with increased rates of AVs - With high traffic volume scenarios, high rates of CAVs lead to increased capacity, smoother lane changes, maintained high speed and improved stability, however, low rates showed small negative impacts - With low traffic volume scenarios, compared to RV traffic, the CAVs implementation showed negative impacts even with higher rates
Lu et al., 2020 [11]	CAV	Urban network	Micro-simulation	Capacity, stability, and flow were improving with the increase of CAVs rate

				Flow significantly increased with 50% CAVs rate
F. Zheng et al., 2019 [33]	CAV	Single lane circular road	Simulation	- Portion of stop-and-go traffic decreased and led to improved stability with the increasing rate of CAVs - Rates from 10% to 50% showed similar performance - CAVs distribution did not show significant impacts
Zhou et al., 2020 [71]	ACC,CAC C	Multi-lane highway	Numerical simulation (Considered lane changing)	- Increase of CACC rate significantly decreased traffic congestions and improved the capacity and stability - ACC implementation did not show any improvement on the stability
Fakhrmoosavi et al., 2020 [51]	CV,AV, CAV	Network level	Meso-simulation	CVs and AVs, mainly with higher rates, led to significant improvement in traffic flow, capacity, however, AVs were more significant than CVs
Abdulsattar et al., 2020 [32]	CAV	Multi-lane highway	Simulation (Considered lane changing)	- CAV significantly increased the capacity with high rates (50% and above), however, lower rates (less than 40%) did not show improvement - The capacity in the free flow were directly proportional with rate of CAV
Zhong et al., 2020 [72]	CAV	Multi-lane highway	Micro-simulation (Considered lane changing)	Average lane change of RVs increased till 30% rate of CAVs is reached. After that, it decreased as CAVs rate increased
Jin et al., 2020 [41]	CAV	A single-lane ring road	Numerical simulations	- Stability was related to driver's reaction delay, rate of CAV, and the information obtained by CAVs - CAVs implementation increased the traffic flow - Driver's reaction delay decreased the stability - As the rate of the CAVs increased, stability improved and the propagation of lead vehicle disturbance gradually disappeared

Table 2-3 Review of the Studies Related to the Impacts AVs on the Traffic Flow Characteristics

Study [Reference No.]	Study variables		Study type	Main findings
	AV's type	Network type		
Hoogendoorn et al., 2014 [10]	AV	Highway level	Review	• AV implementation had positive impacts on the capacity and stability • Congestion delay decreased by 30%, 60% with 10%, 50% rates of AVs, respectively. • Impact of AVs were highly affected by the time headway and speed choice
Bohm and Häger, 2015 [6]	Full AV (level 3)	Urban network	Simulation	• With high traffic volume scenarios, full AV traffic increased the capacity, decreased delay and number of stops by 56% and 54% and increased speed by 34 % • With low volumes scenarios, full AV traffic increased the delay by 1.3%, decreased speed by 0.38% and increased number of stops by 2.9 %
B. Friedrich, 2016 [58]	AV	Highway and signalized intersection	Mathematical Modeling	• Capacity increased as the rate of AVs increased • A single RV in the lane decreased the speeds and therefore decreased the capacity improvement
Peter Wagner, 2016 [58]	AV	Different network levels	Macro-simulation	• At high volume scenarios, the capacity of traffic signal was doubled, however, at low volumes no improvement was found
Liu et al., 2017 [12]	AV	Multi-lane highway	Meso-simulation (Considered lane changing)	• AVs significantly improved the capacity, stability, and free-flow speed mainly with high rates • Car following maneuvers contributed more to the improvement than the smarter lane-changing • Different lane changing rules had little impacts • Implementation rate of 50% was the optimal rate of lowering congestion level
Chen et al., 2017 [73]	AV	Multi-lane highway	Theoretical framework	• Strict segregation of AVs and RVs decreased the capacity, however, mixed-use policies increased it
Elvarsson, 2017 [74]	AV	Urban network	Simulation	• Slow improvement of network performance was observed until 40% AV rate, however, after 60% rate the performance degraded

Stern et al., 2018 [75]	AV	Single-lane circular road	Field experiment	• AV improved the stability • A single AV significantly decreased the stop-and-go waves that were produced by 20 RVs around it • A 5% rate of AVs led to significant positive impacts on stability
Y. Zheng et al., 2020 [27]	AV	Single lane ring road	Control-theoretic study	• AVs significantly suppressed the unstable waves and led to smoother flow • Speed increased by more than 6% with 5% rate of AV
F. Zheng et al., 2020 [28]	AV	Single lane highway	Numerical experiment	• AV improved the stability and decreased the uncertainty of the RV behavior • Uncertainty of RVs was lower in congested conditions compared to free flow • The improvement was more significant with high rates of AVs (50%) • Reaction time and position of AVs showed negligible impacts

2.3.1 Traffic Capacity

This sub-section will include a discussion of the findings related to the impacts of AVs implementation on the traffic capacity and its components for each AV type. Based on the literature, different researches have showed that the implementation of different levels and types of AVs in the network may have significant impacts on the improvement of the traffic capacity. The following parts will include a detailed literature with respect to each type.

A. ACC Environment

Some studies have showed that the implementation of ACC may have significant impacts on the traffic capacity. For example, using Enhanced Intelligent Driver Model (EIDM), Kesting et al. concluded that the ACC may increase traffic flow and recovery from traffic breakdowns mainly at higher implementation rates [60]. The maximum flow was increased by 0.3% per 1% increase in the implementation rate of ACC and the outflow from traffic jams was increased 0.24% per 1% increase in the implementation rate of ACC. Even low implementation rates of ACC (25%) can decrease traffic congestions. Jerath and Brennan, using a general motors' car-following model, concluded that the ACC may increase the traffic capacity even with lower implementation rates [61]. The capacity and traffic flow increase mainly with increases in ACC implementation rates. Ntousakis et al., using different time-gap settings and different network levels, concluded that smaller time gaps increased the capacity linearly with the implementation rate [62]. In contrast to the above positive impacts Shladover et al., using realistic headway choices, concluded that ACC did not significantly increase the capacity of single lane highway [57]. Calvert et al. confirmed that ACC with less than 70% implementation rates has little negative impact on traffic capacity [24]. The capacity drop is slightly increased with the increase

in the ACC rate. Li et al., using modified IDM, indicated that ACC may reduce the capacity as a result of higher time gaps and deceleration rates [63].

B. CACC or CAV Environment

Some studies have showed that the implementation of CACC or CAV may have significant impacts on traffic capacity. Different studies indicated the capacity improvement due to CACC implementation mainly with higher rates ([57],[52],[67]). Milanese et al., based on field testing, confirmed that CACC can increase the capacity of urban network due to the reduced inter-vehicular gaps [68]. Nikolos et al. concluded that CACC increase the capacity and traffic dynamics mainly at on-ramp bottlenecks [62]. Talebpour and Mahmassani concluded that CAV with shorter headways can increase the flow and capacity mainly with increase in the implementation rate [29]. This improvement was significant even with low implementation rates. Makridis Michail et al. concluded that the positive impacts of the CAV may be observed only at high traffic volume scenarios and it is clearly observed with higher implementation rates [70]. The improved characteristics of the CAV, such as the reduction of the time headways, gaps and reaction times, lead to improved capacity. However, for the scenarios of low traffic volume, CAV did not perform well compare to the RVs even with higher implementation rates. They justified that by the CAV's inability to overcome the speed limits. Lu et al. and Zhou et al. also confirmed that CAV implementation increase the capacity ([11],[71]). Abdulsattar et al. also confirmed these findings mainly with high implementation rates due to short following distance between two consecutive CAVs [32]. In contrast to the above positive impacts, Zhou et al. [5] and Ye and Yamamoto [9] concluded that CAV implementation with long desired time gaps may decrease the capacity. Both Mena-Oreja et al. and Makridis Michail et al. concluded that when the implementation rate of CACC is less than 20%, the capacity and the flow decreased as

resulted by high number of aborted maneuvers due to the obstruction caused by RVs ([59],[70]). However, when the rate of CACC is more than 20%, the capacity and flow increased which is concluded by previous studies.

C. AV Environment

As mentioned before, the term autonomous vehicle may be referred the full automated vehicle, with Level 5 automation, without connectivity capabilities or as in some studies it may referred to any type of autonomous vehicle. Some studies have showed that the implementation of the AV may have significant impacts on traffic capacity. For example, the review made by Hoogendoorn et al. indicated that AVs implementation has positive impacts on the traffic capacity [10]. B. Friedrich [58] concluded that the capacity and flow are increasing as the implementation rate of AVs increasing. Using different behavioral models of AVs, Bailey and Kroll also confirmed these findings and concluded that the flow of the AVs increase and delay decrease as AVs implementation rate is increase [2]. Liu et al. also confirmed that the implementation of AV may significantly increase the capacity of the highway [12]. Fakhrrmoosavi et al. concluded that CVs and AVs may significantly increase the intersection capacity [38].

2.3.2 Traffic Stability

This sub-section will include a discussion of the findings related to the impacts of AVs implementation on the traffic stability and it's components for each AV type. Examples of these components may include: throughput (flow), speed, and shockwave formation and propagation, traffic congestion. Based on the literature, some studies in the literature have tried to discuss the

possible impacts of partial implementation of AVs on traffic stability considering different levels and types of AVs. The following parts will include a detailed literature with respect to each type.

A. ACC Environment

Some studies have showed that the implementation of ACC may have significant impacts on the traffic stability. For example, Bose et al. [29] and Kesting et al. [60] concluded that ACC may improve the stability in highway system. Ntousakis et al. concluded that higher implementation of ACC may improve traffic stability by reducing the intensity of congestion waves [62]. Li et al. concluded that ACC with longer time gaps and higher deceleration rates may improve stability of highway [63]. In contrast to the above positive impacts, Zhou et al. concluded that the implementation of ACC in highway deteriorate the stability of the traffic flow [71]. Kerner concluded that the classical ACC model may cause speed disturbance due to the long headway and therefore deteriorate the stability by initiating traffic breakdowns [64]. However, the improved ACC models may decrease these disturbances and therefore either does not have negative impacts or improve the stability.

B. CACC or CAV Environment

Some studies have showed that the implementation of CACC or CAV may have significant impacts on the traffic stability. For example, Van Arem et al., using good vehicle dynamics and driver behavior models, concluded that higher implementation rates of CACC in high traffic volume scenarios may significantly improve traffic stability, increase flow, reduce shockwave impacts and increase the average speed [55]. Schakel et al., using IDM+ car-following model, concluded that CACC can improve the traffic stability by the fast damp of the shockwaves even with low implementation rates [66]. The simulation results of Arnaout and Arnaout, Milanés et

al. and Nikolos et al. confirmed the improved stability due to CACC implementation ([67],[68],[62]). Zhou et al. [5] also confirmed that CAV with application of long desired time gaps may decrease speed dispersion, improve traffic stability and safety. Also, Talebpour and Mahmassani and Ye et al. concluded that CAV implementation may improve the stability by the reduction of shockwave impacts ([29],[50]). Makridis Michail et al. concluded that CAVs had a positive impacts on traffic stability in high traffic volume scenarios and that is improving with the increase in the implementation rates due to smoother lane changes and the maintained high speed of the CAV [70]. F. Zheng et al., using stochastic lagrangian model, concluded that CAVs can improve the stability of the traffic flow by reduction of the stop and go waves [33]. Lu et al. confirmed that CAV implementation improve the stability and increase the flow mainly with the increase of CAVs implementation [11]. Zhou et al. concluded that the increase of CACC implementation may significantly decrease traffic congestions and improve traffic stability [71]. Jin et al. confirmed that CAV implementation may increase traffic flow; however, they highlighted the importance of the proper consideration of the information from vehicles ahead of CAV [41]. In contrast to the above findings, Makridis Michail et al. concluded that low implementation rates of CAVs may leads to little negative impacts on the traffic stability [70].

C. AV Environment

Some studies have showed that the implementation of AV may have significant impacts on the traffic stability. For example, the review made by Hoogendoorn et al. indicated that AVs implementation has positive impacts on the traffic stability [10]. Congestion delay can be decreased by 30% and 60% with 10%, 50% implementation rates of AVs, respectively, due to their increased throughput in traffic flow. Liu et al. confirmed that AVs may improve traffic stability and increase free-flow speed of the highway mainly with higher implementation rates

due to smart maneuvers of AVs [12]. Stern et al. confirmed that the AV implementation, even with lower implementation rates, may improve the stability by decreasing stop-and-go waves in the traffic. A single AV can substantially decrease those waves that produced by 20 RVs around it in a circular road [75]. Y. Zheng et al. concluded that AVs can suppress unstable traffic waves and increase the speed of the flow. The speed increased by more than 6% when there are only 5% AVs [27]. F. Zheng et al. also confirmed that AVs can improve the stability by decreasing speed variations in the traffic flow [28]. This improvement is more significant with higher implementation rates of AVs. Fakharmoosavi et al. concluded that the implementation of CVs and AVs leads to significant improvements in traffic flow and faster recovery [51]. In contrast to the above findings, Makridis Michail et al. concluded that low implementation rate of AV may have a negative impacts on the traffic stability [70]. The average speed decreased while density and congestion increased with increased implementation rates of AVs.

2.4 Basic Factors Controlling Impacts of AVs Implementation in Mixed Traffic Environment

In general, the obtained results of the different studies are somehow controversial due to differences in their study type's , tested AV's type including their modeling and settings, network level, traffic composition, traffic conditions and driver behavior. The relationship between the implementation of the AVs and its impacts on mixed traffic environment of AVs and RVs is complex and is based on different factors. Some of the studies discussed the importance of some examples of those factors. Impacts of AVs on traffic stability are influenced by implementation rate, connection, platoon size, safe and desired gap, and driver behavior [33]. According to Jin et al., the stability of mixed traffic is dependent on the reaction time of drivers, the implementation rate of CAVs, and the information that CAVs may collect [41]. Narayanan

et al. mentioned that there are 19 related factors including acceleration and deceleration profiles, lane changing rule, longitudinal driving behavior, presence of connectivity between AVs, desired gap, network level, vehicle distribution in the network, implemented optimization function, the use of dedicated lanes for CAVs and AVs, intersection control method, platoon size and presence of variable speed limits (VSL) [5]. On the other hand, F. Zheng et al. concluded that the reaction time and the position of AVs are not considered as significant factors in terms of the AVs impacts on the traffic stability [28]. F. Zheng et al. concluded that there are no significant impacts of CAV's distribution on the traffic stability [33].

In general, this review has indicated that those discussed expected impacts of different types of AV in mixed traffic environment are depending on some basic factors that may affect the level and the magnitude of their impacts. These main factors basically may include:

- Implementation rate of the AVs
- AV characteristics
- Modeling and operational settings of the AVs
- Traffic volume
- Human driving behavior in mixed traffic environment

All of these factors differ in their significant effects on the traffic flow impacts. Those factors, including their effects with supporting examples; will be discussed separately in details in the following parts of this section. In addition to those, there are some other factors such as, the application of the platooning concept and the use of dedicated lane for the AVs. However, their related studies were not included since that it is not part of the main focus of this review as mentioned earlier.

2.4.1 Implementation Rate of the AVs

Most of the studies have investigated the expected impacts of different types of AVs on the mixed traffic environment using different implementation rates. For example, Van Arem et al. confirmed that the implementation rate of CACC is only critical with high traffic volumes scenarios and found that the critical rate that starts to indicate significant impacts is above 40%. With low traffic volumes, there were no significant impacts of different implementation rates [55]. Schakel et al. concluded that when the implementation rate increased, the duration of the shockwaves decreased leading to improved stability [66]. Kesting et al. concluded that with increasing rates of ACC in highway, the flow and the outflow from traffic breakdowns is increasing [60]. Tientrakool et al. concluded that the capacity increased slightly until CACC implementation rate exceeded 85% [56]. Jerath and Brennan concluded that low rates of ACC may lead to increase the congestion level [61]. Shladover et al. concluded that higher implementation rates of CACC is required in order to have significant positive impacts on the traffic flow [57]. Jones and Philips concluded that the positive impacts on the stability and flow will be noticed only when the implementation rate of CACC is above 40% [54]. Zhao and Sun [52] and B. Friedrich [58] concluded that the capacity increases as implementation rate of AV increases. Arnaout and Arnaout confirmed that there were no significant impacts of different implementations rates at low volume traffic scenarios [67]. With high volume traffic scenarios, with implementation rates of less than 40%, their impacts were minimal, however, when it is more than 40%, the increase in CACC implementation rates lead to a significant increase in traffic flow. Ntousakis et al. also confirmed that higher implementation of ACC led to improved stability [62]. Zhou et al. [5] also concluded that the traffic flow is increasing with the increase in the implementation rate of CAVs. In addition, Talebpour and Mahmassani confirmed that higher

implementation rates of CAVs can increase the flow and capacity of the traffic network [29]. On the other hand, Calvert et al. concluded that the critical implementation rate of ACC that may start to indicated an improvement in traffic flow is above 70% [24]. Liu et al. concluded that that the increase of AV implementation rate improves the capacity, traffic stability, and free-flow speed [12]. The implementation rate of 50% is optimal in terms of lowering congestion level. Ye and Yamamoto concluded that with the use of proper time gap, capacity increases with an increase in CAV implementation rate and it is more significant with rates of higher than 30% [9]. Mena-Oreja et al. concluded that when the implementation rate of CACC is of less than 20%, CACC had a negative impacts on the traffic, however, when the rates is more than 20%, it leads to an improvement [59]. Stern et al. concluded that even low implementation rates of AVs, such as 5%, may lead to positive impacts on traffic stability [75]. Makridis Michail et al. concluded that compared to the RVs, AV has negative impacts even at low implementation rates, however, higher rates mainly in high volume traffic have showed some improvement [70]. Zhou et al. concluded that the improvement of traffic capacity and stability is increasing with the increase in the implementation rate of CACC [71]. Lu et al. also confirmed that the implementation rate of AVs in mixed traffic may highly impacts the capacity, stability, and flow [11]. The capacity increase is more intensive with 50% CAVs implementation. F. Zheng et al., using stochastic lagrangian model, concluded that the stop-and-go traffic was decreased and the stability improved with an increasing implementation rate of CAVs [33]. However, the implementation rates 10% to 50% showed similar performance. Fakhmoosavi et al. also confirmed that higher implementation rates of CVs and AVs may result in slightly higher flow, and improved stability [38]. F. Zheng et al. concluded that the improvement of the traffic stability is more significant with high implementation rates of AVs (50%) [28]. Abdulsattar et

al. concluded that the capacity in the free flow phase is directly proportional with implementation rate of CAVs [32]. In congested flow, rates of less than 40% did not show improvement on the capacity. The critical rate in terms of capacity improvement was found to be 50%. Jin et al. found that when the implementation rate of CAVs grows, stability improves and lead vehicle disturbance propagation fades away [41]. Many studies confirmed that the implementation rate of AV is highly an important factor that significantly affects the level of their impacts. Some of these studies have indicated that implementation rate is critical factor only with high traffic volumes conditions. Most of the studies have confirmed that increasing rate of AV in the traffic leads to more significant improvement of the different flow characteristics. However, few studies have indicated that with low implementation rates, there is no expected significant improvement or even it may worsen the traffic conditions.

2.4.2 AV Characteristics

In general, the automated driving can refer to a wide range of different operational levels of AVs [2], which differ in their driving capabilities, ranging from zero automation to full driving automation. In addition, there are different types of the AVs in terms of their connectivity capabilities. Different studies have used different levels or types of AVs. The literature has indicated that one of the important factors that may highly affects the level of expected impacts of AV implementation in a mixed traffic environment is the characteristics of the implemented AV. As indicated earlier, these different types of AVs may behave differently in the traffic flow due to their specific operational characteristics and therefore, their impacts may vary mainly in case if mixed traffic environment. The studies have confirmed that through different obtained conclusions about their expected impacts.

The literature has somehow compared the characteristics of these different types of AVs. For example, the performance of ACC systems is depending only on the behavior of the leading vehicle. In terms of CACC or CAV performance, they have advanced communication capabilities that gather and utilize more information of the vehicles ahead or in further downstream in order to automatically control the longitudinal following behavior based on the behavior of its leading and following vehicles. In terms of AV performance, unconnected AV's conservative conduct and inability to forecast nearby automobile's movements are the reasons for their potential decreased capacity to produce favorable traffic flow impacts [5].

Some studies have directly compared the expected impacts of these different types of AV under mixed traffic environment. For example, Tientrakool et al. concluded that compared to full ACC traffic, full CACC traffic showed much improved capacity [56]. Shladover et al. found that ACC did not show a significant capacity improvement; however, CACC significantly improved the capacity [57]. In terms of traffic stability impacts, Nikolos et al. concluded that CACC implementation improve the stability of traffic flow compared to ACC [62]. Due to the ability to overcome sensor constraints, CAVs can provide a smoother and more dependable driving experience than AVs [29]. They highlighted that AVs and CAVs should be treated differently in micro simulations. Zhou et al. concluded that CACC improve the traffic stability while ACC cause instability of the traffic flow [71]. Fakhrmoosavi et al. concluded that AVs are more significant than CVs in terms of improvement of the traffic flow and stability in urban network [51].

In general, it may be concluded that the implementation of CACC or CAV is better than the non-connected AV or ACC in terms of improvement of traffic capacity and stability. However, there are some factors that may affect their effective positive impacts including their implementation

rate and their distribution and position in the traffic flow in addition to the type and the characteristics of the leading vehicle. The literature has showed that if the preceding vehicle of the connected vehicle is non-connected, it may not be able to offer such positive impacts in the traffic flow. For example, the desired time headway may not be assumed as a fixed number if the AVs are following RV. Moreover, CAV may allow closer vehicle following mainly when following another CAV, but if it is following a RV or non-connected AV, it may behave similarly to these vehicles [8]. According to Makridis Michail et al., CAVs that follow AVs or RVs react as AVs, since they do not have any information from other vehicles to make use of their connectivity capabilities [70]. This is actually somehow related to the importance of CAV implementation rate since that with low rates, the probability of connected platoon formation of CAV is lower than the probability of a CAV following RV or an AV [70]. This fact may justify the insignificant impacts of low implementation rates of CAVs in mixed traffic environment due to their required longer headways. However, the lower reaction times of connected vehicle may be achievable due to their radar detection systems [32].

On the other hand, the literature did not include clear definition for these different types of AVs. It was noticed that there are some studies that assumed that AVs are connected to other vehicles and have real-time information through V-I. For example, Talebpour and Mahmassani stated that the automation and connectivity are sometimes used interchangeably by different studies [29]. It should be noted that some of the studies did not even discuss or specify the exact characteristics of the AV and they just named it as AVs. However, in order to have reliable and logical comparable results with other studies in terms of evaluating the impacts of AVs, it is important to include a clear description of AVs and RVs characteristics including their selected driving models, operational settings and their connectivity capabilities with other objects in the traffic

flow and other needed assumptions for modeling the AVs. In current literature, we have tried our best, with available information in the studies, to specify the type of the used AVs within each study in order to have clear conclusions about their impacts.

2.4.3 Modeling and Operational Settings of the AVs

The other important factor is related to the selection of the driving models and the operational settings of the AVs. Those represent the basic characteristics of each AV type. Bailey and Kroll confirmed that the different behavioral models and parameters of the AVs may have different significant impacts on traffic flow [2].

A. Modeling of AVs

Several driving models have been proposed in the literature for modeling different types of AVs for the simulation works. Examples may include: Intelligent Driver Model (IDM), Cooperative IDM, Gipps driver model and different acceleration frameworks. For more information in this regard, in 2015, Ntousakis et al. conducted an extended review on the existing microscopic modeling of ACC [62], while Gora et al. in 2020 conducted a review on the microscopic simulation models for CAV [76]. In general, the specific driving models of AVs may involve two main groups: car following and lane changing models. The literature has indicated that the selection of the car following models is more critical than the lane changing models. For example, Liu et al. concluded that the car following maneuvers of the AVs contributes more to the improvement than the lane changing [12]. Lane changing in traffic flow usually leads to longer time headways in the origin and destination lanes. The vehicle requires a sufficient gap in the destination lane in addition to leaving a gap in origin lane. As a result, more lane changes could lead to negative impacts on the capacity. In terms of lane changing modeling of AVs, few

studies have investigated the impacts of the lane changing behavior in mixed traffic environment. Generally speaking, some of these studies have stated that the adjusted lane changing behavior may cause some impacts on the traffic flow. For example, Makridis Michail et al. concluded that smoother lane changes of AV can improve the capacity and stability [70]. In contrast, Liu et al. concluded that the use of different lane changing rules of AVs had small impacts on the traffic flow [12]. Calvert et al. concluded that the impacts of lane changing modeling of ACC, such as fewer lane changes, does not show significant impacts and they stated that their expected impacts may only be claimed in theory [24]. Next part of this sub-section section will focus and discuss the importance of the selection of the operational settings of the car following models.

B. Operational Settings of the AVs

Each type of the AVs has a special adjusted operational settings that controls it's driving behavior and therefore differently affects it's expected impacts on the traffic flow characteristics. In general, the literature has highly confirmed that the selection of the operational settings of car following models of AV is an important factor. For example, Hoogendoorn et al. concluded that the expected impacts of AVs is highly affected by the time headway and speed choice [10]. Li et al. also confirmed that ACC performance is highly affected by the parameter settings [63]. Inappropriate parameter settings may increase the collision risks and therefore cause traffic instability. However, the optimal parameters are expected to be different for different traffic conditions. Mena-Oreja et al. confirmed that the settings of the safe and desired gap and maximum platoon length are important factors for the expected capacity improvement due to CACC implementation [59]. Kerner concluded that the possibility of traffic instability is highly depending on the dynamic parameters of ACC [64]. Main examples of the critical car following

settings in terms of traffic flow impacts may include: time and space headways, acceleration and deceleration rates, speed and reaction time.

Let's discuss the impacts of the setting of the time and space headways (or gaps) of AVs on the traffic characteristics. Different studies have indicated that the most important settings of AV are the settings of headway parameters. For example, VanderWerf et al. concluded that a critical time gap of 1.4 sec is the limit between the deterioration and the improvement of the traffic flow, however, that is valid only for when the implementation rate of CACC is higher than 60% [65]. Ntousakis et al. tested different time gap settings and concluded that the capacity improvement of mixed traffic of ACC and RV is highly depending on these settings [62]. With time gaps of less than 1.1 sec, the capacity increased linearly with the increase in the implementation rate of ACC; however, with time gaps of 1.5 seconds or more, it decreased even when ACC implementation rate increased. Talebpour and Mahmassani also confirmed that CAVs with shorter headway can increase the throughput and capacity mainly with higher implementation rates [29]. In contrast, the increased time headway may have some negative impacts such as reduced capacity and increased delays; however, it may improve the traffic stability ([29],[63],[9]). Calvert et al. also confirmed that with the partial implementation of ACC [24]. On the other hand, Ye and Yamamoto concluded that CAV's capability to maintain shorter headways is negligible at lower implementation rates [9]. Mena-Oreja et al. tested different time gaps settings in full CACC environment and found that with the use of desired gaps of 10m, 5m and 1m, the flow increases by 9.39%, 26.09% and 39.21% respectively compared to full RVs environment [59]. The review made by Narayanan et al. in 2020 indicated that longer time gaps may reduce speed dispersion, improve traffic stability and safety; however it may decrease the

capacity [5]. Kerner confirmed that the possible large speed disturbance of ACC traffic may results from their wide range of the long desired time headway to the preceding vehicle [64].

Another important aspect of car following driving models is the settings related to speed distributions and acceleration/deceleration rates of AVs. For example, Le Vine et al. investigated the impacts of CAV at signalized intersection and concluded that CAVs operated with smoother acceleration/deceleration profile may have negative impacts on capacity, because of the restriction on the dynamics of the vehicles [69]. Li et al. also confirmed that higher deceleration rates may improve stability and safety; however that may decrease the capacity [63]. According to Ye et al., the smoother traffic flow with rising CAV implementation rate is attributable to a decrease in the percentage of high deceleration rate [50]. Makridis Michail et al. concluded that the expected negative impacts of the low implementation rates of the AVs are due to their longer headways and lower maximum deceleration and acceleration compared to the RVs [70].

In general, the findings of the literature have indicated that the exact driving behavior of different types of AVs in mixed traffic environment is complex and still not understood. Most of the studies are based on different assumptions of the driving behavior of these AVs such as car following and lane changing behavior. There are some technical components regarding the modeling and simulation of AVs that may highly affect it's obtained expected impacts that indicated by these different studies. Zeidler et al. stated that there is no common agreement or recommendations on parameter settings when modeling AVs in micro-simulation software [53]. The above findings have indicated that even with the same type of AVs, the different applied operational settings, mainly those related to time headways, may highly affect it's impacts on the traffic flow. The literature have indicated that the AVs with shorter headways will lead to increase the road capacity and that is confirmed the fact regarding the inversely proportional

relation between the capacity and the minimum average time headway between the vehicles. However, some studies have concluded that short headways may have negative impacts on the traffic stability. So, a clear knowledge of these settings of the AVs for the simulation is very important to explain or verify the different obtained findings.

2.4.4 Traffic Volume

Some studies have indicated that the level of the traffic volume may affect the impacts of the different AVs in mixed traffic environment. Some of these studies have indicated that the significant impacts of the AVs will be clear only at high traffic volume scenarios. For example, Van Arem et al. concluded that at low traffic volumes, there were no significant impacts of different implementation rates of CACC on the traffic stability [55]. However, at high traffic flows, their impacts were significant. Arnaout and Arnaout also confirmed that in terms of the improvement of the traffic flow due to CACC implementation [67]. Bohm and Häger confirmed that for a high traffic volume, the full AV implementation highly increased the capacity [6]. However, for the low volumes, AVs deteriorated the traffic characteristics. Peter Wagner [58] confirmed the increased capacity of signalized intersection due to the AV implementation in case of high traffic volumes, while the low traffic volumes indicated no improvement. Makridis Michail et al. also concluded that when the traffic volume was high, the impacts of CAVs were positive; however, when the volume is low, they have found that the RVs outperformed CAVs [70].

2.4.5 Human Driving Behavior in Mixed Traffic Environment

As indicated earlier, it is totally known that human driving behavior of the RVs and automated driving behavior of the AVs are not the same. In fact, each has different driving models and

logics. For example, with human driving, the acceptable safe time gap is determined based on the human's perception and reaction time that is highly affected by different factors such as the driver's experiences, visional abilities and expectations about the behaviors of other vehicles including different types of AVs. Another example is that human drivers may take the risks while driving, trying to predict the movement of nearby vehicles in the entire traffic stream in addition to the immediate vehicle ([29],[70]). It is highly expected that the implementation of AVs in the mixed traffic environment will cause some impacts on driving behavior of RVs as a result of their interactions. However, the literature has indicated that still there are uncertainties of these impacts that may be justified by the limitation of the real data and complexity of the reliable simulation and modeling of this complex traffic environment. From the available reviewed related studies, it can be concluded that the human driving behavior of RV, including their reactions and adaptation, may affect the expected impacts of the AV implementation. Schakel et al. concluded that the increased headway variability, caused by the presence of mixed traffic of CACC and RVs, had small impacts on the traffic stability [66]. Jerath and Brennan concluded that any increase of the RVs rate in a mixed traffic with ACC may lead to higher susceptibility of congestions [61]. B. Friedrich [58] concluded that a single RV in the traffic lane may lead to slower speeds and decrease the improved capacity of the AV implementation. On the other hand, F. Zheng et al. concluded that higher rates of AVs can decrease the uncertainty of the RV behavior mainly in congested traffic conditions compared to free flow where the heterogeneous behavior impacts is more significant due to increased mean speed variance [28]. Zhong et al. concluded that the average lane change of RVs increases till 30% implementation rate of CAVs is reached [72]. After that, it decreases as CAVs implementation rate increases. Jin et al. concluded that one of the main factors that may affect the impacts of CAV in mixed traffic

is the driver's reaction delay that may cause traffic instability [41]. Kerner concluded that if the dynamics of the AVs is qualitatively different from those of RVs, the AV might be considered an obstacle for the RVs and that may decrease the capacity [64].

2.5 Policy Implications

The implementation of the AV will transform transportation systems and traffic flow characteristics depending on many associated factors. Eliminating human errors and providing real-time information on vehicles from the connected infrastructure and other vehicles can result in significant driving behavioral improvements. Many policymakers wonder how AVs will change the future traffic demands, and how that may affect the planning for different transportation infrastructures such as roads, parking, and public transportation systems, and whether strategies and laws should encourage or limit their implementation [77]. In order to formulate policies, the first step is to identify problems that need to be addressed, determine which issues require the greatest attention, and specify what the nature of the problem is [21].

The existing traffic environment of road networks mainly includes RVs and some different types of semi-autonomous vehicles with different driving assisting systems. However, in the coming future, it is expected that the implementation rate of different types of AVs, including the full AVs level, in the traffic environment will increase and therefore it will cause different impacts on the traffic systems. The findings of this review have confirmed these related impacts of its implementation on the traffic capacity and on the components of the traffic stability. Also, it have confirmed the importance of some critical relate factors that may control the level and magnitude of the expected impacts. As a result, the traffic authorities and engineers have to consider the specific characteristics of different AV types along with their expected impacts,

under different future traffic compositions, in order to propose effective policies for future traffic operation and control. The main outcomes of the included discussions in this research may be significantly utilized in order to achieve that. Examples of these policies can be related to optimization of the AV driving parameters, such as desired speed and headway, under different traffic environment compositions or network levels. Other important policies can be related to design or optimization of the traffic control systems, such as signalized intersection control, under shared environment of AVs and RVs. Such policies and more are very important to insure traffic efficiency and safety in the real practice of the AV traffic environment [78].

Through extended literature review, this research has investigated the impacts of the implementation of different types of AVs under full and mixed environment on the traffic capacity and stability. The findings have indicated that the full implementation of different types of AVs may significantly increase the traffic capacity compared to full RV traffic environment. None of the studies have showed negative impacts on the traffic stability under full AV environment; however, it is logically assumed by different studies that full stability will be achieved. In the case of full AV traffic, the desired driving parameters of the AVs can be controlled and optimized to achieve the optimum traffic flow parameters. The presence of connectivity between AVs is a very critical aspect in AV modeling. The obtained findings have indicated that implementation of CAVs may enhance the efficiency and reliability of AV performance.

Due to different factors, it may take a very long time to reach a 100% implementation of the AV in our traffic networks. The findings have indicated that the partial implementation of the AVs has different impacts on the traffic flow characteristics. Some of the studies have indicated that it may lead to different levels of improvement and others have conflicted that due to different

factors. The related investigation works have considered different AV types, different car following models and different operational driving settings. In terms of the ACC impacts, some studies have indicated that in general the ACC implementation may increase traffic capacity and improve the stability of the traffic flow mainly with higher implementation rates. In contrast, some other studies have indicated that the ACC may have negative impacts on the capacity or stability. In terms of the CACC or CAV impacts, in general, most of the studies have also confirmed that their implementation may improve the capacity and stability mainly with higher implementation rates. In contrast, some studies have indicated that the CACC or CAV may have negative impacts on the capacity or stability when their implementation rate is low. Two reviewed studies Zhou et al. [5] and Ye and Yamamoto [9] indicated negative impacts of CAV on traffic capacity with any rate. In terms of the AV impacts, in general, most of the studies have also confirmed that the AV may increase the capacity and improve the stability mainly with higher implementation rates. However, only one study concluded that the AVs may have negative impacts on the traffic stability even with higher implementation rates [70]. None of the studies have indicated negative impacts of AVs on the capacity of mixed traffic environment.

So, as indicated earlier, due to their improved operational characteristics, the implementation of AVs may offer several potential positive impacts that may improve the overall efficiency of traffic mobility. However, these expected impacts are based on some important factors that should be considered while evaluating the AV impacts on the traffic flow under mixed traffic environment. That is highly important in order to maximize its positive impacts with the complex interaction with RVs. These factors mainly related to their implementation rate, AV characteristics, modeling and operational settings of the AVs and the level of the traffic volume in addition to the impacts of human driving behavior.

The implementation rate of the AVs is the most critical factor that may affect its expected impacts in a mixed traffic environment. Most of the studies have confirmed that the level of the expected improvement increases as the implementation rate increases. According to this review, the critical implementation rate should be above 40% in order to have positive significant impacts on the traffic capacity and stability. The policy makers should encourage and support the implementation of AVs in traffic network by proposing different strategies mainly in cities with high traffic density. Moreover, the connectivity capabilities of the AVs can highly affect the level and the magnitude of the expected improvement on the traffic flow mainly in case of mixed traffic environment. The review has indicated that the implementation of CAVs is better than the non-connected AVs in terms of improvement of traffic capacity and stability. This superiority is due to their significant advanced characteristics, such as their ability to communicate and obtain more valued information about the traffic, and therefore enable smarter control of car following and lane changing maneuvers. That may benefit the vehicles to maintain a better driving behavior by allowing shorter headways between them, faster reaction times, and perform complex maneuvers, such as platooning and improved merging or lane changing, with less disturbances to the traffic flow. All of that can result in more utilization and optimization of the road capacity. In contrast to the CAVs, the behavior of the non-connected vehicles is governed by specific theories. For example, the gap acceptance theory in which the driver has critical spacing to perform safe lane merging [8]. Narayanan et al. concluded that the policy makers should enforce laws to ensure connectivity between AVs to maintain significant the positive impacts of the AV implementation [5]. The findings also have indicated another important aspect that should be considered, while evaluating the impacts of different types of AVs is the position and the distribution of the AVs in the traffic flow in addition to the type of the following or

leading vehicles of the AV. Most of the related studies in the literature have only focused on the implementation rates of each type ignoring these important factors. However, in order to achieve the optimum policy for future traffic environment, it is highly important to conduct a reliable investigation considering several possible combinations regarding the type of each following or leading vehicle of an AV in the traffic flow considering different types of AVs in addition to the RVs.

On the other hand, the selection of the driving models of the AVs and its operational settings is also considered as a critical factor of the expected impacts. Among them, these impacts mostly resulted due to the adjustment of the car following driving behavior mainly the headways and speed settings. However, the optimization of these settings is highly complex since that these may leads to different impacts on different flow characteristics. In addition, these adjusted settings may cause several impacts on other aspects such as traffic safety and driver comfort. So, the policy makers should realized that the optimum selection of these parameters may depend on different factors such as the implementation rate of the AVs and the network level in addition to other targeted objectives of the AV implementation. In terms of human driving behavior in mixed traffic environment, the review has indicated that the possible negative impacts of the AVs on the RV deriving behavior may be gradually decrease with the increase of the AVs rates. Moreover, as recommended by Kerner, the future systems for AVs should be developed whose rules are consistent with those of RVs in which both the car following and lane changing models should learn from driver behavior of the RV [64].

2.6 Summary of Chapter 2

This chapter included a comprehensive literature review to investigate the AV implementation impacts on the traffic flow characteristics under mixed traffic environment with RVs. It summarized the main findings of the reviewed studies considering their specific study variables including the AV's type, network type and the study type. In addition, the chapter discussed important related factors that may affect the level of the discussed impacts.

The review has showed that most of the related studies have been focused on investigating the possible impacts of the full implementation of the AVs. Few studies have considered the issue of its expected impacts under mixed traffic environment. Most of the studies have focused on the impacts of the partial automation levels of AVs (ACC, CACC).

In general, it concluded that the implementation of AVs may offer several potential positive impacts that may improve the overall efficiency of traffic system. However, in terms of mixed traffic environment, there are contradictory results about their expected impacts on the traffic flow characteristics. Different studies have indicated that compared to full environment of RVs; the partial implementation of different types of AVs, mainly the CAV, may increase the traffic capacity, improve the traffic flow stability, increase throughput-and decrease the probability of traffic breakdown, including shockwave formation and propagation, and therefore decrease the intensity and quantity of congestion waves. However, those are based on some important factors that should be considered including the implementation rate, AV characteristics, modeling and operational settings of the AVs and the level of the traffic volume in addition to the impacts of human driving behavior. The critical implementation rate, that may significantly have a high potential to improve traffic characteristics, was found to be higher than 40%. The connectivity of

the AV is highly important to enable smarter control of the operational driving behavior. However, important consideration should be made to the operational settings of the AVs mainly those related to car following modeling. Different adjusted numbers of these setting may improve some of the traffic flow parameters and may deteriorate some other parameters. The position and distribution of AVs in the traffic flow in addition to in the type of the leading or following vehicles may also play a role in maximizing their positive impacts.

CHAPTER 3

SIMULATION-BASED INVESTIGATION OF THE IMPACTS OF AV IMPLEMENTATION ON THE PERFORMANCE OF SIGNALIZED INTERSECTION

As indicated by the previous chapter, investigations focusing on urban networks, primarily under the partial implementation of full automation levels in different traffic conditions, are scarce [4]. To overcome these research limitations, the aim of the study, reported in this chapter, is to conduct reliable investigation considering various possible scenarios. As mentioned earlier, the expected impacts of AV implementation may be influenced by the AV implementation rate, network-level, and AV characteristics [4] including its operational settings and connectivity capabilities. Based on that, the significant contribution herein is to investigate and analyze the impacts of introducing AVs in a mixed traffic environment, considering different AV characteristics and gradual implementation rates, under different traffic volume conditions at an urban signalized intersection. It is a more comprehensive study than existing studies and addresses several gaps found in the literature. The expected impacts of partial AV implementation, including high and low rates, are analyzed in addition to its relations with the level of traffic congestion. In addition, the performance of different automated driving capabilities is analyzed and compared.

The real-world implementation of AVs is yet to be realized, and it may be several years before AVs achieve sufficient market penetration and generate enough real-world traffic data to permit detailed studies on AV driving behavior. Consequently, the application of traffic simulation tools

is considered to be a suitable alternative for investigating the expected impacts of AVs [79]. Accordingly, a microscopic traffic simulation is performed herein using PTV Vissim (version 11) to evaluate the performance of a signalized intersection considering different performance measures. Studies have shown that the PTV Vissim can accurately mimic the autonomous features of AVs ([53],[6],[80],[26]). So, such a simulator is considered as a reliable alternative that can overcome the absence of real traffic data that represents mixed AV traffic conditions. Therefore, the results presented herein can be treated as a preliminary theoretical experiment with the use of microscopic traffic simulations. To the best of our knowledge, Vissim has not been used to simulate different AV models, considering the objectives of this study, in any previous research. The simulation herein considers a mixed traffic environment where AVs and RVs share the same traffic lanes. Different AV implementation rates are used to represent various traffic compositions. The vehicles are modeled by focusing on the parameters related to the car-following behavior and vehicle behavior at traffic signals and the desired acceleration and deceleration functions and speed distributions. The AV driving behavior is simulated using the built-in models available on Vissim, which are adjusted to create different AV models. These models are tested to investigate the impacts of AVs with different characteristics and operational settings. Accordingly, different test scenarios are evaluated under different traffic volume conditions.

The sections of this chapter are organized as follows. Section 1 includes a review of the different related works of the study. Section 2 includes the detailed methodology of the investigation. In section 3, the obtained results are presented. Section 4 includes the discussion of the result considering. Finally, section 5 includes a summary of the chapter.

3.1 Related Works

Various studies have investigated the potential impacts of AV implementation on traffic flow characteristics [4]. Owing to the lack of real traffic data on AV traffic environments, most of these studies have been modeling or simulation-based studies, considering different AV traffic environments with different AV characteristics, AV implementation rates, and network levels.

Most studies have focused on the expected impacts of different AV models on highway networks, under fully autonomous or mixed traffic environments ([65],[55],[60],[61],[52],[68],[62],[29],[73],[9],[75],[59],[33],[71],[32],[41],[27],[31]). Some

studies have also focused on the impacts of AVs on urban networks [4]. Some of these have considered the impacts of partial automation levels, such as ACC or CACC, in fully autonomous and mixed traffic environments. Tientrakool et al. investigated the impacts of full ACC and CACC implementation on the performance of an urban signalized intersection [56]. They revealed that compared to full RV traffic, full ACC implementation increased the capacity of the intersection by 43%, whereas full CACC implementation increased the capacity by 273%. Bailey and Kroll investigated the impacts of ACC and CACC at an urban signalized intersection considering different signal plans, AV implementation rates, and traffic volumes [2]. They observed that different behavioral models and AV parameters, as well as the implementation rate, had different impacts on the traffic flow. Cao et al. investigated the impacts of CACC on urban roads considering a mixed traffic environment [81]. They discovered that increasing the implementation rate can significantly improve the traffic flow efficiency by reducing the queue length and total travel time.

Some researchers have investigated the impacts of full automation levels of AVs, including CAVs, at the network level [4]. Most of these investigations have been performed considering a

full AV implementation environment. Bohm and Häger investigated the impacts of AVs on the traffic capacity of an urban network [6]. They revealed that when the traffic volume was high, compared to a full RV environment, a full AV traffic environment reduced the delay and number of stops by 56% and 54%, respectively, and increased the speed by 34%. However, when the traffic volume was low, the full AV environment had slightly negative impacts. B. Friedrich used mathematical modeling and discovered that, compared to a full RV traffic environment, a full AV environment increases the capacity of an urban network increases by 40% [82].

There have been few studies on the impacts of different full automation levels at the networks level with mixed traffic environments [4]. However, these studies have either considered a single AV model or assumed fixed traffic conditions of either traffic volume or implementation rate of AV. Le Vine et al. investigated the impacts of AVs on the performance of a signalized intersection [69]. They observed that AVs with smoother acceleration/deceleration rates had negative impacts on the traffic capacity and increased traffic delays. Levin and Boyles investigated the impacts of AVs on different intersection networks [83]. They revealed that the implementation of AVs can improve the applied intersection control performance. For a single intersection, the delay decreased linearly with the increase in the AV implementation rate from 0 to 60%; however, above this threshold, the delay remained relatively constant. In contrast, for multiple intersections, higher AV implementation rates (above 80%) were required to improve the control performance. B. Friedrich investigated the impacts of AVs on a signalized intersection [82]. They discovered that as the AV implementation rate increases, the capacity of the intersection increases. They attributed this to the shorter headways between AVs. A single RV in a mixed traffic environment can decrease the average speed and capacity of the network. Peter Wagner also investigated the impacts of AVs on a signalized intersection and found that in

high volume scenarios, the capacity of the traffic signal doubled [84] . However, at low traffic volumes, the AVs did not offer any improvement. Elvarsson investigated the impacts of AVs on an urban network and observed an improvement in the network performance up to an AV implementation rate of 40% [74]. However, above an implementation rate of 60%, the performance of the network decreased. Sukennik et al. investigated the impacts of AVs on the traffic flow in an urban network comprising single-lane roads without any signalized intersections [26]. They demonstrated that the increase in road capacity in a low-speed environment is moderate and the AV implementation rate has an approximately linear impact on the capacity of the network. Fakhrmoosavi et al. investigated the impacts of CAVs at the network level considering spatially- and temporally-varying distributions of different vehicle types (CAVs, RVs, and CVs) and different CAV implementation rates [38]. They found that higher implementation rates of CVs and CAVs led to significant improvements in the flow, capacity, and stability of traffic. Furthermore, AVs had a higher impact than CVs, particularly at lower RV implementation rates. Lu et al. investigated the impacts of AVs on an urban network and found that the capacity, stability, and flow of traffic slowly increased with the increase in the CAV implementation rate [25]. Notably, above an implementation rate of 40%, the improvement in the traffic characteristics increased significantly. Maryam et al. investigated the impacts of AVs on the safety and operation of urban arterial roads under different traffic conditions [85]. They discovered that the implementation of AVs significantly improves the traffic density, especially at high traffic volumes. Higher implementation rates at lower traffic volumes increased the mean speed by almost 6%. Furthermore, the increase in the AV implementation rate significantly reduced the number of rear-end and lane-changing conflicts. P. Liu and Fan investigated the impacts of CAVs on mobility at signalized intersections considering a mixed

traffic environment composed of RVs, AVs, and CAVs, with different AV implementation rates [86]. They revealed that the implementation of CAVs with a proposed speed control strategy reduced vehicle delays even at lower CAV implementation rates. Song et al. investigated the impacts of different AV models on the performance of fixed and actuated signalized intersections, considering different traffic volume conditions [87]. They observed that CAVs with CACC systems can outperform AVs with ACC or IDM systems and could reduce delays in low and high demand scenarios by 49% and 96%, respectively. With CACC systems, a significant reduction in delays was observed at an implementation rate of 20%. However, with ACC and IDM systems, a significant reduction in delays was only observed at high implementation rates. Obaid investigated the impacts of AVs on roads from a macroscopic perspective and found that that AV implementation could significantly reduce the total daily delay and increase the average network speed [88].

These studies indicate that the relationship between the implementation rate of AVs and their expected impacts in a mixed traffic environment is complex and based on different factors [4]. The implementation rate of AVs in a network has a significant effect on its expected impact ([52],[83],[12],[75],[25],[31],[32],[41]). Most studies have confirmed that the expected improvement increases with the increase in the implementation rate. The connectivity capabilities of CAVs can affect their performance, which in turn affects their impact on the traffic system ([29],[33],[5]). The implementation of CAVs achieves greater improvements than that of AVs owing to their advanced communication capabilities that enable the acquisition of more traffic information, which can be used to improve driving behavior and lead to more positive impacts on the traffic flow [4]. The driving behavior models and operational settings of AVs may also affect their performance ([2],[33],[10],[29],[63],[9],[69],[50]). In addition, the

traffic volume conditions may also affect the impacts of AVs ([6],[70]). Various studies have shown that human driving behavior in mixed traffic environments can also affect the impacts of AVs ([33],[31],[72],[41],[64]). The findings from different studies have indicated that the network level also affects the expected impact of AV implementation ([33],[5]).

3.2 Methodology

The general methodology of the study is shown in Figure 3-1. First, the experimental design was developed based on the objectives of the study. Different traffic volume levels, network configurations, traffic signal plans, and vehicle models were developed for the simulation using Vissim. After setting up the simulation environment, the required inputs were assigned to each simulation scenario. Subsequently, the simulation was performed, and different performance measures were recorded. Finally, the results were summarized, presented, and analyzed, considering the main objectives of the study. Each step of the methodology is explained in detail in the following sub-sections.

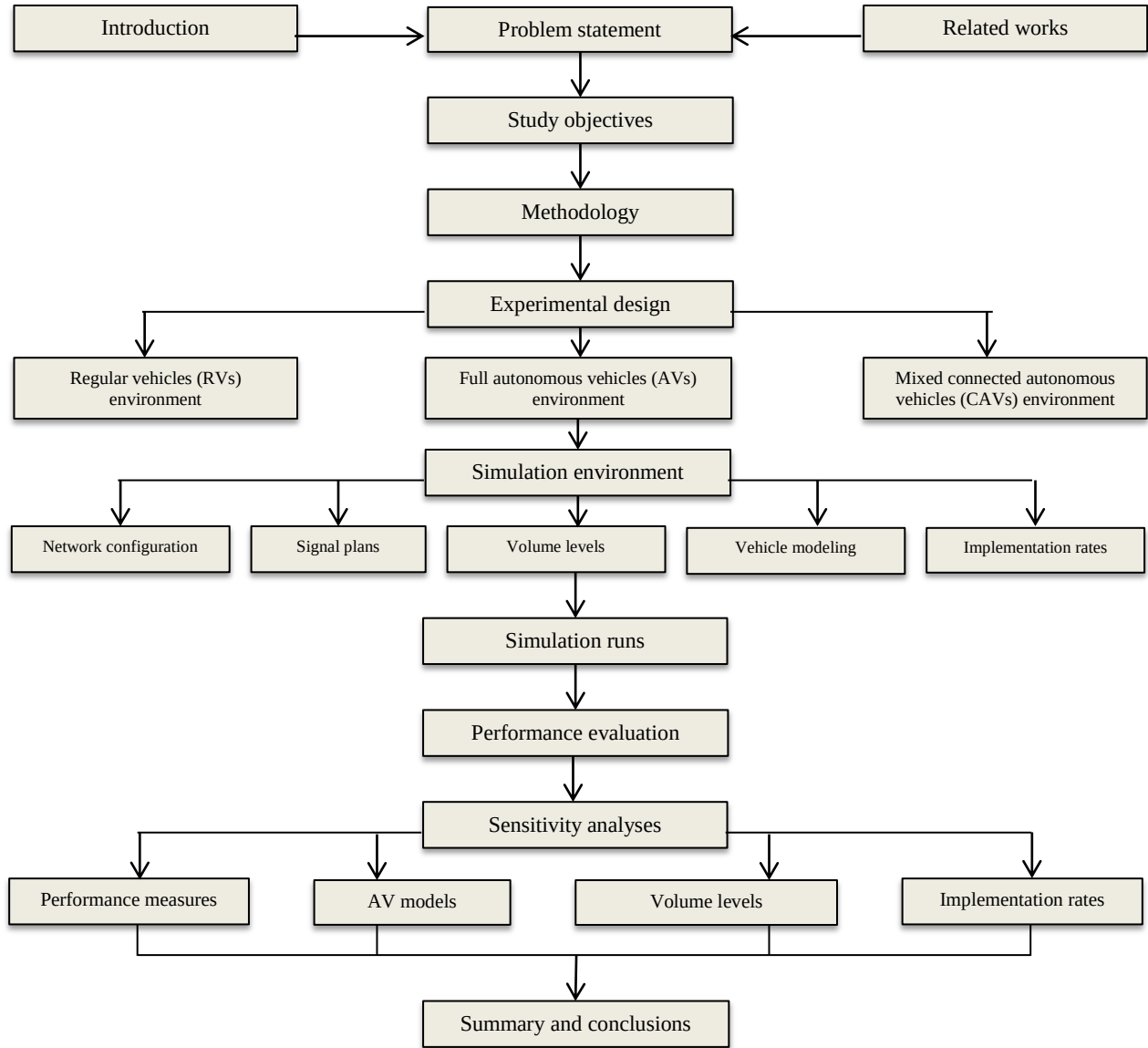


Figure 3-1 General Methodology of the Study

3.2.1 Experimental Design

The aim of this study is to investigate the impacts of AV implementation under different traffic conditions. Accordingly, the experimental design of the simulation scenarios includes three primary inputs. First, three traffic volume levels were considered to represent different traffic volume conditions. These levels are described in further detail Section 3.2. Second, three different driving behavior models were considered to represent the different characteristics of

AVs. These models and the RV model are described in Sub-section 3.4. Third, to represent different CAV implementation levels, six different implementation rates (%) were considered herein: 0, 10%, 25%, 50%, 75%, and 100%. A total of eight simulation scenarios were developed and simulated considering the same network. The details of each scenario are listed in Table 3-1. Each scenario was evaluated under three different traffic volumes, resulting in a total of 24 simulation scenarios.

Table 3-1 Description of the Simulation Scenarios

Scenario No.	Traffic composition	Scenario Description
1	100% RV	Full regular traffic environment
2	100% AV (aggressive)	Full AV (aggressive) traffic environment
3	100% AV	Full AV traffic environment
4	100% CAV	Full CAV traffic environment
5	90% RV–10% CAV	Mixed traffic environment with low CAV implementation rate
6	75% RV–25% CAV	Mixed traffic environment with low CAV implementation rate
7	50% RV–50% CAV	Mixed traffic environment with equally shared traffic
8	25% RV–75% CAV	Mixed traffic environment with high CAV implementation rate

3.2.2 Traffic Volume Levels and Turning Options

The three traffic volume levels considered herein are Low, Med, and High. The High level represents traffic conditions with a moderate level of traffic congestion (LOS = E) at a signalized intersection. The LOS levels defined herein are based on the results of the average vehicle delay and are comparable to the LOS defined in the American Highway Capacity Manual of 2010. The Low level represents almost free-flow conditions (LOS = B). The total traffic volume in the Low level was 10% of that in the High level. The Med level represents a moderate level between the High and Low levels, with a total traffic volume of 50% of that of the High level (LOS = C).

These levels were implemented using different traffic approaches, with different hypothetical traffic volumes for a given level. However, the movement and lane distribution rates were similar for each approach. Considering the movement distribution, 60% of the vehicles move through, 30% turn left, and 10% turn right. Considering the lane distribution, for through movement, 70% of the vehicles use the middle lane, 13% use the left lane, and 17% use the right lane; the left turning movements are entirely from the left lane, and the right turning movements are entirely from the right lane. The details of the traffic volume levels (vehicles/h) are shown in Table 3-2. The number of vehicles used to represent the three volume levels, in addition to the movement and lane distributions, were selected based on the volume data recorded at a similar intersection in a previous study [30].

Table 3-2 Traffic Volumes (Vehicles/h) at the Intersection Considering Three Traffic Volume Levels

Volume level	Movement	Approach			
		Eastbound (EB)	Westbound (WB)	Northbound (NB)	Southbound (SB)
High level	Left turning	300	264	312	288
	Through	600	528	624	576
	Right turning	100	88	104	96
	Total	1000	880	1040	960
Med level	Left turning	150	132	156	144
	Through	300	264	312	288
	Right turning	50	44	52	48
	Total	500	440	520	480
Low level	Left turning	30	26	31	29
	Through	60	53	62	58
	Right turning	10	9	10	10
	Total	100	88	104	96

3.2.3 Simulation Environment

A. Network Configuration

The primary aim of this study is to investigate the impacts of AV implementation at an urban signalized intersection. To represent a typical common signalized intersection, a hypothetical

isolated four-leg signalized intersection was created in Vissim. Each road approaching the intersection comprises three lanes in each direction, with a lane width of 3.5 m. The roads were connected using suitable connectors to replicate all the movements that occur at a typical signalized intersection. The layout of the network is shown in Figure 3-2. As shown, the intersection does not contain any left or right turning bays. In addition, reduced speed areas were created for the right and left turns at each approach, and the speed limit of the network was set to 80 km/h.

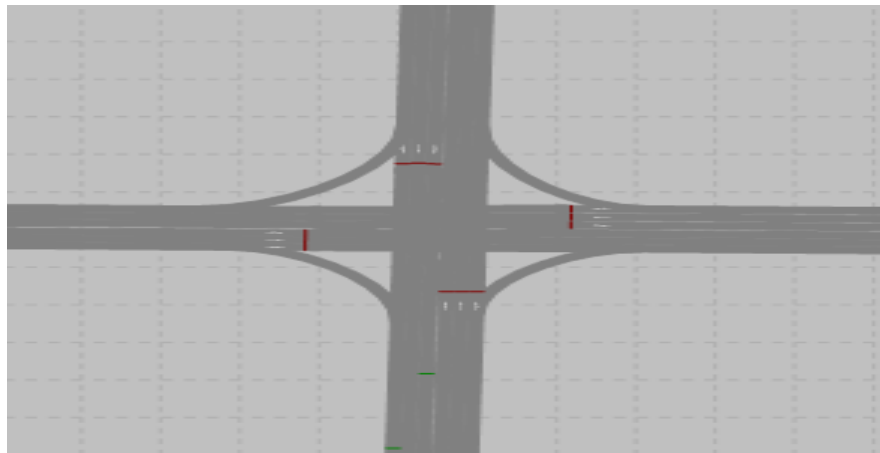


Figure 3-2 Layout of the Signalized Intersection (Source: PTV Vissim)

B. Signalized Intersection Control

The signalized intersection is controlled by a traffic signal with a four-phase fixed plan system with protected left turns. To ensure the safe operation of the signalized intersection, vehicles are allowed to move through from any lane, turn left only from the left lane, and turn right only from the right lane. Furthermore, U-turns are not allowed at the intersection. All four approaches include the same turning option configurations. The simulated vehicles were prohibited from making lane changes as they approached the intersection. Consequently, vehicles can pass

through the intersection without the formation of any conflict areas. To reliably evaluate the impact of AVs on the signal performance, three signal plans were created for each of the three volume levels. Each signal plan included four signal groups with the same phase sequence. The cycle length for each plan was optimized using the empirical equation developed by the Transport Research Laboratory (TRL) considering the critical-lane traffic volumes [89]. The effective green times were calculated based on the degree of traffic in each approach [89]. The signal plans were built and applied to the simulation in Vissim. The detailed signal plans are shown in Table 3-3.

Table 3-3 Detailed Signal Plans for Different Volume Levels

Signal group	Northbound (NB)			Southbound (SB)			Westbound (WB)			Eastbound (EB)		
Phase	R	G	A	R	G	A	R	G	A	R	G	A
Phase sequences												
Traffic volume level/Phase duration												
Low (C = 32 s) *	0	6	3	0	5	3	0	4	3	0	5	3
Med (C = 42 s)	0	9	3	0	8	3	0	6	3	0	7	3
High (C = 210 s)	0	51	3	0	50	3	0	48	3	0	49	3

* C: Cycle length (s), R: Red (s), G: Green (s), A: Amber (s)

C. Performance Measures

To investigate the impacts of AV implementation, the performance of the signalized intersection was evaluated using four performance measures that are reported by Vissim as node evaluation attributes. These are, the average vehicle delay (s), average stopped delay (s), average number of stops, and average queue length (m). The average vehicle delay, which has been widely used in previous studies to measure the LOS, is defined as the additional time required for a vehicle to cross the intersection. It is obtained by subtracting the theoretical travel time from the actual

travel time. The average stopped delay (per vehicle) is defined as the waiting time spent in the queue from the instant a vehicle is stopped by a red signal till the signal turns green.

D. Simulation Set-up and Parameters

The traffic simulations were conducted using PTV Vissim, which is a microscopic traffic simulation software package. The Vissim software includes the mathematical models required to run traffic flow models [90]. A recent version (Version 11) of Vissim, which includes advanced built-in features such as AV modeling [79], was used herein. Considering the modeling of automated driving behavior, Vissim offers a significant advantage as it includes several adjustable parameters that can be effectively used to simulate different AV models [6]. Each simulation scenario was run for 5400 s. To saturate the system and eliminate the start-up period, the results were only recorded after 3600 s. To gather statistically valid data, each scenario was simulated ten times, with each simulation performed with a default random seed of 42 with an increment of 1. Therefore, the final results of the recorded performance measures for each scenario were based on the average of the 10 simulations. The simulation resolution was set to one time step (s) per simulation second.

3.2.4 Vehicles and Driving Behavior Models

The vehicles in the simulation are either RVs or AVs. As discussed in Section 1, RVs are driven by humans and are non-connected vehicles. Different operational and connectivity characteristics were considered for the AVs by adjusting different driving settings. The two types of vehicles not only differ in terms of their driving behavior but also have different functions and distributions [79]. Different acceleration and deceleration functions can be defined in Vissim for different vehicle types. Accordingly, different functions of the desired acceleration and deceleration were created and assigned to the RVs and AVs. For the RVs, the acceleration or

deceleration rates are stochastically selected between the two boundary curves, whereas for the AVs, considering their deterministic behavior, the acceleration and deceleration rates are constant. The designed acceleration and deceleration functions of the RVs and AVs are shown in Figures 3-3, 3-4, 3-5 and 3-6. Different types of distributions can be defined for each vehicle type in Vissim. Accordingly, three desired speed distributions were created and assigned to the RVs and AVs: the main speed, left-turning speed, and right turning speed. The speed values are stochastically selected for the RVs, whereas for the AVs, considering their deterministic behavior and ability to maintain the desired speed, the speed values are constant. The different speed distributions of the RVs and AVs are shown in Figure 3-7.

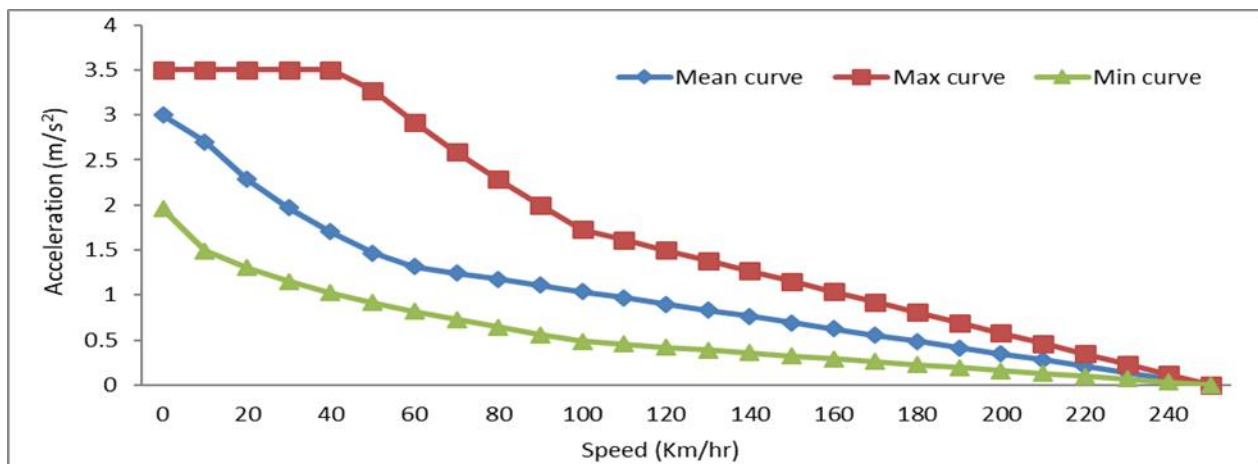


Figure 3-3 Desired Acceleration Function of the RVs

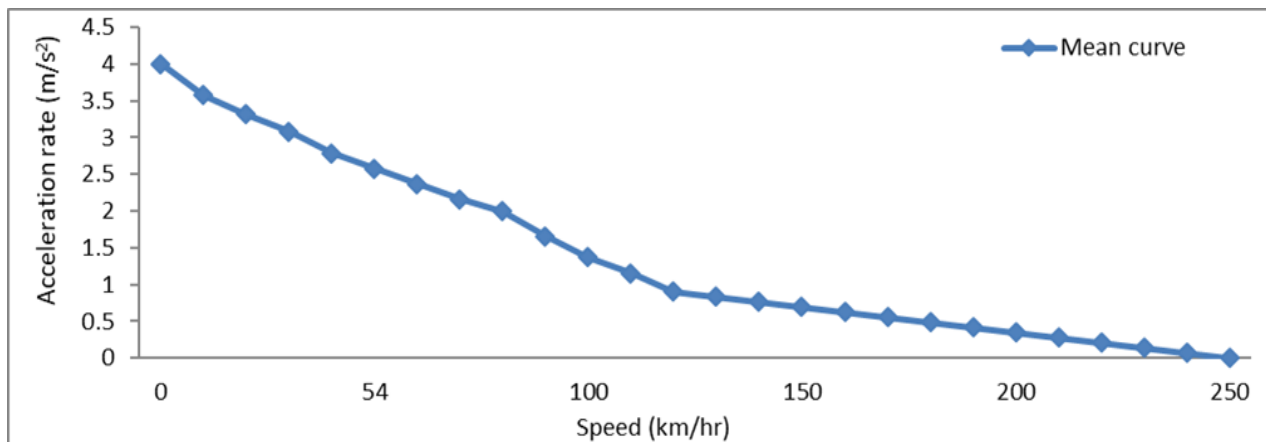


Figure 3-4 Desired Acceleration Function of the AVs

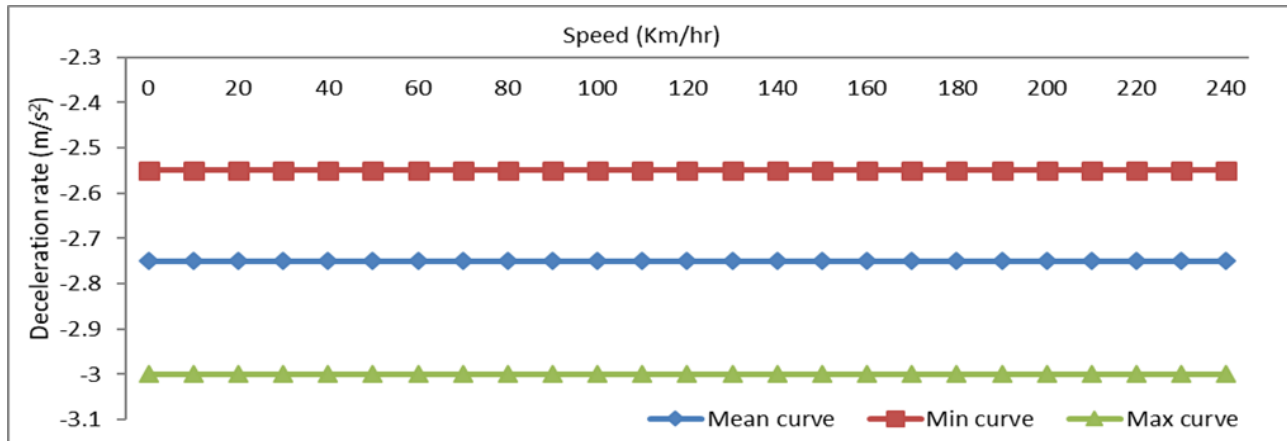


Figure 3-5 Desired Deceleration Function of the RVs

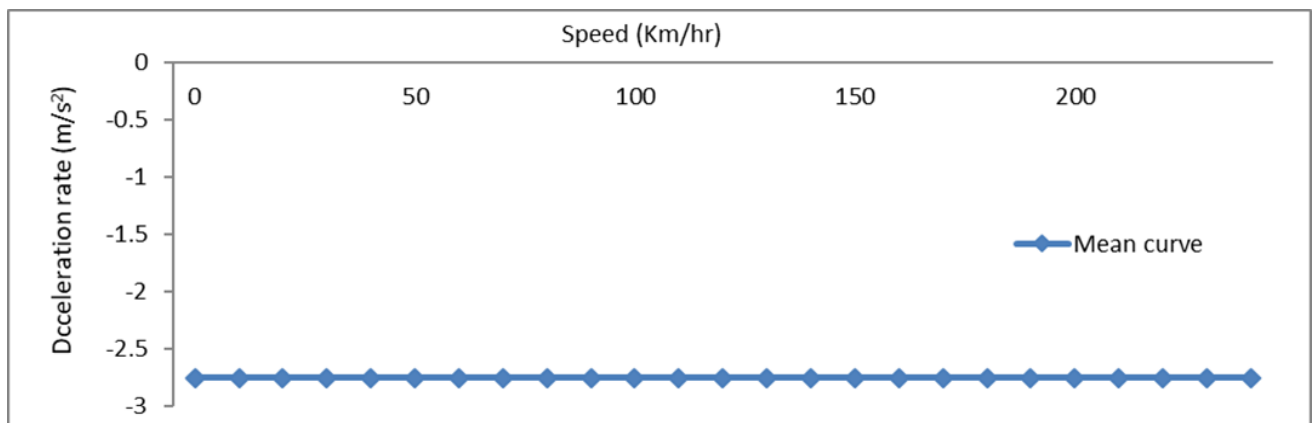


Figure 3-6 Desired Deceleration Function of the AVs

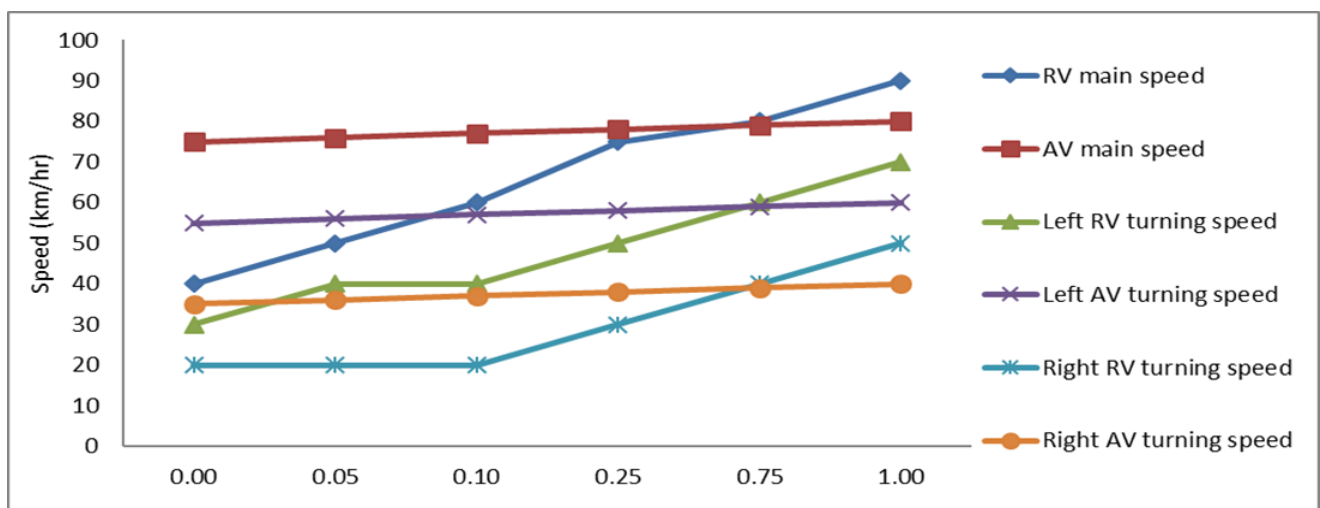


Figure 3-7 Probability of Different Speed Distributions of the RVs and AVs

In microscopic traffic simulations, the driving behavior of vehicles is calculated by the algorithms of the simulator. The driving behavior is represented and governed by various functions, distributions, and driving parameters [2]. The driving parameters control driving behavior characteristics such as car following, lane changing, gap acceptance, and vehicle behavior at a traffic signal. These behaviors may include the speed, acceleration, and deceleration of the vehicle, the headway and safe distance between vehicles, and the reaction times. To model the car-following behavior of the AVs, the Wiedemann 99 model was selected as the base model herein as it has numerous parameters that can be easily adjusted to model different AV characteristics ([6],[80],[26]). The Wiedemann 99 model is a psycho-physical model (also referred to as action point models) that considers human shortcomings in the perception of speed and distance [90]. It assumes a linear relationship between speed and following distance, and assumes that vehicles maintain their desired speed if the leading vehicle does not influence their behavior [53]. Several AV-related features in PTV Vissim have been implemented within CoEXist project. The results, from the field data, of the project showed that there is a linear relationship between headway and speed when the AV is following RVs or AVs [3].

The driving models control the different driving behaviors of the vehicles based on different settings. A total of four driving behavior models were considered herein, each with different car-following and traffic signal behaviors. One model represents typical human driving behavior (RVs), and the other three models represent autonomous driving behavior (AVs). As vast amounts of data exist for RV driving behavior, the settings of the RV model can be derived from various field data. The default settings of the default urban driving behavior (Urban-motorized)

in Vissim were used for the RV model. However, the reaction time distribution parameter was adjusted to more realistically simulate human driving behavior at a traffic signal.

Compared to the RV model, the AV models are expected to maintain smaller distances [25] and shorter space and time headways [25] between vehicles. Furthermore, they must strictly maintain the desired speed and accelerate and decelerate uniformly with no oscillations in the following distance [26] and speed [3]. Considering reaction times, AVs have more accurate and faster reactions than RVs ([83],[26],[70]). Overall, they are expected to have better and more stable driving behavior than RVs. However, unlike RVs, there is a lack of real data relating to AV driving behavior. Consequently, the behavioral models of the AVs in the simulations are hypothetical and primarily determined from various logical assumptions available in the literature [53]. In Vissim, the Wiedemann 99 parameters can be adjusted to model the AV car-following behavior at different network levels including urban network ([26],[53]). Zeidler et al. analyzed the real data of the standstill distances (CC0) and headway (CC1) used in ACC and CACC models operating in real-world scenarios [53]. The following behavior of these models was compared to the simulated following behavior of the Wiedemann 99 model in Vissim. The results indicated that the behavior of the CACC model is reproduced well in Vissim. Sukennik et al. recommended different settings to model the AV-related features and its driving behavior [3]. Different studies have used Wiedemann 99 car-following model to model AV behavior at signalized intersections of mixed traffic environment ([91],[92],[93]).

Based on different AV characteristics represented by the driving behavior settings, three AV models were considered herein as representative models: AV (aggressive), AV, and CAV. The AV (aggressive) model is a default AV model present in Vissim 11. The different settings of this model were proposed by PTV based on empirical studies and co-simulation data recorded in a

mixed traffic environment under the CoExist project, as well as other assumptions [3]. The AV and CAV models were new models that were created by adjusting the default settings of the driving behavior parameters, based on the autonomous features of full AVs obtained from the literature ([6],[62],[2],[83],[70],[94],[53],[23],[25],[79]). The AV model represents unconnected AV driving behavior, which is similar to the RV driving behavior, but with improved and deterministic operational behavior. Based on the data obtained from sensors, the vehicle can accurately detect the distance to other vehicles, thereby increasing safety. Compared to the RV model, the AV model has a significantly smaller oscillation in its vehicle following behavior. The CAV model represents connected AV driving behavior, which is similar to the AV driving behavior, but with improved operational behavior owing to its connectivity capabilities. Herein, we assume that CAVs are aware of the entire traffic situation. Compared to the other AV models, the CAV model observes more vehicles within the traffic network, leading to shorter headways and gaps.

Table 3-4 shows the main settings of the driving behavior models employed herein. As shown, the look-ahead distance in the AV (aggressive) and CAV models is higher than that in the other models, which may lead to better scanning of the traffic environment. The connectivity characteristics of the AVs was modeled by directly setting the number of interaction objects and vehicles. For example, if the number of interaction vehicles is 1, as in the case of the AV model, which is not connected, the vehicle can only observe a single leading vehicle. As the number of interaction objects in the AV model is 2, a traffic signal ahead of the leading vehicle would still be observed by the vehicle. A higher number of interaction vehicles, as in the AV (aggressive) and CAV models, indicates a higher accuracy in predicting the movements of other vehicles [6]. To model and reflect the limitations and randomness of human driving behavior in the RV

model, most of its settings were modeled using stochastic features. Unlike RVs, AVs can operate deterministically, precisely following the assigned settings, which represents homogenous behavior. Therefore, AVs do not have any internal stochastic variations. In general, the following differences can be observed in the settings of the applied models with respect to the car-following behavior. Considering the standstill distance (CC0), the AV and CAV models had a lower setting than the other model. The CAV model had the shortest headway time (CC1) (0.50 s) of all the AV models. The higher the value of the CC1 setting, the more cautious the following behavior, leading to longer safety distances and consequently, a lower capacity. Furthermore, this parameter is also indirectly related to the reaction time. The shorter the reaction time, the shorter the headway between vehicles, which results in reduced travel time and improved capacity. Therefore, connectivity can be indirectly modeled by adjusting the headway time and other car following parameters [3]. The safe distance between vehicles is represented by the following distance oscillation (CC2). Unlike the RV model, the assigned settings of the AV models have no variations. The perception threshold for following (CC3) controls the start of the deceleration process (in s) before the vehicle reaches the safety distance. This parameter was lower in the AV (aggressive) and CAV models compared to the setting in the AV model. The negative (CC4) and positive speed difference (CC5) settings of the three AV models were similar. Compared to the RV, the speed variation of the AV models during the following process is more sensitive to the acceleration or deceleration of the leading vehicle. The speed dependency of oscillation (CC6) is set to zero in the AV models indicating that the distance has no influence on the speed oscillation. In contrast, with the RV model the speed oscillation increases with the increase in distance. The parameters CC7, CC8, and CC9 represent the different acceleration behavior settings. The oscillation with the AV models during acceleration

is lesser than that with the RV model. The parameters CC8 and CC9 are limited by the defined acceleration functions. Considering the driving behavior at a traffic signal, the three AV models have a zero reaction time and react faster than the RV model, which has a reaction time distribution of 0.5–2.0 s. If the first vehicle in the queue has a slower reaction, the start-up time lost in response to the traffic signal increases. It should be noted that the models contain additional parameters that are not included in the table. The default settings were used for these parameters in all the models owing to different assumptions of their expected impacts on the network. Furthermore, these parameters are not relevant to the problem investigated herein and lie outside the focus of this study. For example, as lane changing is prohibited beyond a certain distance from the stop line, the default settings were used for the lateral and lane changing behavior of the models.

Table 3-4 Driving Behavior Settings of the Driving Behavior Models

Attribute	Driving behavior model			
	RV	AV (aggressive)	AV	CAV
Following Behavior				
Max look-ahead distance (m)	250	300	250	300
Number of interaction objects	4	10	2	10
Number of interaction vehicles	99	8	1	8
Use implicit stochastics	On	Off	Off	Off
Car following behavior (based on the Wiedemann 99 model)				
CC0: Standstill distance (m)		1.00	0.50	0.50
CC1: Headway time (s)		0.60	0.90	0.50
CC2: Following distance oscillation (m)		0.00	0.00	0.00
CC3: Perception threshold for following (s)		−6.00	−8.00	−6.00
CC4: Negative speed difference (m/s)		−0.10	−0.10	−0.10
CC5: Positive speed difference (m/s)		0.10	0.10	0.10
CC6: Speed dependency of oscillation (1/(m/s))		0.00	0.00	0.00

CC7: Oscillation acceleration (m/s ²)		0.10	0.10	0.10
CC8: Standstill acceleration (m/s ²)		4.00	3.8	3.8
CC9: Acceleration at 80 km/h (m/s ²)		2.00	1.50	2.00
Behavior at traffic signal				
Desired position at free flow	Continuous checking	One decision	One decision	One decision
Behavior at red/amber signal	Go	Stop	Stop	Stop
Reaction time distribution (s) (after green signal)	0.50–2.00	0.00	0.00	0.00

3.3 Results

The simulation results of the signalized intersection performance are presented in this section. The performance measures recorded for each simulation scenario under each volume level (Low, Med, and High) are the average vehicle delay, average stopped delay, average number of stops, and average queue length. These measures are key indicators of the impacts of AV implementation on the performance of the intersection. First, we evaluated the performance with the full implementation of the RV and AV models in the traffic network. Each model was set up and linked with its specific driving behavior settings, deceleration and acceleration functions, and speed distributions. The results of the four scenarios corresponding to each of the four models at different volume levels are shown in Table 3-5. Subsequently, we evaluated the performance of the intersection after CAV implementation, considering different implementation rates in a mixed traffic network with RVs. These scenarios were implemented in Vissim by changing the traffic composition. The results of the four scenarios with mixed traffic environments at different volume levels are shown in Table 3-6. In addition, Table 3-7 shows the improvement (%) in each performance measure relative to the base scenario (Scenario 1), considering different AV implementation rates, under each volume level.

**Table 3-5 Results of Signalized Intersection Performance with Full Implementation of each
Vehicle Model**

Performance measure	Low volume	Med volume	High volume
Scenario 1: 100% RV			
Average vehicle delay (s)	13.42	23.79	78.54
Average stopped delay (s)	5.61	13.05	65.78
Average queue lengths (m)	0.29	3.51	29.94
Average number of stops	0.56	0.86	0.93
Level of service (LOS) (A–F)	B	C	E
Scenario 2: 100% AV (Aggressive)			
Average vehicle delay (s)	11.48	16.50	69.12
Average stopped delay (s)	4.11	8.09	57.95
Average queue lengths (m)	0.23	2.00	24.14
Average number of stops	0.49	0.65	1.08
LOS (A–F)	B	B	E
Scenario 3: 100% AV			
Average vehicle delay (s)	11.49	17.47	66.61
Average stopped delay (s)	4.08	8.49	55.57
Average queue lengths (m)	0.23	1.94	20.64
Average number of stops	0.49	0.72	1.30
LOS (A–F)	B	B	E
Scenario 4: 100% CAV			
Average vehicle delay (s)	11.41	16.14	66.68
Average stopped delay (s)	4.03	7.68	56.46
Average queue lengths (m)	0.23	1.80	21.22
Average number of stops	0.48	0.65	0.95
LOS (A–F)	B	B	E

Table 3-6 Results of Signalized Intersection Performance with Different CAV Implementation Rates

Performance measure	Low volume	Med volume	High volume
Scenario 5: 90% RV–10% CAV			
Average vehicle delay (s)	13.12	22.85	78.04
Average stopped delay (s)	5.37	12.56	65.39
Average queue lengths (m)	0.27	3.06	29.43
Average number of stops	0.54	0.83	0.95
LOS (A–F)	B	C	E
Scenario 6: 75% RV–25% CAV			
Average vehicle delay (s)	12.87	21.48	75.23
Average stopped delay (s)	5.22	11.62	62.98
Average queue lengths (m)	0.27	2.78	27.39
Average number of stops	0.55	0.80	0.94
LOS (A–F)	B	C	E
Scenario 7: 50% RV–50% CAV			
Average vehicle delay (s)	12.27	18.94	72.32
Average stopped delay (s)	4.83	9.81	60.96
Average queue lengths (m)	0.26	2.31	25.14
Average number of stops	0.52	0.73	0.95
LOS (A–F)	B	B	E
Scenario 8: 25% RV–75% CAV			
Average vehicle delay (s)	11.41	17.17	69.02
Average stopped delay (s)	4.27	8.57	58.21
Average queue lengths (m)	0.23	2.02	23.01
Average number of stops	0.49	0.67	0.94
LOS (A–F)	B	B	E

Table 3-7 Improvement (%) in Signalized Intersection Performance with Different CAV Implementation Rates

Performance measure	Low volume	Med volume	High volume
Scenario: 90% RV–10% CAV			
Average vehicle delay	2.25	3.95	0.64
Average stopped delay	4.28	3.75	0.59
Average queue lengths	6.90	12.82	1.70
Average number of stops	3.57	3.49	–2.10
Scenario: 75% RV–25% CAV			
Average vehicle delay	4.10	9.71	4.21
Average stopped delay	6.95	10.96	4.26
Average queue lengths	6.90	20.80	8.52
Average number of stops	1.79	6.98	–1.06
Scenario: 50% RV–50% CAV			
Average vehicle delay	8.57	20.39	7.92
Average stopped delay	13.90	24.83	7.33
Average queue lengths	10.34	34.19	16.03
Average number of stops	7.14	15.12	–2.10
Scenario: 25% RV–75% CAV			
Average vehicle delay	14.98	27.83	12.12
Average stopped delay	23.88	34.33	11.51
Average queue lengths	20.69	42.45	23.15
Average number of stops	12.50	22.09	–1.06
Scenario: 0% RV–100% CAV			
Average vehicle delay	17.44	32.16	15.10
Average stopped delay	28.16	41.15	14.17
Average queue lengths	20.69	48.72	29.62
Average number of stops	14.28	24.42	–2.10

3.4 Discussion

3.4.1 Impacts of Full AV Implementation

A sensitivity analysis was performed to investigate the impacts of full AV implementation, considering each AV model, by analyzing the performance results under different traffic volume levels. Accordingly, the effectiveness of full AV implementation was evaluated relative to the base scenario (Scenario 1). The impacts of the different AV characteristics were compared as well. Figures 3-8, 3-9, 3-10 and 3-11 depict the average vehicle delay, average stopped delay,

average number of stops, and average queue length, respectively, after the full implementation of the designed models under different volume levels.

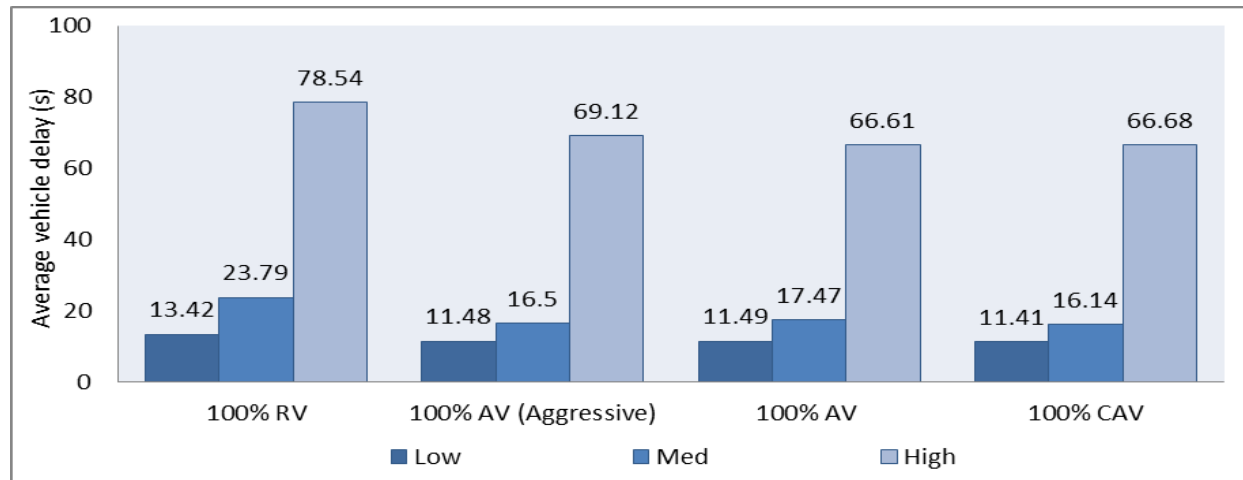


Figure 3-8 Average Vehicle Delay with Full Implementation of each Model under Different Volume Levels

Considering the average vehicle delay, as shown in Figure 3-8, at the Low volume level, the three AV models performed better than the RV model, with an average delay of 11.46 s, which corresponds to an improvement of 14.60% compared to the base scenario. Notably, the CAV model had a lesser average delay than the AV (aggressive) and AV models, which had similar impacts. At the Med volume level, the performance of the three AV models differed slightly, with an average delay of 16.70 s, which corresponds to an improvement of 29.80% compared to the base scenario. Once again, the CAV model had the best performance among the three AV models, whereas the AV model had the worst. At the High volume level, the three AV models exhibited an average vehicle delay of 67.47 s, which corresponds to an improvement of 14.10% compared to the base scenario. At this volume level, the CAV and AV models exhibited better performance than the AV (aggressive) model. Therefore, the improvement offered by the AV

models relative to the RV model was the highest at the Med volume level, with an improvement of 29.80%, compared to improvements of 14.60% and 14.10% at the Low and High volume levels respectively. Similar findings were observed for the average stopped delay and queue length as discussed below.

Considering the average stopped delay, as shown in Figure 3-9, at the Low volume level, the three AV models had almost the same positive impact, with an improvement of approximately 27.45% compared to the base scenario. The CAV model performed slightly better than the other AV models. At the Med volume level, the three AV models significantly reduced the average stopped delay. However, their impacts differed slightly, with the CAV model exhibiting a superior performance compared to the other two AV models, resulting in an improvement of 41.21% compared to the base scenario. At the High volume level, all three AV models exhibited improved performance, with an average improvement of approximately 13.86% compared to the base scenario. Notably, the AV model reduced the average stopped delay more than the other two AV models.

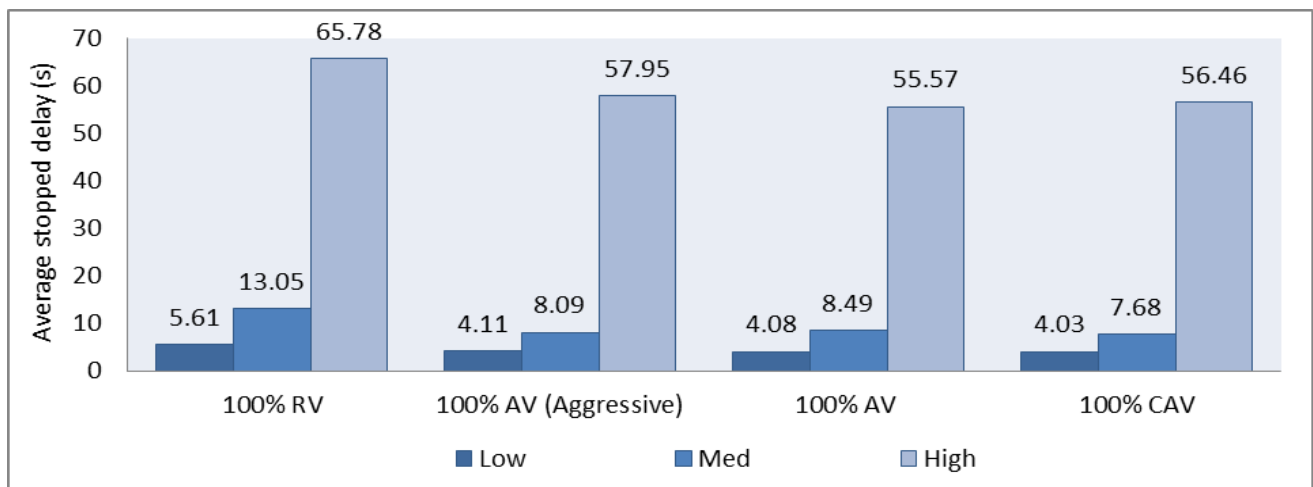


Figure 3-9 Average Stopped Delay with Full Implementation of each Model under Different Volume Levels

Considering the average number of stops, as shown in Figure 3-10, at the Low volume level, the three AV models performed better than the RV model, exhibiting almost the same values, with an average of 0.49, which corresponds to an improvement of approximately 12.50% compared to the base scenario. At the Med volume level, the three AV models reduced the number of stops by an average of approximately 22% compared to the RV model. Notably, the AV (aggressive) and CAV models performed better than the AV model. At the High volume level, the implementation of the three AV models did not reduce the number of stops, which is an unexpected result. Although the number of stops increased by approximately 2.00% compared to the RV model, the CAV model had the best performance among the AV models.

Considering the average queue length, as shown in Figure 3-11, at the Low volume level, the three AV models performed better than the RV model, with the same value of 0.23 m, corresponding to an improvement of approximately 20.70% compared to the base scenario. At the Med volume level, the performance of the three AV models differed slightly, with an average value of 1.91 m, which represents a significant improvement compared to the base scenario. The CAV model had the best performance among the AV models, with an improvement of approximately 48.72% compared to the RV model. Furthermore, the AV (aggressive) model was better than the AV model. At the High volume level, the three AV models had similar impacts on the average queue length. Among the three AV models, the AV model had the highest improvement, reducing the queue length by approximately 31.02% compared to the base scenario.

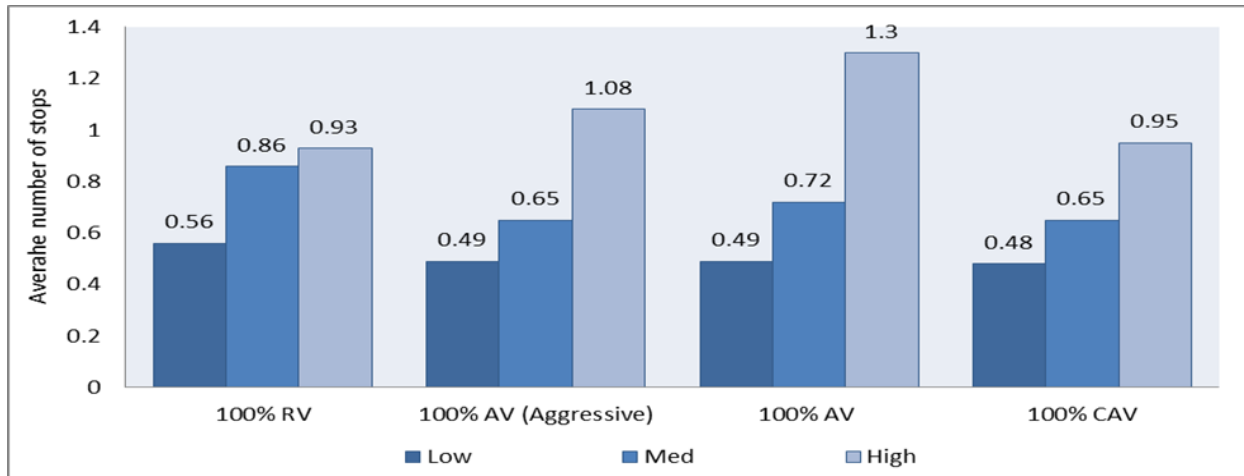


Figure 3-10 Average Number of Stops with Full Implementation of each Model under Different Volume Levels

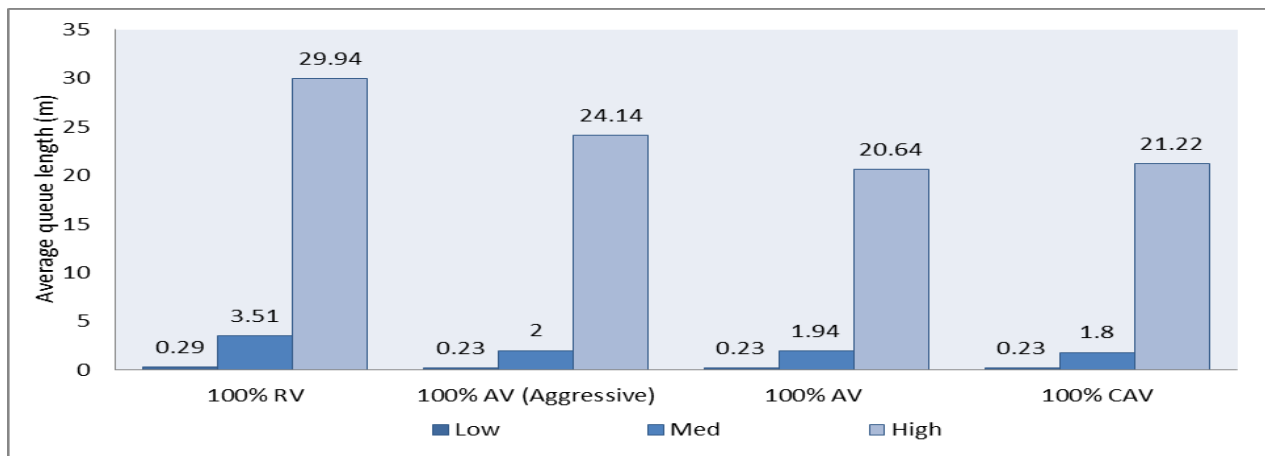


Figure 3-11 Average Queue Length with Full Implementation of each Model under Different Volume Levels

In summary, the queue length experienced the highest positive improvement after full AV implementation under all three volume conditions; in contrast, the number of stops experienced the least positive impact. Full AV implementation reduced the number of stops at the Low and Med volume levels, whereas at the High volume level, full AV implementation slightly increased

the number of stops. At the Low and Med volume levels, the average stopped delay experienced the second highest improvement after the queue length.

The level of improvement derived from full AV implementation depends on the traffic volume conditions. The expected improvement was higher at the Med volume level compared to the Low of High volume levels. At the Low volume level, full AV implementation reduced the average vehicle delay, stopped delay, number of stops, and queue length by 14.60%, 27.45%, 12.50%, and 20%, respectively; at the Med volume level, the corresponding reductions were 29.80%, 41.21%, 24.42%, and 48.72%, respectively; at the High volume level, the corresponding reductions were 14.10%, 13.86%, -2.00%, and 31.02%, respectively. Comparing the Low and High volume levels, the extent of positive improvement varies. The average stopped delay and number of stops experienced higher improvement at the Low volume level, whereas the queue length experienced higher improvements at the High volume level. Both these volume levels lead to similar improvements in the average vehicle delay.

Comparing the impacts of the three AV models applied herein, in general, they had comparable performance with no significant differences between them, especially at the Low and Med volume levels. However, at the High volume level, their performance differed slightly. The CAV model slightly outperformed the other two AV models, especially at the Low and Med volume levels. The superiority of the CAV model in terms of the reduction in the average delay and queue length were significant at the Med volume level. At the High volume level, the AV model provided a higher reduction in the average stopped delay and queue length, whereas the CAV model provided a higher reduction in the number of stops. All three AV models had similar impacts on the average vehicle delay.

Compared to the RV model, the improvements offered by the AV models can be primarily attributed to their deterministic driving behaviors and the lack of variation in their driving settings. The constant speed distributions and uniform deceleration and acceleration functions of the AV models did not influence their performance. However, the operational driving settings had a significant effect on their performance. In particular, the results indicated that the following longitudinal distance oscillation and the reaction time distribution at a signal made the highest contributions to the performance of the AV models.

3.4.2 Impacts of Partial AV Implementation

The results of the full AV implementation indicated that, in general, the applied AV models have similar impacts on the performance of the signalized intersection. However, the CAV model performed slightly better than the other two AV models. Consequently, the CAV model was used to investigate the impacts of different AV implementation rates in a mixed traffic environment with RVs. A sensitivity analysis was performed to investigate the impacts of partial AV implementation on the different performance measures. Specifically, the effectiveness of different partial implementation rates, compared to the base scenario, under different volume levels, was evaluated herein. As discussed in Section 3.1, AV implementation rates of 10% and 25% represent low implementation rates, a 50% implementation rate represents an equally shared traffic environment with RVs, and a 75% implementation rate represents a high implementation rate. Figures 3-12, 3-13, 3-14 and 3-15 depict the average vehicle delay, average stopped delay, average number of stops, and average queue length, respectively, considering different CAV implementation rates, under different volume levels.

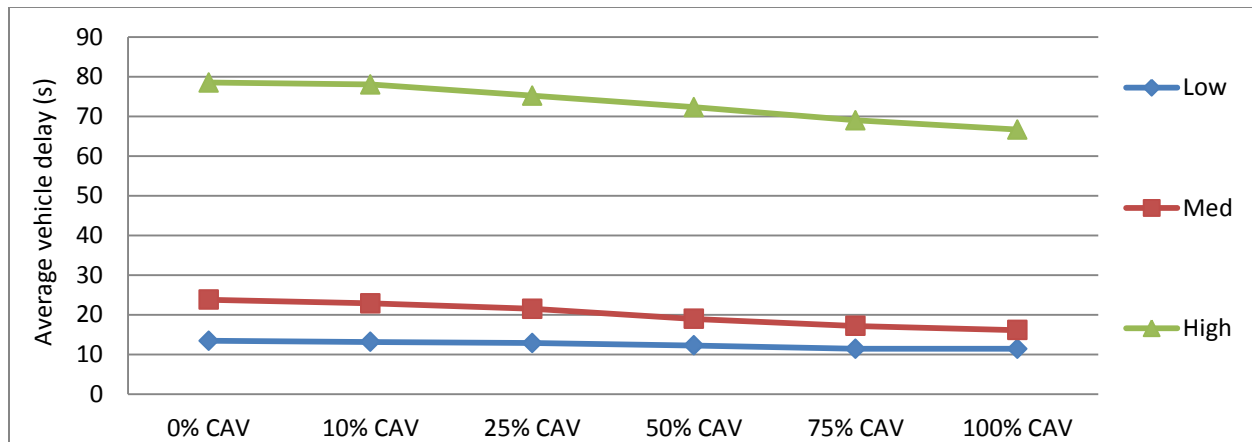


Figure 3-12 Average Vehicle Delay with Different CAV Implementation Rates under Different Volume Levels

Considering the average vehicle delay, as shown in Figure 3-12, at the Low volume level, the average delay slightly (from 13.42 s to 11.41 s) as the CAV implementation rate increased from 0 to 100%. At an implementation rate of 25%, the delay was 4% lesser than that of the base scenario. At high implementation rates, the reduction in the average delay was more significant. At implementation rates of 75% and 100%, the CAV model provided an improvement of 15%. At the Med volume level, the average delay decreased significantly (from 23.79 s to 16.14 s) as the CAV implementation rate increased. At an implementation rate of 25%, the delay decreased by approximately 10% compared to the base scenario. At an implementation rate of 75%, the delay decreased by approximately 28% compared to the base scenario. At the High volume level, the delay decreased from 78.54 s to 66.68 s as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the average delay was minimal. At an implementation rate of 25%, the average delay decreased by approximately 4% compared to the base scenario. At an implementation rate of 75%, the average delay decreased by approximately 12% compared to the base scenario. Thus, the improvement provided by CAV implementation

increases with the increase in the implementation rate, and becomes more significant at higher implementation rates. For example, at the Med volume level, an implementation rate of 50% doubled the improvement achieved at low implementation rates, and a further increase in the implementation rate to 75% provided an additional improvement of 8%. Compared to the other volume levels, the observed improvement was most significant at the Med volume level. For example, the 75% CAV implementation rate reduced the average delay by almost 28% at the Med volume level, whereas at Low and High volume levels, the reductions in the average delay were only 15% and 12%, respectively.

Considering the average stopped delay, as shown in Figure 3-13, at the Low volume level, the delay decreased from 5.61 s to 4.03 s as the CAV implementation rate increased from 0 to 100%. At an implementation rate of 75%, the delay decreased by approximately 24% compared to the base scenario. At the Med volume level, the delay decreased significantly (from 13.05 s to 7.68 s) as the CAV implementation rate increased. At low implementation rates, the improvement derived from CAV implementation compared to the base scenario was small. In contrast, at high implementation rates, the implementation of the CAV model provided significant improvement. At an implementation rate of 75%, the improvement was approximately 34%. At the High volume level, the delay decreased from 65.78 s to 56.46 s as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the delay was small. At higher implementation rates, the reduction in the delay increased significantly. At an implementation rate of 75%, the reduction in the delay was approximately 11.50%.

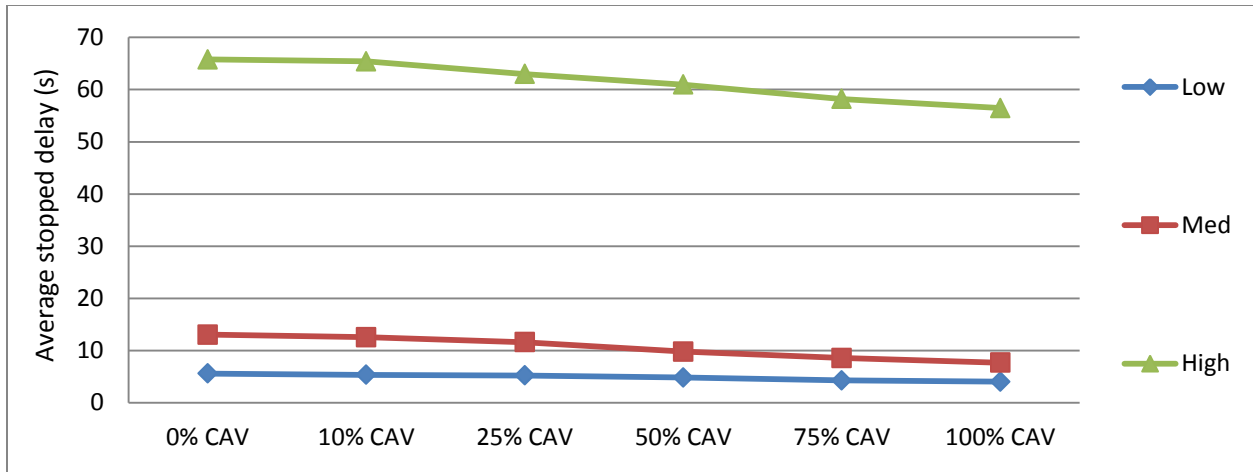


Figure 3-13 Average Stopped Delay with Different CAV Implementation Rates under Different Traffic Volume Levels

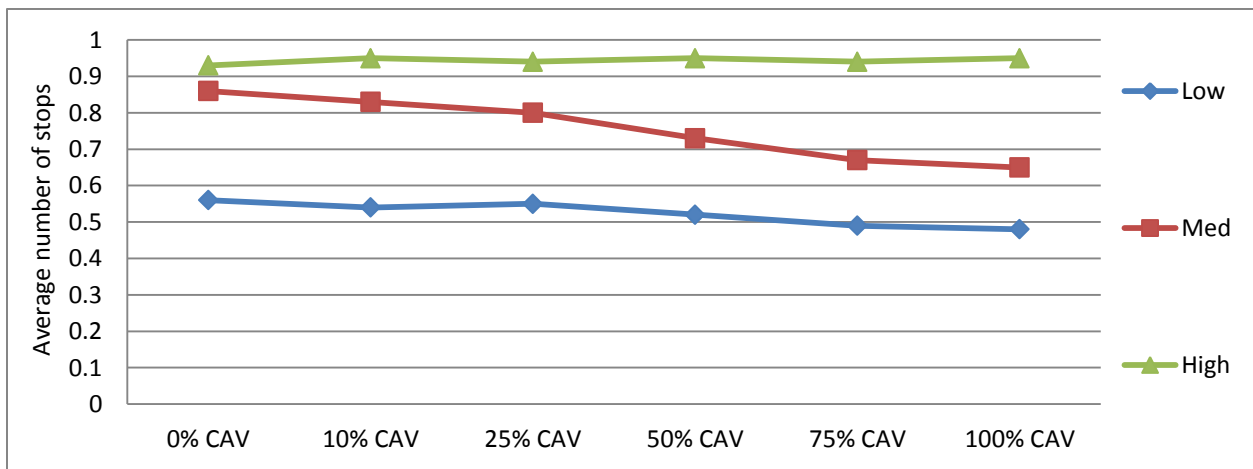


Figure 3-14 Average Number of Stops with Different CAV Implementation Rates under Different Traffic Volume Levels

Considering the average number of stops, as shown in Figure 3-14, at the Low volume level, the average number of stops decreased slightly (from 0.56 to 0.48) as the CAV implementation rate increased from 0 to 100%. At low implementation rates (10% and 25%), the number of stops were similar, with an average value of 0.545. At an implementation rate of 75%, the number of

stops decreased by approximately 12.5% compared to the base scenario. At the Med volume level, the number of stops decreased from 0.86 to 0.65 as the CAV implementation rate increased. At low implementation rates, the improvement derived from CAV implementation, compared to the base scenario, was minimal. At high implementation rates, the improvement derived from CAV implementation was more significant. At an implementation rate of 75%, the improvement was approximately 24.50%. At the High volume level, the number of stops did not decrease regardless of the implementation rate, which is an unexpected result. As the CAV implementation rate increased, the number of stops varied between 0.95 and 0.94. At an implementation rate of 75%, the number of stops increased by 1% compared to the base scenario.

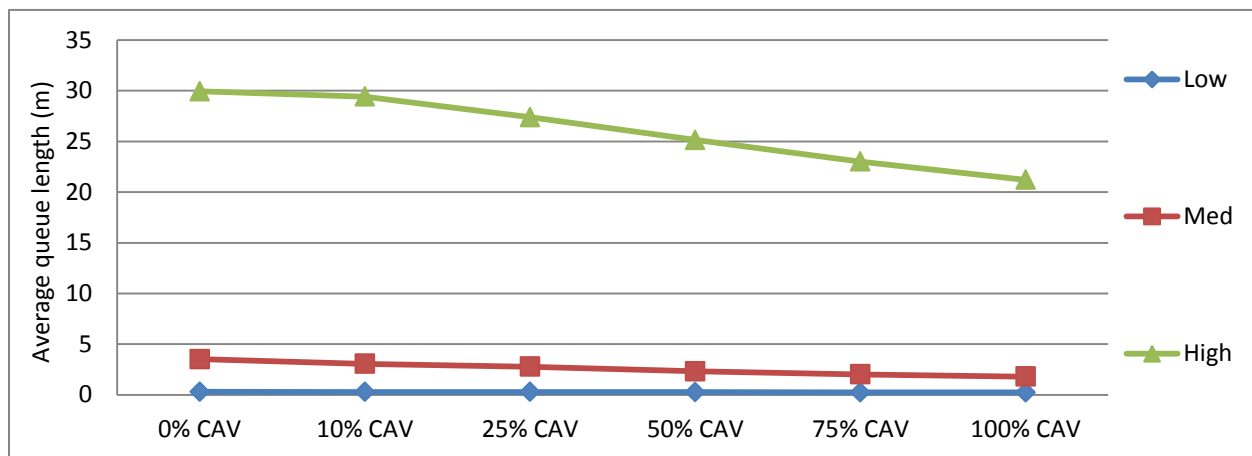


Figure 3-15 Average Queue Length with Different CAV Implementation Rates under Different Traffic Volume Levels

Considering the average queue length, as shown in Figure 3-15, at the Low volume level, the queue length decreased (from 0.29 m to 0.23 m) as the CAV implementation rate increased from 0 to 100%. At low implementation rates, the queue lengths decreased by approximately 7% compared to the base scenario. At implementation rates of 75% and 100%, the queue lengths

decreased by approximately 21% compared to the base scenario. At the Med volume level, the queue lengths decreased significantly from 3.51 m to 1.80 m as the CAV implementation rate increased. At an implementation rate of 75%, the reduction in the queue length was approximately 42.5% compared to the base scenario. At the High volume level, the queue lengths decreased from 29.94 m to 21.22 m as the CAV implementation rate increased. At an implementation rate of 10%, the reduction in the queue length was minimal. Above an implementation rate of 25%, the reduction in queue length became more significant. At an implementation rate of 75%, the improvement compared to the base scenario was 23%. Figures 3-16, 3-17, 3-18 and 3-19 depict the improvement (%) in the average vehicle delay, average stopped delay, average number of stops, and average queue length, respectively, with different CAV implementation rates, under different volume levels, compared to the base scenario.

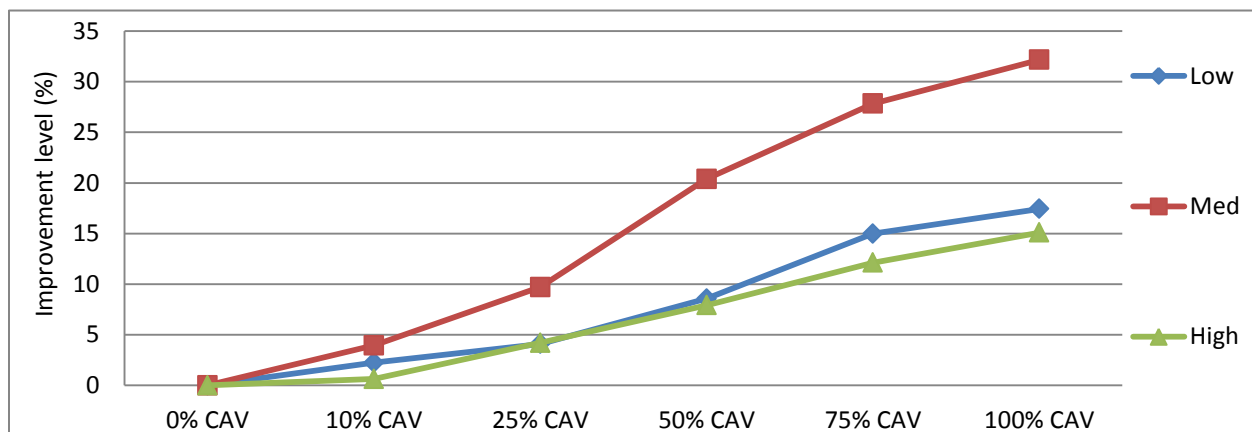


Figure 3-16 Improvement in Average Vehicle Delay with Different CAV Implementation Rates under Different Traffic Volume Levels

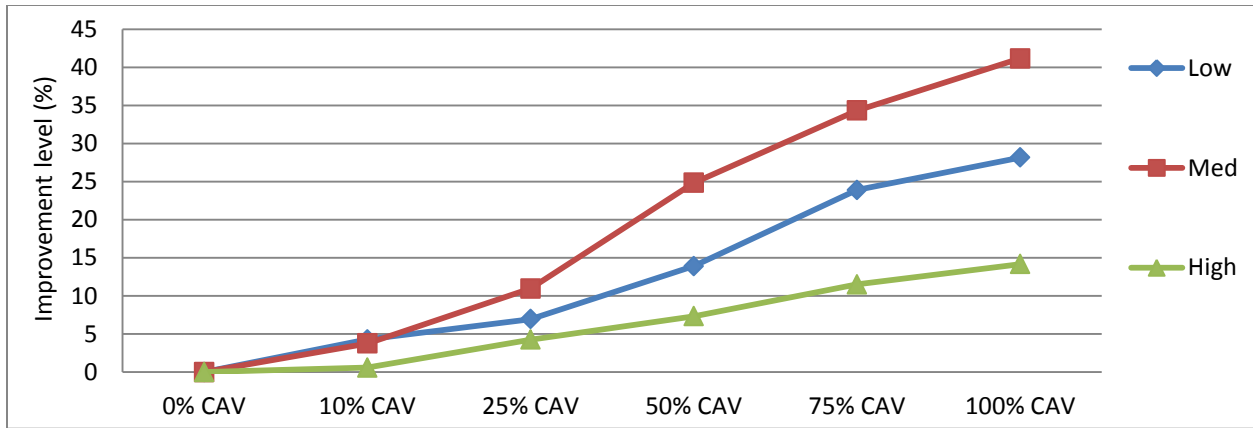


Figure 3-17 Improvement in Average Stopped Delay with Different CAV Implementation Rates under Different Traffic Volume Levels

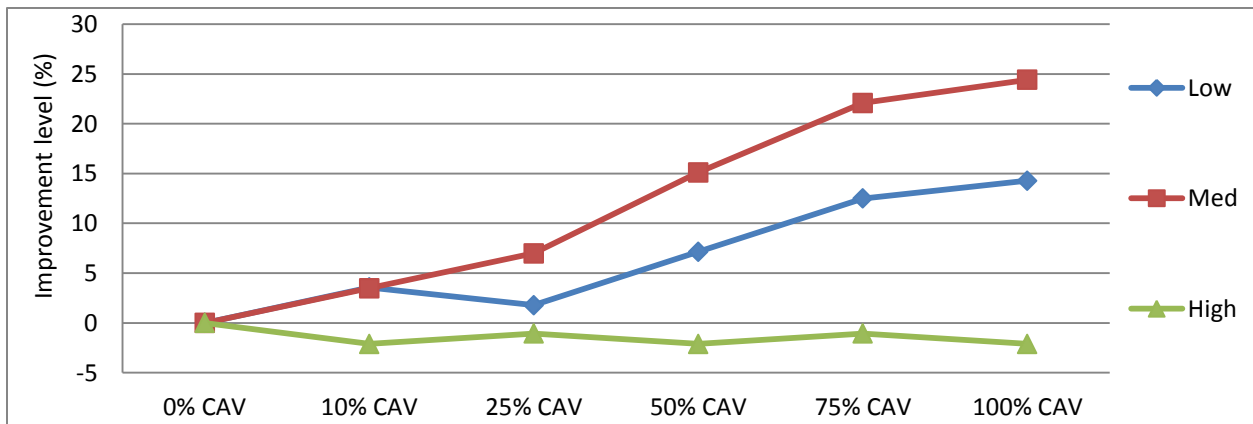


Figure 3-18 Improvement in Average Number of Stops with Different CAV Implementation Rates under Different Traffic Volume Levels

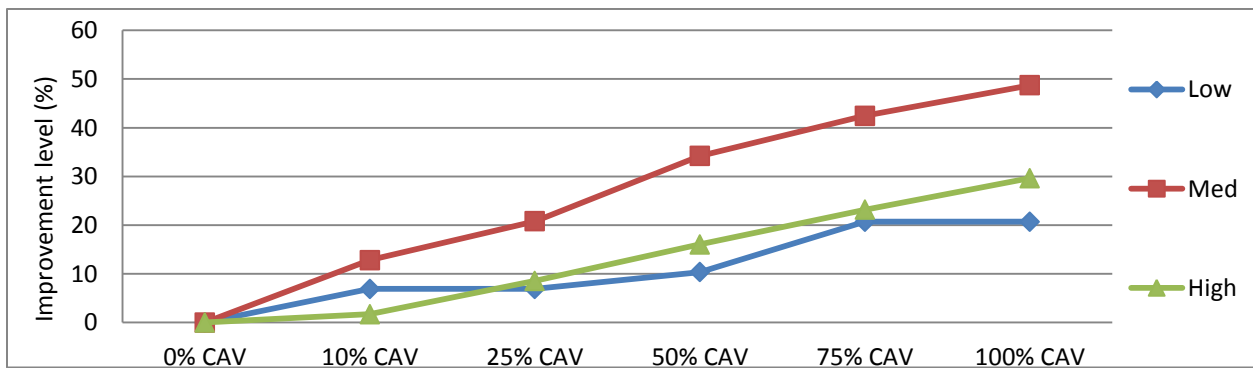


Figure 3-19 Improvement in Average Queue Length with Different CAV Implementation Rates under Different Traffic Volume Levels

In summary, in general, partial AV implementation reduced the average vehicle delay, stopped delay, and queue length, regardless of the traffic volume level. However, the number of stops only reduced at the Low and Med volume levels, and increased at the High volume level, regardless of the AV implementation rate. The level of positive improvement in performance increases with the increase in the AV implementation rate, and becomes significant at higher implementation rates (50% and above). The level of improvement also depends on the traffic volume conditions. The level of improvement is more significant at the Med volume level compared to the other two volume levels. At the Low volume level, the AV implementation does not significantly affect the performance of the intersection compared with full RV traffic. At the High volume level, the expected impacts of the improved driving behavior of AVs are mitigated by the high traffic volumes. Therefore, the level of positive improvements at the Low and High volume levels varies. Considering the average stopped delay and number of stops, the improvement derived from AV implementation is higher at the Low volume level. Considering the queue length, the improvement derived from AV implementation is higher at the High volume level. Considering the average vehicle delay, both Low and High volume levels provide similar improvements.

Partial AV implementation has a more significant impact on the queue length compared to the other measures at the Med and High volume levels. In contrast, at the Low volume level, partial AV implementation has a stronger impact on the average stopped delay. At the Med volume level, the average stopped delay experiences the second highest improvement, whereas the average vehicle delay experiences the least improvement.

Considering the impacts of AV implementation on the LOS of the signalized intersection at the Low volume level, increasing the implementation rate from 10% to 100% did not improve the LOS compared to the base scenario (LOS remained constant at B). At the Med volume level, at low implementation rates, the LOS did not improve (LOS remained constant at C). However, at higher implementation rates (50% and above), the LOS improved from C to B. At the High volume level, increasing the implementation rate did not improve the LOS (LOS remained constant at E). These findings confirm that AV implementation offers significant improvements at the Med volume level.

3.5 Summary of Chapter 3

In this chapter, a simulation-based investigation study was presented to investigate the impacts of AV implementation on the performance of an urban signalized intersection considering a mixed AV-based traffic environment. The expected impacts of partial AV implementation, including high and low rates, are analyzed in addition to its relations with the level of traffic congestion. In addition, the performance of different automated driving capabilities is analyzed and compared. It is a more comprehensive study than existing studies and addresses several gaps found in the literature.

The results revealed that, compared to full RV traffic, the implementation of different AV models provides significant performance improvements by reducing the vehicle delay, stopped delay, and queue length at a signalized intersection. Considering different performance measures, the queue length experiences the highest positive improvement; in contrast, the number of stops experiences the least positive impact. Even partial AV implementation, including low implementation rates, in a mixed traffic environment provides improvement in the signalized intersection performance. The results revealed that, level of improvement in performance

depends on the AV implementation rate. The improvement increases with the increase in the AV implementation rate, and becomes significant at higher implementation rates (50% and above). The level of improvement depends also on the traffic volume conditions. All the performance measures experienced the highest improvement at the Med volume level. There are no significant differences between the performances of the three AV models especially at the Low and Med volume levels. Nevertheless, the CAV model was slightly superior to the other two AV models particularly in terms of reducing the delay and queue length.

The study presented in this chapter can potentially serve as the starting point for further studies on the impacts of AVs under mixed traffic environments, which is essential for increasing the efficiency of the AV adoption in the near future. The findings obtained herein can provide new insights into the potential impacts of AV implementation and can be used to design analytical models that incorporate mixed traffic environments in an urban transportation network. These models can be used to improve the efficiency of traffic networks. For example, in terms of signalized intersection control under AV-based traffic, the traffic signal parameters can be optimized considering different AV implementation rates. On the other hand, the findings can also be used to compare the behavior of AVs and RVs and their impacts on signalized intersection performance. Furthermore, the findings can help AV manufactures and traffic authorities to program the operational settings of AVs to better optimize AV implementation in urban networks.

CHAPTER 4

COMPREHENSIVE LITERATURE REVIEW ON THE SIGNALIZED INTERSECTION CONTROL UNDER MIXED TRAFFIC ENVIRONMENT

As indicated earlier, the implementation of AVs may affect the design and operation of signalized intersection control [23]. Optimum utilization of driving behavior and advanced capabilities of the AVs has enabled researchers to propose autonomous cooperative-based methods for signalized intersection control under an AV traffic environment. Different methods have been proposed to control the AVs at intersections under full AV environment ([44],[45]). Namazi et al. in 2019 [40] included detailed literature on signalized intersection control under full AV environment. However, few researchers reviewed the proposed methods that considered the signalized intersection control under a mixed traffic environment ([46],[47]). In 2016, Chen and Englund [44] discussed different cooperative-based methods. However, most studies considered a fully connected environment with more focus on controlling the non-signalized intersections. Namazi et al. [40] discussed the performance of different methods in terms of efficiency, safety, ecology, and passenger comfort. They included seven related studies, but two of these studies ([95],[96]) did not consider the mixed environment conditions. In 2019, Guo et al. [45], part of their review on the CAV implementation, discussed the signalized intersection control methods that were proposed to optimize traffic signal plans. However, most of the included studies in their review considered the full CV environment rather than AV environment.

The main objective of this chapter is to conduct a critical comprehensive review of proposed methods for the signalized intersection control under mixed AV traffic environment, mainly when AVs are sharing the same intersections with RVs without the application of dedicated AV lanes. In addition, based on the review findings, different limitations of the proposed methods are discussed. The sections of this chapter are organized as follows. Section 1 includes the research methodology of the review. In section 2, the extended review of the signalized intersection control under mixed AV traffic environment is presented. It begins with the classification of signalized intersection control methods and then includes a literature review of the proposed methods under mixed AV traffic environment. In section 3, the different obtained limitations of signalized intersection control under mixed AV traffic environments are discussed in detail. Section 4 is the policy implications pertinent to the alternatives of signalized intersection control under a mixed traffic environment. Finally, section 5 includes a summary of the chapter.

4.1 Methodology

A systematic review approach was adopted for conducting this study (Figure 4-1). At the beginning of this work, the research questions, search keywords, and the inclusion and exclusion criteria of the collected studies were determined. In this study, four main research questions were identified. First, what are the proposed methods of signalized intersection control under an AV traffic environment? Second, whether these methods have considered the case of mixed traffic environment of AVs and RVs? Third, what are the limitations of the actual application of the proposed methods? Fourth, what are the alternatives that may overcome these limitations? The search keywords included the following: autonomous (automated) vehicles, regular (human-driven) vehicles, AV environment, mixed (heterogeneous) traffic, signalized intersection control, autonomous (cooperative-intelligence-smart) intersection control, and signal optimization.

However, this review excluded any study which considered the application of dedicated lane(s) for AVs. The contents of the collected studies were reviewed to conduct thematic analysis and achieve the objectives of this study.

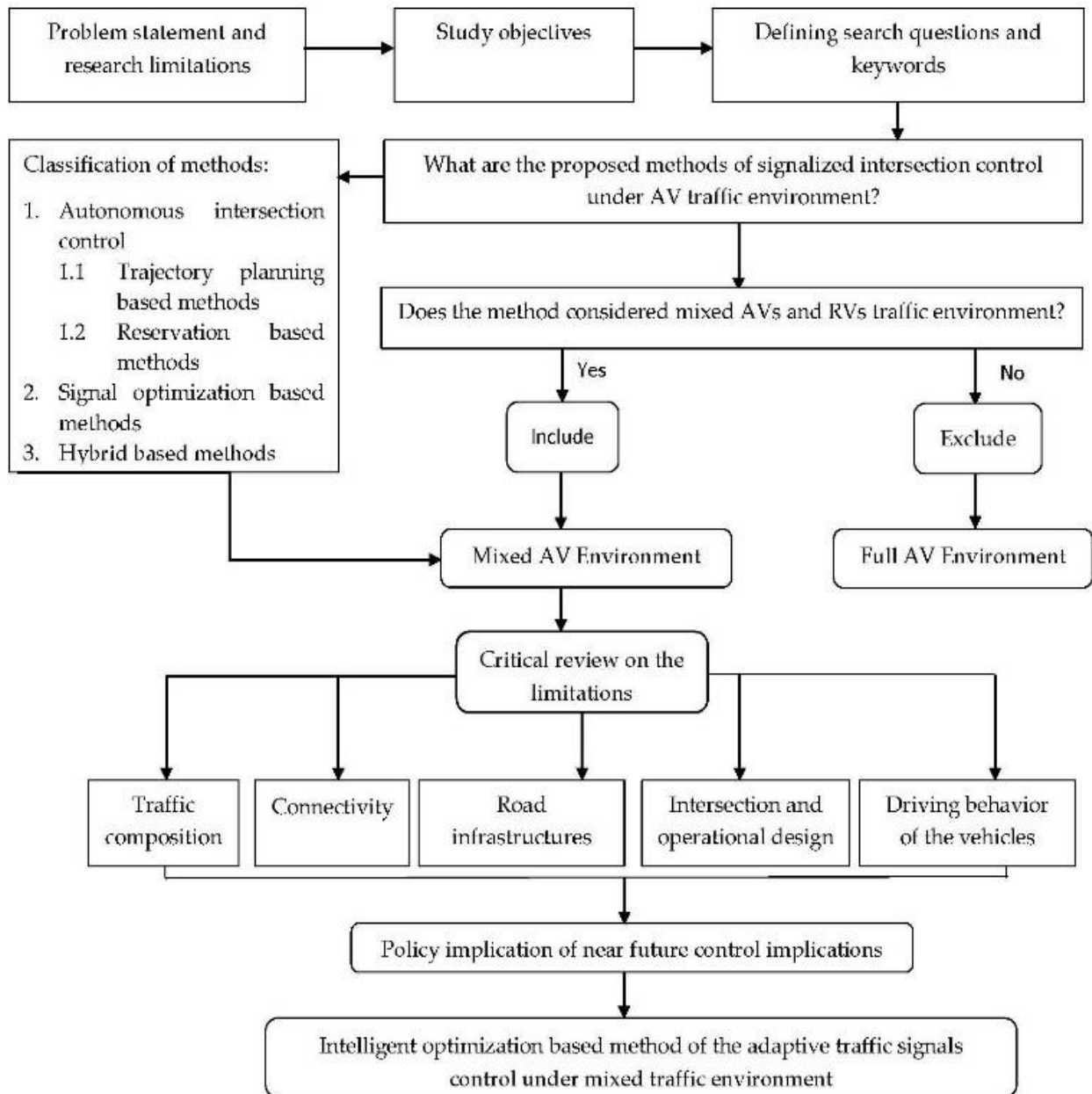


Figure 4-1 General Flow Chart of the Study

4.2 Signalized Intersection Control under Mixed AV Traffic Environment

Signalized intersection control is essential to enhance the traffic flow by optimizing intersections in different aspects [97]. It manages the order and right-of-way of vehicles to cross intersections effectively. The main objectives of these methods are to utilize and optimize the space within an intersection more efficiently to increase the flow, decrease delays and fuel consumption, and improve safety ([44],[98]). In the case of a full RV environment, the literature has indicated that different methods have been used for signalized intersection control. These methods are divided into three main systems groups: fixed, actuated, and adaptive systems [99]. Most existing systems rely on fixed signal plans optimized regularly by traffic engineers [100]. However, the fixed systems cannot adapt to the increasing and varying traffic demands leading to different traffic problems ([101],[102],[30]). The adaptive traffic signal systems, in general, use the data collected by the upstream detector to estimate incoming traffic and try to find an optimum signal plan that can maximize or minimize the control target. Compared with fixed and actuated types, different studies have indicated that it can improve the signal efficiency leading to better optimization of the intersection capacity ([103],[104]). However, one of the limitations of the simple adaptive based system, under RV traffic environment, is that its basic detectors can provide limited types of traffic information, such as average occupancy, and may miss important information, such as vehicle states ([105],[97]). In addition, most of these systems are based on traditional traffic prediction models, which lack self-learning capabilities that can improve the system's performance [42].

Under the AV traffic environment, different methods have been proposed to control the AVs for crossing the signalized intersections. However, these methods differ in their control architectures and logic, the distribution of computations, or they may vary in their required infrastructures for

the real applications and targeted objectives. The control methods of the signalized intersections under AV environment may be classified into three main classes: autonomous intersection control, signal optimization-based methods, and hybrid-based methods. The following sub-sections will include a brief description of each class.

4.2.1 Autonomous Intersection Control

This class of methods includes those intelligent or cooperative-based methods that eliminate the traffic signal. It uses different algorithms to optimize the vehicle's crossing of the intersection. Some papers referred to these methods as autonomous intersection management (AIM) ([40],[106]). From its control architectures aspects, these methods can be divided into two categories of centralized and distributed-based methods [43].

The centralized-based methods include a central coordination unit that communicates with vehicles, receives real-time information about vehicles, and gives instructions to guide the vehicles to cross an intersection safely [43]. This central agent makes the control decisions globally for all vehicles [47]. The second important aspect of the centralized methods is the vehicle agent within each vehicle, which controls the crossing of AVs [106]. So, it only requires communications between the centralized units and the vehicles without the requirement of vehicle-to-vehicle (V-V) communications. However, the different complex computations rely on the single intersection control agent. Therefore, the high computational requirement is considered a critical concern and needs great efforts to ensure system reliability and robustness ([44],[107]). Different meta-heuristics and mathematical methods, such as linear and dynamic programming, have been widely applied to many autonomous intersection-based methods [43]. In contrast, the distributed-based methods are based on the communications between the vehicles to negotiate and agree on vehicle

priorities to safely and effectively cross the intersection [43]. Most of these methods are applied in agents based manner where different agents (such as an AV) interact and coordinate their behaviors to achieve specific objectives. In other words, the vehicles collect the required information and make the control decisions by themselves. Compared to the centralized-based method, the advantage of distributed-based methods is that it requires less infrastructure support since it needs only V-V communications. In addition, it has fewer computational problems since the crossing decisions are made locally, and the computations are distributed among vehicles [44]. However, it relies entirely on the performance of the communication channel and the negotiation protocol between the vehicles [43]. L. Chen and Englund and Pourmehrab et al. ([44],[98]) classified the autonomous intersection-based methods for fully AV environments into two main classes, including: reservation-based and trajectory planning-based methods. These classes are generally described in the following parts.

A. Trajectory Planning Based Methods

The intersection crossing with the application of these methods is considered as a passing sequence optimization problem aiming at maximizing certain utilities with constraints to ensure intersection safety and vehicle maneuvering limits [44]. It is based on different vehicle trajectories, such as the location and speed of the vehicles. The main objective is to find the optimal sequence, such as optimal departure at the intersection, for each vehicle considering the connectivity and programmability of AVs. With these methods, space tiles are planned and allocated consecutively as travel routes. AVs are controlled along the planned trajectories to safely cross the intersection, with unimpeded movement, strategically guiding AVs to adjust their approaching trajectories. These methods can be improved by exploiting the optimization of vehicle control parameters. Most of the trajectory planning-based methods are based on the application of centralized-based

methods. The role of the central unit is to optimize the feasible motion plans for AVs based on different information, then, it assigns specific crossing instructions to AVs.

B. Reservation Based Methods

It considers the intersection crossing as a discrete resource allocation or scheduling problem. Some of the studies referred to this class as suitable resource reservation-based methods [44] or signal scheduling-based methods [98]. It aims mainly to reserve exclusive time slots and intersection space for each vehicle to cross the intersection safely. It focuses on finding the optimal sequence of serving lanes by sorting incoming requests from the vehicles and allocating the right of way of the intersection based on a set of predefined rules [98].

4.2.2 Signal Optimization-Based Methods

The signal optimization-based methods require traffic signals. These methods are applied to generate optimal traffic signal timing plans using different methods such as classical optimization methods, heuristics optimization algorithms, and machine learning-based optimization methods. Guo et al. [45] classified the CAV-based signalized intersection control methods into three main classes, including adaptive traffic signals control, platoon-based control and planning-based control. The adaptive-based methods, using CAVs data, can optimize the signal plan based on current traffic states and do not apply prediction. The platoon-based methods, using CAVs coordination, can optimize the signal plan by grouping incoming vehicles into platoons thought predicting their traffic flow status. The planning-based methods, also using CAVs coordination, treat each vehicle individually by considering its detailed trajectories and optimizing the signal plan in a forward time horizon by adopting more accurate and complex models.

4.2.3 Hybrid Based Methods

These methods combine autonomous intersection control-based methods (Class 1) and signal optimization-based methods (Class 2). These methods jointly optimize AV trajectories and signal timing at the same time. This combination can significantly improve signalized intersection performance. For example, optimizing the arrival time of the vehicles to the intersection may result in better utilization of green durations [37]. Another example, when the signal plans are identified, the desired speed of the AVs can be optimized to ensure that they can cross the intersection without stopping [108].

The literature included in this study indicated that most of the proposed methods of signalized intersection control focused on the full AV traffic environment. However, a limited number of studies have focused on solving the problems of signalized intersection control under a mixed traffic environment of AVs and RVs sharing the same network. Namazi et al. in their review, found that out of 103 reviewed studies, 94% of these studies considered full AV environment, while only around 6% considered the mixed traffic environment [40]. This finding regarding the research limitations is also confirmed in this current review. In addition to the reviewed studies by [40], we found 14 additional related studies until September 2021. Figure 4-2 shows the distribution of different methods under a mixed traffic environment. About 68% of the proposed methods are autonomous intersection control-based methods, 11% are signal optimization-based methods, and 21% are hybrid-based methods. Table 4-1 summarizes the collected studies, including study variables: class of the proposed method, traffic environment, and method name.

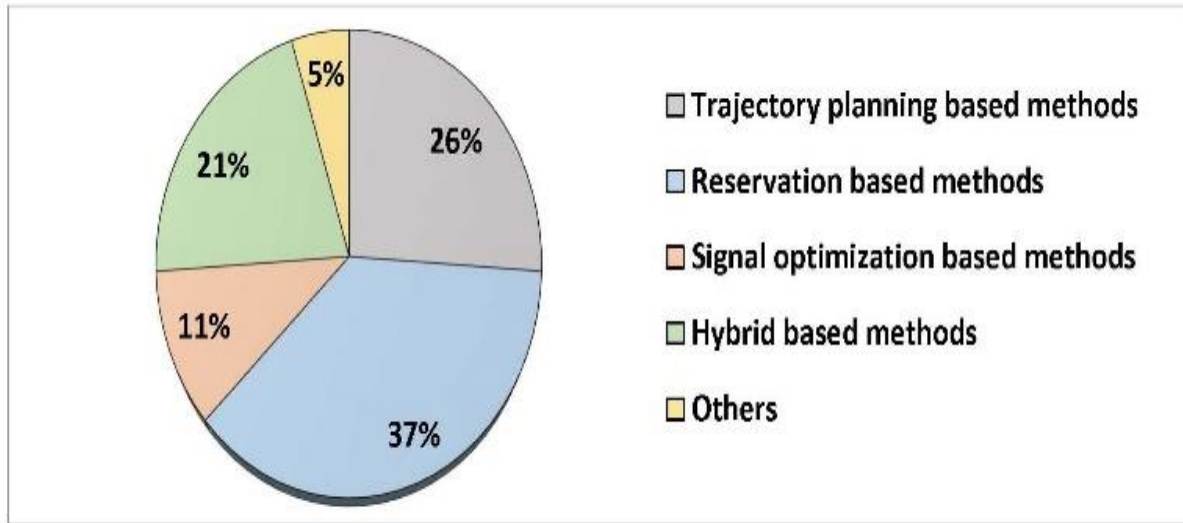


Figure 4-2 Distribution of Methods of Signalized Intersection Control under Mixed Traffic Environment

Table 4-1 Proposed Signalized Intersection Control Methods for Mixed Traffic Environment

Study [Reference No.]	Class of Method	Traffic Environment	Method Name
Dresner and Stone, 2004 [36]	Time slot reservation	AV and RV	First come, first served (FCFS) light
Bento et al., 2013 [109]	Spatial-temporal reservation	AV and RV	Legacy early method for intelligent traffic management (LEMITM)
Qian et al., 2014 [110]	Reservation	AV and RV	Priority-preserving order based method
Yang et al., 2016 [111]	Trajectory planning	AV,CV and RV	Optimal departure sequence using a branch and bound technique
Sharon and Stone, 2017 [106]	Reservation	CAV and RV	Hybrid autonomous intersection management (H-AIM)
Lin et al., 2017 [112]	Trajectory planning	CAV and RV	Buffer-assignment based coordinated method
Li and Zhou, 2017 [113]	Hybrid	CAV and RV	Intersection automation policy (IAP) optimization method
Zhao et al., 2018 [114]	Trajectory planning	AV and RV	Real-time distributed cooperative eco-driving strategy-based method
Liang et al., 2019 [108]	Hybrid	AV,CV and RV	Rolling-horizon optimization framework
Liu et al., 2019 [16]	Trajectory planning	CAV and RV	Permission assignment policy with a coordination protocol
Barthauer and Friedrich, 2019 [115]	Autonomous intersection control	AV and RV	Pre-sorting and pre-signaling based method
Reddy et al., 2019 [46]	Reservation	AV and RV	Synchronous intersection management protocol (SIMP)
Pourmehrab et al., 2020 [98]	Hybrid	AV and RV	Intelligent intersection control system (IICS)

Bashiri, 2020 [43]	Signal optimization	CAV and RV	Real-time Data-driven adaptive signal control
Baz et al., 2020 [14]	Trajectory planning	AV and RV	Game-theory-based priority control
Qi et al., 2020 [7]	Signal optimization	AV and RV	Particle swarm optimization (PSO) method
Yao and Li, 2020 [47]	Trajectory planning	CAV and RV	A decentralized based method
Chen et al., 2021 [116]	Trajectory planning	CAV and RV	Platoon-based optimal control framework
Tajalli and Hajbabaie, 2021 [37]	Hybrid	CAV and RV	Mixed-integer non-linear program

4.3 Limitations of Signalized Intersection Control under Mixed AV Traffic Environment

In general, the conducted review indicated that the autonomous intersection control-based methods are expected to improve the efficiency of the signalized intersections under the AV environment ([40],[47]). Unlike the trajectory planning-based methods, the main drawback of reservation based methods in minimizing delay at a signalized intersection is that they do not consider the added benefit of optimizing AV trajectories [98]. The main problem of applying such autonomous-based methods in a mixed traffic environment is that each control policy requires a traffic signal model so that the RVs understand the crossing instructions. Compared to the autonomous-based methods, the hybrid-based methods may lead to significantly different performance [40]. However, some studies indicated that the effective combination of both methods is complex and requires significant efforts to develop methods that can balance computational complexity and control performance. For example, it is not likely that a centralized unit can handle all the required computations to cooperate between the signal controller and approaching vehicles [37].

The findings from this review indicated that the applications of both autonomous or hybrid-based methods are built on some different assumptions, requirements, and constraints. Those are related to the network environment, including the traffic composition, connectivity, road infrastructures, intersection and functional network design, in addition to the driving behavior. Those will lead to different limitations of their possible practicability and reliability of controlling signalized intersections under different conditions of mixed traffic environment of AVs and RVs. In the following parts, we will discuss some of these limitations supported with examples.

4.3.1 Traffic Composition

The traffic composition of a mixed environment may include different implementation rates of AVs and RVs. Some of the proposed methods have assumed a specific traffic composition for the application of their methods. For example, some methods were proposed to be applied only at under-saturated traffic flow conditions [98]. The trajectories-based methods may not be effective with scenarios of high traffic volume since that the trajectories of all involved vehicles need to be optimized for each signal cycle. Other methods have shown improvement only at specific conditions of the traffic composition. For example, different proposed reservation based methods showed improved performance only at lower implementation rates of RVs (less than 10%) ([36],[109]). Other methods showed improvement when the implementation rate of CAVs is more than 10% [106]. Some trajectory planning based methods showed improvement only when the implementation rate of AVs is more than 50% [111]. In contrast, other methods showed improvement only when the implementation rate of CAV was less than 21% [112]. The above findings indicated that most of the proposed methods would not be applicable at any traffic composition or traffic flow conditions that may occur in the transition period of the expected mixed traffic environment.

4.3.2 Connectivity

The autonomous or hybrid-based methods assumed different required levels of connectivity of the traffic environment. The connectivity enables other communications to exchange the required information, including crossing requests or crossing instructions, between the vehicles or with intersection control units. For example, the centralized-based methods can be applied only under a fully connected environment where the involved vehicles and the intersection units must be

connected. On the other hand, in terms of vehicles capabilities, all of these methods assumed that the involved vehicles have V-V, V-I, and I-V communications. The proposed method by C. Chen et al. assumed that the RVs are connected to the central unit and can exchange the required information [116]. In their proposed method, Reddy et al. assumed that the RVs have the same sensing capabilities as AVs [46]. In the case of a mixed traffic environment, unlike the CAVs, most of the existing RVs do not include these required connectivity capabilities. Therefore, RVs will not be able to exchange or receive the required information on how to cross the intersections with cooperative methods safely. The availability of connectivity is not the only concern. Indeed, the performance of the cooperative-based methods will be built on the quality and performance of the different involved communications. That brought up concerns about its accurate performance and safety guarantee for real-world conditions under a mixed traffic environment ([43],[44]). For example, some studies have shown different constraints related to communication ranges.

4.3.3 Road Infrastructures

Some of the proposed methods of signalized intersection control under a mixed traffic environment have required different modifications of the existing road infrastructures. To provide the required V-V and V-I communications, the central-based method's main problem is that it requires establishing and installing centralized units at each intersection [112]. Also, to collect the required information, different supported roadside units at each intersection must be installed. For example, most proposed autonomous or hybrid-based methods require various sensors to detect traffic information [37]. Other methods have used different prediction models, such as kinematic wave theory and Newell's car-following model, to predict the information of the RVs, such as their arrival sequence and trajectories. These road infrastructures must be provided at each intersection of the existing network, which is considered highly costly ([43],[44]). As a result, the most

proposed methods may face difficulties in their real application because of the additional constraints regarding the required infrastructure. To overcome that, some of the proposed methods assumed that the information of the RVs can be provided by the AVs or the CVs ([108],[111]). However, the RV information level and accuracy will depend on its implementation rate in the mixed traffic environment. With low implementation rates, the performance of these methods may not be effective.

4.3.4 Intersection and Functional Network Design

The findings indicated that the autonomous-based methods' performance could be sensitive to different turning options at the intersection, considering different involved vehicle types. To solve the related issues, some of the proposed methods have assumed specific operational configurations. A method is applied when left-turn movements operate exclusively [37]. Another method assumed only one-way traffic without turning movements [14]. Some of these special configurations, mainly in the case of a mixed environment, may lead to increased delays for the AVs [110]. On the other hand, other proposed methods have assumed specific intersection designs. For example, some methods were applied only for intersections with single-lane roads ([46],[47],[113]). Some studies have indicated that the hybrid control-based methods may improve the performance of the signalized intersection; however, it may lead to negative impacts on the intersection capacity. Barthauer and Friedrich concluded that the application of the pre-sorting and pre-signaling decrease the capacity of the intersection by 50% compared to a conventional method [115]. Most of these modifications in terms of operation and intersection designs were considered to include collision-free features to ensure the safety of the vehicles crossing. However, applying these modifications to each existing intersection is complex due to different related aspects. Alternative intersection designs, such as the tandem intersection concept, require more space than a traditional

four-leg intersection [115]. In addition to that, these modifications may improve safety, however, they may cause negative impacts on the intersection operational performance, such as increased delays [115].

4.3.5 Driving Behavior

Another common assumption of the autonomous and hybrid-based methods is related to the driving behavior of the involved vehicles. There are sets of constraints in terms of vehicle operational characteristics related to the design or application of the method or related to the safety requirements. Examples include safe headway, speed limits, acceleration, deceleration limits, and lane-changing capabilities [44]. Some autonomous-based methods assumed that all of the involved vehicles are highly automated that have similar operational settings [44]. Some reservation based methods assumed that RVs could keep a safe distance from their leading vehicles [117]. However, the RVs have stochastic driving behavior that may vary based on different factors. The main difference that should be realized is that the RVs have complete freedom to change a control input at any time, while the AVs can only adjust control input at periodic discrete times [16]. With the application of such autonomous-based methods, all of the involved vehicles are assumed to follow exact assigned instructions of crossing the intersection, given by the control system, without any unplanned maneuvers such as overtaking or lane-changing [44]. For example, some proposed methods assumed that the RVs strictly follow the path and will not perform undesired or illegal maneuvers ([110],[116]). However, in case of a mixed traffic environment, the critical concern is that whether the RVs with human control are able to respond to the crossing instructions completely and cope with the AV driving behavior ([110],[26]). Unlike the AVs, we have to realize that the driving actions of the RVs cannot be identified by the control system [118]. So, it

may be concluded that the reliability of the RV driving behavior should be highly considered while designing or evaluating the performance of different proposed methods.

4.4 Policy Implications

The existing traffic environment of road networks mainly includes RVs and different types of semi-autonomous vehicles. However, in the coming near future, it is expected that full AV will gradually be introduced into the traffic networks of many cities. Therefore, full AV will share networks, including intersections, with the RVs. The proposed autonomous and hybrid-based methods of signalized intersection control, in the literature, can be applied in the case of a mixed traffic environment. However, the effective application of such methods will be based on specific requirements and assumptions of the AV traffic environment. As discussed in the previous section, these requirements and assumptions will lead to different types of limitations which may affect the generalization of applying such methods to control any existing signalized intersection in a mixed traffic environment of urban networks in the actual practice. Examples of the limitations may include required communication protocols, computational power, and other required modifications in addition to the different assumptions related to the traffic composition and driving behavior of the RVs. Moreover, one of the main drawbacks of most proposed autonomous and hybrid-based methods is that it have focused on the vehicle's movements and ignored the other users such as pedestrians and bicycles at the intersections [49]. However, in the case of an urban signalized intersection, the movement of such users should be considered. On the other hand, another important aspect that should also be considered and evaluated carefully is the duration of the execution time of such cooperative-based control methods that may induce extra delay due to the required computations and communications. As an example of extra expected delay, one of the

reservation-based methods limitations is that the frequent switches of right-of-way may disrupt platoons resulting in increased traffic delays [98].

The main outcome of the included discussion in this section may be significantly utilized to build new signalized intersection control methods that can overcome the limitations of the proposed methods. In a mixed traffic environment, the control methods should be applicable at different conditions of traffic compositions. The traffic signal may be applied effectively regardless of the implementation rates of AVs and RVs without any constraint or assumption of traffic compositions or saturation traffic flow conditions. In terms of connectivity, unlike the autonomous or hybrid-based methods, traffic signals do not require any level of V-V or V-I communications within the traffic environment. Based on the collected data of the different detectors, the signal agents need to send the required phase information to the AVs. So, the traffic signal-based methods can be applied even when the involved vehicles, including RVs, are not connected to each other or to the infrastructure. Moreover, with an application of the traffic signals, the requirements of the extra modifications of the existing road infrastructures can be eliminated. It may only require simple traffic detectors to detect specific information, such as traffic volume and vehicle type, as the case of the existing adaptive traffic signals in the RV traffic environment. The application of the traffic signal-based methods is considered an effective solution to the existing road network since it can be applied without the need for extra costly modifications of the operational designs and intersection layouts. It can be applied under different features of the road, intersection and operational designs such as highway class, number of lanes and signal phasing. The driving and traffic signal response behavior of the involved vehicles, mainly the RVs, in mixed traffic environment are different and cannot be assumed to be fully controlled or predicted. To overcome the human driving behavioral issues of the control response, we need to apply control methods that

are quite familiar to them, such as traffic signals which can be also easily formulated and controlled to be totally understood and accurately followed by the AVs. In terms of road safety, the traffic signals can provide safety measures inherent, as in the case of the full RV traffic, where there will not be any conflicting trajectories between the involved vehicles during crossing intersections. The traffic signal-based methods are suitable and reliable for both involved vehicle types considering their expected driving behavior and capabilities.

To improve the performance of the traffic signals under a mixed traffic environment, we have to think of how to utilize the advantages of the AV implementation in order to optimize the signal plans. The optimization of existing traffic networks by the effective application of the current artificial intelligent-based methods is becoming an increasingly important aspect for solving different traffic problems. The application of the signal optimization-based methods can easily handle single or multiple objectives and complex traffic conditions [40]. Under the RV traffic environment, the literature indicated that different optimization methods had been applied to optimize the performance of signalized intersection systems. These methods range basically from mathematically based methods to artificial intelligence-based methods ([30],[99],[119],[120],[121],[122]). For example, several heuristics algorithms, such as genetic algorithms (GA) and differential evolution (DE), have been applied to optimize signal plans in order to minimize the delays, number of stops, and queue length [123]. To improve the learning ability of the adaptive control systems, advanced machine learning methods were applied and showed superior performance compared to other shallow learning methods such as the artificial neural networks (ANNs) [13].

Most of the related studies of traffic signal optimization, under the RV environment, have considered and assumed stochastic behavior of human driving and have focused on the solution

quality for the traffic volumes. With the implementation of AVs, to improve the performance of the traffic signals, we have to consider the expected positive impacts of the AVs without compromising the reliability of control systems for the RVs in a mixed traffic environment. The deterministic driving behavior [7] and improved operational and connectivity characteristics of the AVs, in addition to its expected impacts on the traffic flow characteristics, should be significantly utilized for better improvement of the traffic signal optimization [14]. For example, in terms of its advanced capabilities, the shorter perception and reaction time of the AVs may help to minimize the yellow interval or to optimize the duration of green times. Also, the shorter start-up times may decrease the total lost times. In terms of its operational characteristics, the shorter headways may help to minimize the maximum green durations as a result to the improved saturation flow rates. All of that may effectively assist the signal to optimize its main control parameters, such as signal timing parameters, which will result in decreased delays and, therefore, better utilization of the intersection capacities [23].

Basic optimization methods, such as mathematical or dynamic programming, are based on analytical relationships. These cannot be applied for the mixed AV traffic environment due to absence of real existing data or the high computational complexity of the optimization. For example, it is not possible to establish the exact, reliable mathematical models that can represent the traffic conditions or select the optimum control policy in the case of a mixed traffic environment [42]. We need defined functions or equations to relate the inputs and the outputs of this unique environment. This step requires the reformulation of some essential traffic flow functions as a result of the adjusted AVs characteristics and its impacts on the traffic flow characteristics. However, with the application of the ML optimization-based methods, we need only big data for the learning process of the different hidden relationships of the mixed traffic

environment. These methods may be used to overcome the different issues of the basic optimization methods and also may improve the optimization performance due to its intelligent learning.

The findings of the current review have indicated that few efforts have considered the traffic signal optimization for the AV traffic environment. Our review found only two studies that aimed to optimize the traffic signal under a mixed AV environment ([43],[7]). Moreover, the literature indicated that the application of the ML-based methods is still limited and needs more efforts of investigations under a mixed AV traffic environment. Namazi et al. [40] found that out of 103 published studies in the area of signalized intersection control of AV environment, only about 4% of the studies have applied machine learning-based methods.

Nowadays, due to the recent explosion in the development and availability of different information and communications technologies, in addition to the advancement in computing capabilities, there are significant improvements in ML approaches that should be considered in solving the mentioned challenges of signalized intersection control under mixed AV traffic environment. Examples of advanced ML-based methods may include deep learning (DL) and reinforcement learning (RL). Using different concepts, these methods can learn and extract the inherent complex relationships of the system's behavior of the mixed traffic environment without any predefined models or underlying processes. The deep architecture can improve the learning process and produce better results compared to the most of the common shallow networks that usually have only one hidden layer. For example, some studies applied reinforcement learning to improve the performance of adaptive traffic signals under RV traffic environment ([124],[125],[126],[42],[127],[128]). Most of these studies indicated that the reinforcement learning-based method is much superior compared to the common traffic signal control methods.

4.5 Summary of Chapter 4

This chapter included a comprehensive literature review about the different proposed signalized intersection control methods under mixed AV-traffic. Based on the review findings, different limitations of the proposed methods were discussed to provide a policy implications discussion that intended to provide proposed alternative solutions.

The review findings indicates that most of the proposed methods can be applied effectively only for a fully connected traffic environment, mainly where the required connectivity is achievable along with full behavioral control of the involved vehicles. That may occur when we reach a 100% implementation rate of the CAVs in our traffic network, which is not feasible in the near future. Therefore, the proposed methods should be evaluated considering the underlying assumptions and limitations for appropriate generalization and implementation of controlling existing signalized intersections in a mixed traffic environment of urban networks. The control methods should be applicable for both AVs and RVs, considering their different implementation rates and capabilities, under different scenarios in the future. Any proposed method should be designed and operated with minor modifications or requirements of the existing infrastructure.

The significant improvements in ML approaches should be utilized to develop reliable adaptive traffic signal control-based methods. Such methods aim to respond effectively to mixed traffic's dynamic and complex environment using their intelligent continuing learning and adaptation. As a result, the controller can optimize signal plans by smarter utilizing the AV characteristics and their potential impacts. Such systems are recommended to control signalized intersections in the transition period to the full AV environment. The improvement of the proposed alternative is expected to increase gradually with an increase in the AV implementation rate till our traffic network reaches full AV environment where the autonomous or hybrid-based methods may be

easily and effectually applied. The review recommended that the development of such intelligent optimization-based methods of adaptive traffic signals control is still limited and needs more investigation under mixed AV-based traffic.

CHAPTER 5

TRAFFIC SIGNAL OPTIMIZATION FRAMEWORK USING MACHINE LEARNING TECHNIQUE UNDER MIXED TRAFFIC ENVIRONMENT

As mentioned earlier, the implementation of AVs will play a vital role in improving the efficiency of traffic networks [4]. Traffic control engineers need to consider reformulating the control policies of vehicle traffic networks for the potential positive impacts of the expected gradual implementation of AVs although the full implementation of AVs remains years away. In terms of signalized intersection control, the real application of autonomous-based TSC methods cannot be employed without considering the different limitations discussed in chapter 4 ([48],[37],[49]).

Thus far, several studies have investigated the traffic signal optimization of adaptive-based TSC systems under RV traffic environments. These studies focused on solution quality with respect to the performance of the optimization method while considering different traffic flows and TSC information. The main assumption is that RVs maintain stochastic driving behavior for pure traffic involving only RVs. However, given the future implementation of AVs, the optimization problem should be designed for utilizing the deterministic and improved operational characteristics of the AVs and expected positive effects of its implementation for improving optimization performance without compromising other control objectives [14]. The integration of this concept with signal optimization-based methods under mixed autonomous traffic have the potential to overcome the different limitations of autonomous-based TSC methods. Existing

literature indicates that few studies have focused on the development of TSC methods that consider signal optimization under partial AV ([40],[48]).

So, the study, presented in this chapter, aimed to propose a novel machine-learning-based optimization framework for designing intelligent adaptive TSC systems under different conditions of mixed AV-based traffic. This framework utilizes state-of-the-art approaches to represent and design the optimization process of cycle length while considering delay minimization as the main control objective. The overall aim is to use the improved characteristics and resulting impacts of the AVs implementation for improving the optimization performance. Different ML-based approaches are applied and evaluated to develop different components of the proposed framework. The proposed framework can learn and extract the inherent complex relationships of the traffic behavior of a system without using any predefined models. The contributions of this study can be summarized as follows:

- Various recent ML-based models are applied, evaluated, and compared for traffic delay prediction. None of these models are evaluated in terms of their capabilities for delay prediction under various possible scenarios of future AV-based traffic compositions in the previous studies.
- An eXtreme gradient boosting (XGBoost)-based prediction model is developed with an accurate and reliable representation of the mixed AV-based traffic. Model explainability analysis is performed using SHapley Additive exPlanations (SHAP) analysis to assess the significance of input features for delay prediction and the effect of these features on delay.

- Three heuristic algorithms are applied and evaluated to determine the optimum cycle length under different AV-based traffic conditions. Emperor penguin optimization (EPO) is used for the first time in the application of traffic signal optimization.
- The impact of the AV implementation rate on intersection delay and optimization performance is analyzed under different traffic volume conditions.

The remainder of this chapter is organized as follows. Section 1 presents the extended review of the works related to the proposed research. Section 2 describes the methodology of the proposed framework in detail. The results obtained in this study are presented and discussed in section 3. Finally, Section 4 summarizes the main findings of this chapter.

5.1 Related Works

Thus far, different methods have been proposed to control signalized intersections in AV-based traffic environments ([44],[40],[45],[48]). Many studies have proposed different TSC methods for full AV-based traffic ([36],[129],[130],[95],[39],[49],[96],[15]). As mentioned earlier, TSC methods for future traffic are divided into autonomous-, signal optimization-, and hybrid-based methods [48]. Most proposed TSC methods for AV-based traffic are considered autonomous-based TSC methods ([43],[116]).

Some studies proposed autonomous-based TSC methods for mixed autonomous traffic; e.g., reservation-based methods ([36],[109],[117],[106],[46]) and trajectory planning-based methods ([111],[112],[114],[16],[47],[14],[98],[116]). Although these methods demonstrate excellent performances ([40],[47]), their real applications suffer from different limitations related to the traffic environment. Traffic conditions in the future will vary in terms of volume and AV implementation rate. The trajectory-based methods for high traffic demands may not be able to

effectively optimize all vehicle trajectories [48]. The effective application of reservation-based methods requires high AV implementation ([36],[109],[111],[106]). The basic component of autonomous-based TSC methods is the requirement of different communications protocols such as V–V, V–I, and I–V communications [43]. Some proposed autonomous methods assume that RVs have communication capabilities for exchanging data with the signal agent ([116],[46]). However, most existing RV models do not include connectivity capabilities. Although distributed-based methods distribute the involved computations of the control among agents, the resulting performance depends entirely on the quality and communication range among the agents [43]; this can cause some uncertainty in the expected operational and safety performance considering real applications [44]. Further, centralized-based TSC methods such as trajectory planning-based methods can involve complex computations that affect control performance ([107],[98]). Therefore, its application requires a long execution time, and it can cause additional problems such as increased delays [98]. In addition to the above limitations, some autonomous-based TSC methods require additional costly infrastructures to realize different types of control and other supporting roadside units ([112],[37]). Some methods perform conditional modifications in the design ([113],[46],[47]) or operation ([14],[37]) of the signalized intersection for including the collision-free features of the vehicle crossing; this can cause an additional delay ([117],[115]) and require additional land space [115]. For mixed traffic, the assumptions included by some proposed autonomous-based methods in terms of RV driving behavior ([44],[117]) are not realistic because of the nature of the stochastic driving behavior of RVs. Many studies that focus on doubts regarding whether RVs can cope with AV driving behavior have been reported ([117],[26],[16]). Further, unlike AVs, RV actions cannot be recognized or controlled accurately by the control system from the control system side [118].

As mentioned earlier, hybrid-based TSC methods integrate autonomous-based TSC with traffic signal optimization for optimizing both AV trajectories and different parameters of the signal plan. Related studies have proposed hybrid-based TSC methods that consider mixed-based AV traffic ([113],[106],[108],[98],[37],[131],[132]). Although such methods are expected to achieve high performances [40], they involve similar limitations as that of the autonomous-based methods. In addition, the effective application of such methods involves high computations that can negatively affect the resulting performance (mainly with centralized-based methods) because of the complex combination of optimization objectives [37]. Barthauer and Friedrich [115] proposed a hybrid TSC method that combines pre-sorting and pre-signaling techniques; the results suggest that its application decreases the intersection capacity by half compared with the conventional TSC method.

Signal-optimization-based TSC methods utilize an intersection space without compromising road safety and optimizing the time of the signal plan for increasing the flow and minimizing delays and fuel consumption ([44],[98]). Signal optimization utilizes various traffic information such as traffic flow state or vehicle trajectory and coordination for optimizing the signal plan considering the different control objectives of adaptive, platoon, and planning-based TSC systems [45]. Platoon-based systems aim to group the incoming vehicles into platoons using different prediction methods for predicting their traffic flow state; planning-based systems require advanced models to treat each vehicle individually through detailed trajectories for planning the crossing in a forward time manner. Both systems require V–I connectivity to exchange the required data and send crossing instructions. Adaptive-based TSC systems can utilize the different collected traffic data for regulating and optimizing signal plans to achieve desirable objectives in a real-time manner based on the short- and long-term variations of the different

traffic conditions. Compared with fixed and actuated-based TSC systems, the application of adaptive-based TSC systems can help improve the optimization of intersection capacity; thus, it can help enhance the efficiency of traffic flow ([103],[42]). Y. Wang et al. [42] conducted a comprehensive review of the adaptive-based developments of TSC; they stated that modern generation adaptive-based systems are based on self-learning capabilities and high-efficiency computations of advanced vehicle models such as CVs and AVs.

Several studies have attempted to optimize different TSC parameters such as the cycle length and phase status, which considers single- or multiple-based optimization objectives under different conditions of full RV-based traffic [40]. Examples of common optimization objectives include the minimization of traffic delays, travel time, number of stops, queue length, and fuel consumption. Traditional optimization methods such as regression, linear programming, fuzzy logic, and probability-based methods, have been used for optimizing traffic signals before the development of advanced simulation and high-computation-based methods ([133],[134],[135],[136]). Such methods showed limited performances because they do not consider the dynamic and mixed nature of traffic flow conditions at urban signalized intersections. Recent AI-based methods such as heuristics-based algorithms and ML-based methods have been applied to improve signal optimization-based methods for RV traffic ([119],[120],[121],[137],[138],[139]). Common examples of these methods include different genetic algorithm-based algorithms ([140],[30]), ant colony optimization [141], differential evolution [142], immune network algorithms [143], artificial bee colonies [144], RL [145], and other DL-based methods. Most AI-based methods exhibit efficient and robust control performances that can capture the varied characteristics of TSC problems ([146],[147],[111],[148],[149],[143],[144]).

Some research studies considered signal optimization to propose TSC methods for AV-based traffic [40]. Q. Guo et al., 2019 reviewed some of the proposed methods that focus on full AV-based traffic [45]. However, under mixed autonomy traffic, there are only a limited number of studies that have proposed signal-optimization-based methods [48]. Bashiri proposed an adaptive TSC system for controlling signalized intersections under mixed autonomous traffic [43]. In their study, a neural network trained using microscopic simulation data was used to optimize the signal time; a heuristic method was used to predict the routing decisions for representing the traffic state by utilizing different collected information from the CAVs. The results showed that the proposed system performed better when the delay was reduced by 25% compared to that of the Highway Capacity Manual (HCM) methodology. Ma et al. proposed a signal-optimization-based method using a mixed-integer linear programming model [150]. They optimized both the phase sequence and phase duration with the control objective of intersection delay minimization, and their results indicated that the proposed method led to a greater reduction in delay compared to that using vehicle-actuated and fixed-time control.

5.2 Methodology

An optimization framework that can intelligently utilize the advantages of both improved AV driving behavior and intelligent-based approaches is developed in this study to improve TSC optimization. A general flow diagram of the optimization framework is presented in Figure 5-1. In the first stage, the data required for the learning process are generated using a simulation software. In the second stage, different ML-based models are evaluated in terms of delay prediction using the generated data. Then, the best ML-based model is selected based on the performance of the prediction models to represent the simulation of the optimization process. In

the third stage, a heuristic algorithm is applied to determine the optimum cycle length of the TSC under different AV-based traffic environment conditions.

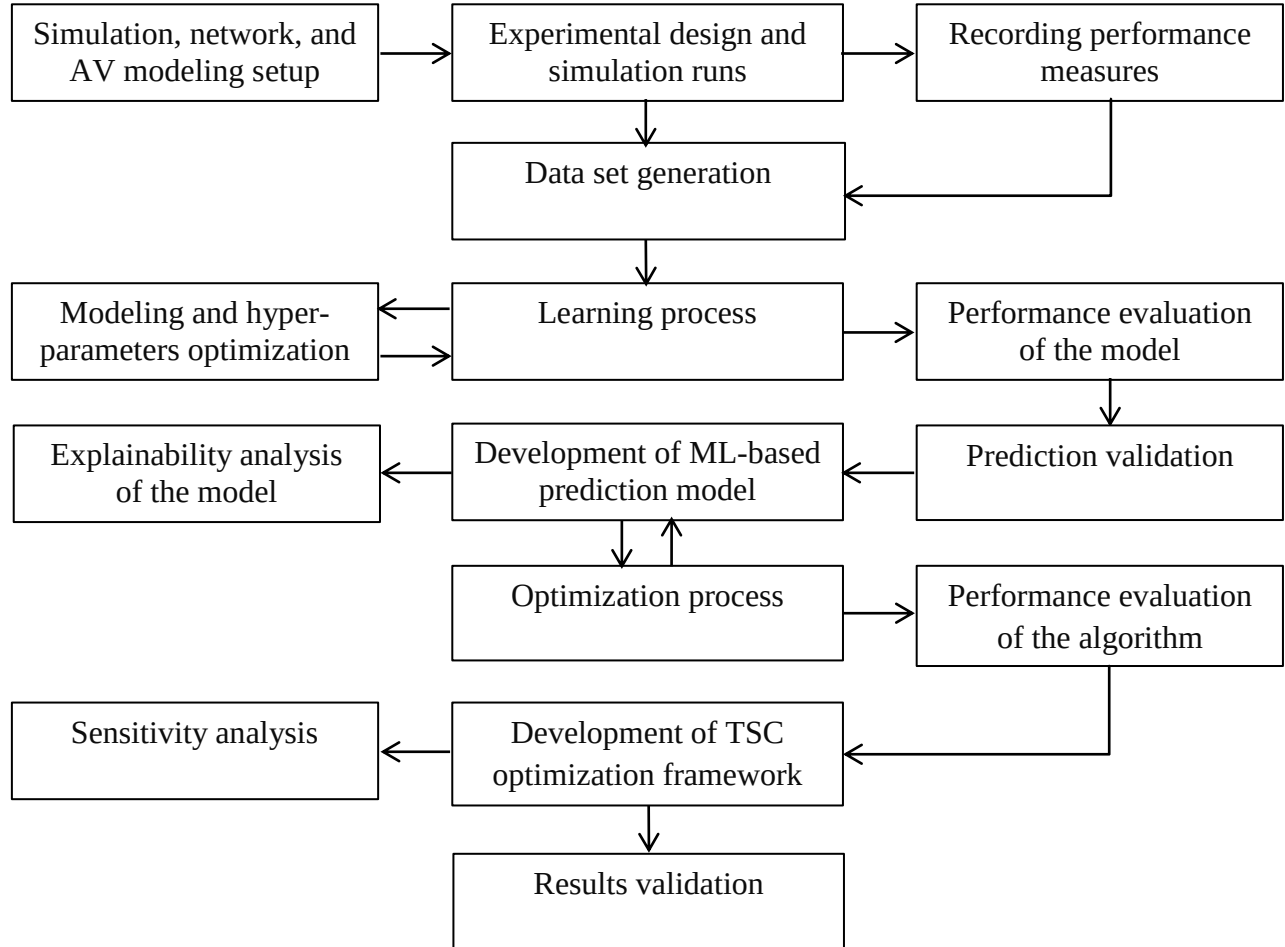


Figure 5-1 Flow Diagram of the Optimization Framework

5.2.1 Simulation and Network Setup

As indicated in chapter 3, there are no sufficient real-world traffic data of mixed AV traffic environment, and most studies related to AV implementation are modeling- or simulation-based studies. The application of advanced simulation software is considered a suitable alternative for AV driving modeling and data generation. To this end, different simulation software have been used; for example, SUMO, CORSIM, and PTV Vissim. Vissim is used in the current study to

generate large datasets for the learning process. Vissim permits users to create different scenarios related to the tested traffic environment. The recent versions of Vissim include advanced built-in features of AV modeling ([6],[79]); further, Vissim can accurately mimic the autonomous features of AVs in real-world scenarios ([53],[3]), and therefore, data generated herein can be treated as preliminary theoretical data obtained using microscopic traffic simulations.

A hypothetical computer-generated traffic environment of a urban isolated four-leg signalized intersection is created using Vissim. Each approach includes three lanes in each direction. The signalized intersection is controlled by a traffic signal using a four-phase fixed-plan system with protected left turns. Signal plans are built and applied to the simulation in Vissim, which uses various cycle lengths. The effective green times of each cycle are calculated based on the degree of traffic (i.e., critical flow ratio) in each approach using Webster's method [89].

Each scenario of the experimental design is simulated 100 times; each simulation is performed using a default random seed of 42 with an increment of 1. The simulation resolution is set to one time step (s) per simulation. Each simulation scenario is run for 5400 s. The data are recorded only after 3600 s to saturate the system and eliminate the start-up period. After setting up the simulation environment, different scenarios are implemented by changing the traffic composition, traffic volume, and cycle length. Subsequently, a simulation is performed and different performance measures are recorded, which includes the average vehicle delay (s) and number of vehicles.

5.2.2 AV Modeling

The vehicles are modeled by focusing on parameters related to car-following and vehicle behaviors at traffic signals. The main parameters include the speed, acceleration, deceleration of

the vehicle, headway, safe distance between vehicles, and reaction time. The default settings of the default urban driving behavior in Vissim (Urban-motorized) are used to model RV driving behavior. Most settings are modeled using stochastic features to model and reflect the limitations and randomness of human driving behavior in the RV model. Unlike RVs, AVs can operate deterministically and precisely following the assigned setting, which represents homogenous behavior. The default settings of the built-in AV model (AV aggressive (CoExit)) in Vissim (Verison 11.00) are used to model and simulate AV driving behavior [151]. The default settings of the AV model are based on empirical studies and co-simulation data of a mixed traffic environment resulting from a PTV partnership with the CoEXist project ([151],[3]). Different studies have used Vissim to model AV behavior at signalized intersections in mixed traffic environments ([91],[43],[92],[93]).

5.2.3 Data Description and Experimental Design

Simulations conducted for data generation consider a mixed-based AV traffic environment in which AVs and RVs share the same traffic lanes at the signalized intersection. The experimental design for the simulation scenarios involves three main input groups:

- 1) Five AV implementation rates ranging from 0% to 100% are used to represent various traffic compositions.
- 2) Simulations are conducted under various volume conditions to verify the resulting performance under different traffic conditions. The number of vehicles ranged from 400 to 4500 (veh/h), which represents three traffic volume levels: low, moderate, and high. A high level represents traffic conditions with a moderate level of traffic congestion (LOS = E); a low level, almost free-flow conditions (LOS = B); and a

moderate level, moderate level between the high and low levels, with a total traffic volume of approximately 50% of that of the high level (LOS = C). The LOS levels are based on the results of the average vehicle delay, and they are comparable to the LOS levels defined in the HCM of 2010 [152]. The volume levels are implemented using different traffic approaches with different hypothetical traffic volumes at a given level. The selected numbers are based on the volume data recorded at a similar intersection in a previous study [30].

- 3) Different traffic scenarios are evaluated under different signal plan cycle lengths to reliably evaluate the different investigated impacts of AV implementation. The ranges of the selected lengths (32–240 s) are selected based on the traffic volume level to enable the reliable investigation of the resulting performance.

5.2.4 Delay Prediction Modeling

Traffic prediction models predict traffic conditions within a specific period using traffic data for improving the management and control of the traffic status. The application of model-based prediction methods such as statistical models can lead to an unacceptable performance in real-life applications of traffic prediction [153]. However, model-free-based methods such as ML-based models indicate better traffic prediction performance in terms of the resulting accuracy, time consumption, and capability for dealing with the dynamic behavior of traffic systems ([154],[155],[156],[157],[158]). The ML-based models are completely data-based and explore hidden and complex relationships among the inputs and outputs through their learning capabilities during the training process. Nguyen et al. and Boukerche and Wang ([159],[160]) reviewed recent studies on ML-based applications for traffic prediction. It is aimed herein to develop an ML-based model that can predict the average vehicle delay based on the traffic

volume, AV rate, and cycle length. Vehicle delay is selected as the main predicted variable because it is a commonly used parameter for reflecting the LOS at signalized intersections as in the case of the HCM of 2010 [152].

ML-based models are used to overcome the lack of required analytical models of traffic flow under the mixed traffic of AVs and RVs [104]. According to existing literature, studies on traffic delay prediction in AV traffic environments with applications of recent ML-based methods remain limited, and further investigation is warranted. To this end, this study investigates the performance of four appropriate candidate models for the prediction capabilities of vehicle delays under different traffic conditions: eXtreme Gradient Boosting (XGBoost), random forest (RF), deep neural network (DNN), and linear regression (LR). XGBoost, RF, and DNN are selected to represent different state-of-the-art models that have been applied recently in previous studies on traffic prediction applications ([161],[162]). The LR model is used for comparison to represent the statistical model. To the best of our knowledge, the selected models have not been used in previous research considering the objectives of this study.

LR is a statistical approach that relates input features to outputs using a linear method. XGBoost and RF are ensemble techniques that ensemble weak classifiers for prediction; they are more robust against overfitting compared to single classifiers ([162],[163]). XGBoost uses decision trees to perform optimization by minimizing the loss function utilizing a boosting technique that allows for differentiable iterations in the local function. Although the samples are left unchanged, various weights are assigned to each sample. Different studies have successfully used the XGBoost model to predict different traffic-related parameters such as traffic accidents and vehicle trajectories ([164],[165],[163],[158]). The XGBoost model results in higher prediction accuracy while requiring less training time compared to other ML-based methods

([163],[162],[158]). To the best of our knowledge, the performance of the XGBoost model for delay prediction in AV-based traffic environments remains unknown. RF is a bagging method, wherein numerous subsets of samples are considered for bagging and the mean of each subgroup is computed [166]. For each iteration of the samples, either bootstrapping or the random selection of the features is considered [167]. Different studies successfully used the RF model for predicting different traffic-related parameters such as vehicle routing and traffic flow ([166],[168],[158]). The DNN is a deep learning method; it is a deep architecture of a feedforward artificial neural network with more than one hidden layer. The model comprises weights and biases in each neuron updated using a backpropagation algorithm for reducing training loss and obtaining the optimum architecture [169]. Different studies have successfully used DNN in traffic prediction applications ([161],[166]).

Modeling is conducted in a Python environment using Scikit-learn and TensorFlow libraries using the dataset explained in the preceding section. The dataset is divided into 70% training, 15% validation, and 15% testing. The hyperparameters of all models are optimized, and the random state is equal to zero for the reproducibility of the experiment. Different performance metrics are used in this study for evaluating the performance of the models: mean percentage error (MPE), mean absolute error (MAE), root mean square error (RMSE), and R^2 .

5.2.5 Methodology of the Optimization Framework

The heuristic approach works as an intelligent method for solving many optimization problems [170]. This stage aims to apply and evaluate the performance of novel heuristic-based algorithms to determine the optimum cycle length of TSC under different conditions (i.e., traffic volume and AV implementation rate) of AV-based traffic for enabling the optimization process of the

proposed optimization framework. The control objective is to optimize the cycle length for minimizing the intersection delay at signalized intersections. The delay is measured using the developed XGBoost-based prediction model. Cycle length optimization is expected to benefit from the parallel, global, and robust search characteristics of the algorithms under the AV-based traffic, as well as from the positive effects of AV implementation.

Different heuristics-based algorithms have been used to optimize different parameters of the TSC. Three algorithms are selected for the application as candidate algorithms for achieving the optimization objective. These include EPO, grey wolf optimization (GWO), and PSO. To the best of our knowledge, none of these have been used for optimizing the cycle length considering the specific objectives of this study, in previous research. In 2018, Dhiman and Kumar [171] introduced a novel heuristics-based algorithm, named as EPO, that was inspired by the huddling behavior of the emperor penguin for survival in the Antarctic winter. The EPO is an effective optimization technique and has been employed in some fields [170]; this algorithm offers a straightforward implementation with few controlling parameters and updating equations for the location of the penguin [170]. Thus far, none of the earlier studies have used EPO in the application of traffic signal optimization. In 2021, Mirjalili [136] developed GWO, which is a recent swarm intelligence-based algorithm; it can simulate the hierarchy and hunting behavior of grey wolves and it aims to avoid falling into local optima during the early iterations. The main advantages of GWO include conceptual simplicity and the ease of implementation [170]. Further, the GWO algorithm shows a decent ability for solving different real-life problems such as the exploitation of unimodal problems and the exploration of multimodal problems [170]. Thus far, only one study has proposed a hybrid-based heuristic algorithm for traffic signal optimization by applying GWO and grasshopper optimization; this algorithm is called GWGO

[136]. PSO established by Eberhart and Kennedy simulates the flocking behavior of birds and their social interactions in nature [139]; it is considered a common algorithm used in traffic signal applications ([172],[7],[173]).

5.3 Results and Discussion

In this section, we present and discuss the results of the study. The first sub-section includes a discussion of the delay prediction performance of the applied models along with the explainability analysis and result validations of the model. The second sub-section includes a discussion of the optimization results, and the third sub-section presents and discusses the validation of the results of the proposed framework.

5.3.1 Delay Prediction Results

A. Model Performance

A detailed comparative analysis was conducted to evaluate the performance of the four models in terms of delay prediction. The optimum model parameters were determined using sci-kit-learn and TensorFlow libraries; a grid search approach was used to obtain the optimum architecture of the models. The optimum hyperparameter settings for the RF and XGBoost models were 500 trees (estimators), a maximum tree depth of 15, and a learning rate of 0.1 and 600 trees, a maximum depth of 10, and a learning rate of 0.1, respectively. Each DNN trained using rectified linear unit function (relu) and comprised four layers with 150 neurons and a dropout rate of 0.1 each; further, it had a batch size of 12, learning rate of 0.001, and 50 epochs. Table 5-1 presents the evaluation performance results of the model for each performance measure; the XGBoost, RF, and DNN models show promising prediction accuracies of the delay, and they showed comparable results where all of them performed outstandingly with high accuracy levels

(Average MAE = 3.188). Among them, the XGBoost model slightly outperformed with the MAE value of 2.919; and the DNN model performed the worst with the MAE model of 3.609. The deep architecture of the DNN model did not improve the learning process compared to the resulted learning of the former models. All three models have captured the different relationships between the inputs and predicted output effectively. Further, compared to the others, the LR model showed a poor prediction performance where the MAE was 14.683. These findings are confirmed by the other performance measures, as indicated in Table 5-1.

The RF, DNN and XGBoost models required similar times to reach their optimum performance; however, the XGBoost model had a shorter time compared to that of the others, where the processing time per instance did not exceed 4.604E-06 s. Figures 5-2 and 5-3 present scatter plot and regression error characteristics (REC) curves of the delay prediction models, respectively. The scatter plot of the models confirms that the LR model cannot capture the complicated relationships in the modeling delay, and therefore, the actual and predicted delays diverge from the normal line. The XGBoost model indicates that the actual and predicted delays are very close to the normal line, both on the training and testing sets, which is clear evidence of the model prediction capability in delay prediction. The REC curves indicate that XGBoost and RF both have reasonable areas under curve (AUC) (i.e., 0.948); DNN is also close to them in terms of this performance measure, whereas the LR covers a much smaller AUC.

Table 5-1 Results of the Performance Measures of the Model

Model	MAE	RMSE	MPE	R²	Inference time (s per instance)
LR	14.683	21.611	0.465	0.638	7.385E-07
DNN	3.609	6.409	0.080	0.971	3.119E-05
RF	3.035	5.991	0.061	0.971	1.111E-05
XGBoost	2.919	5.614	0.060	0.973	4.604E-06

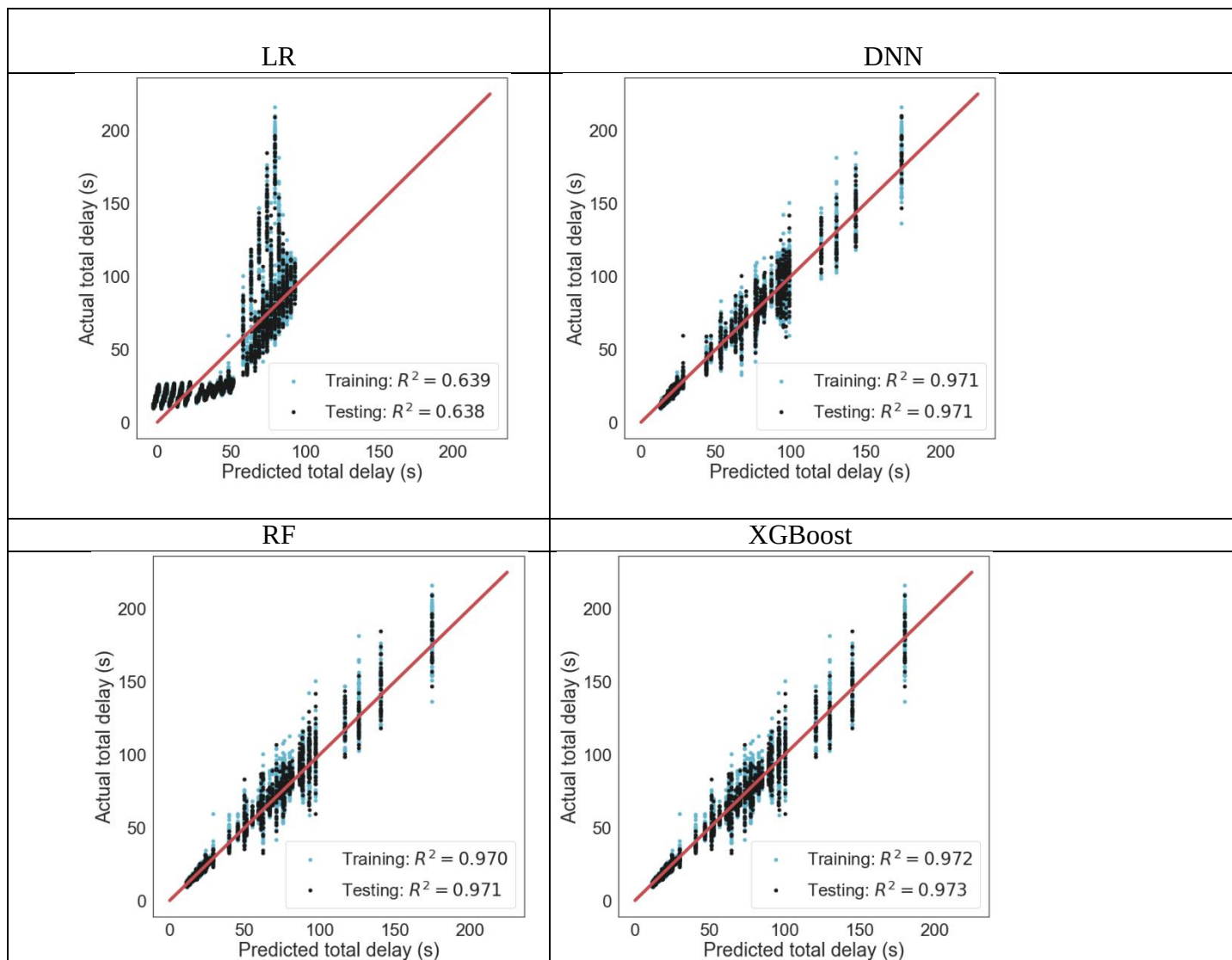


Figure 5-2 Scatter Plot of Delay Models for Training and Testing Sets

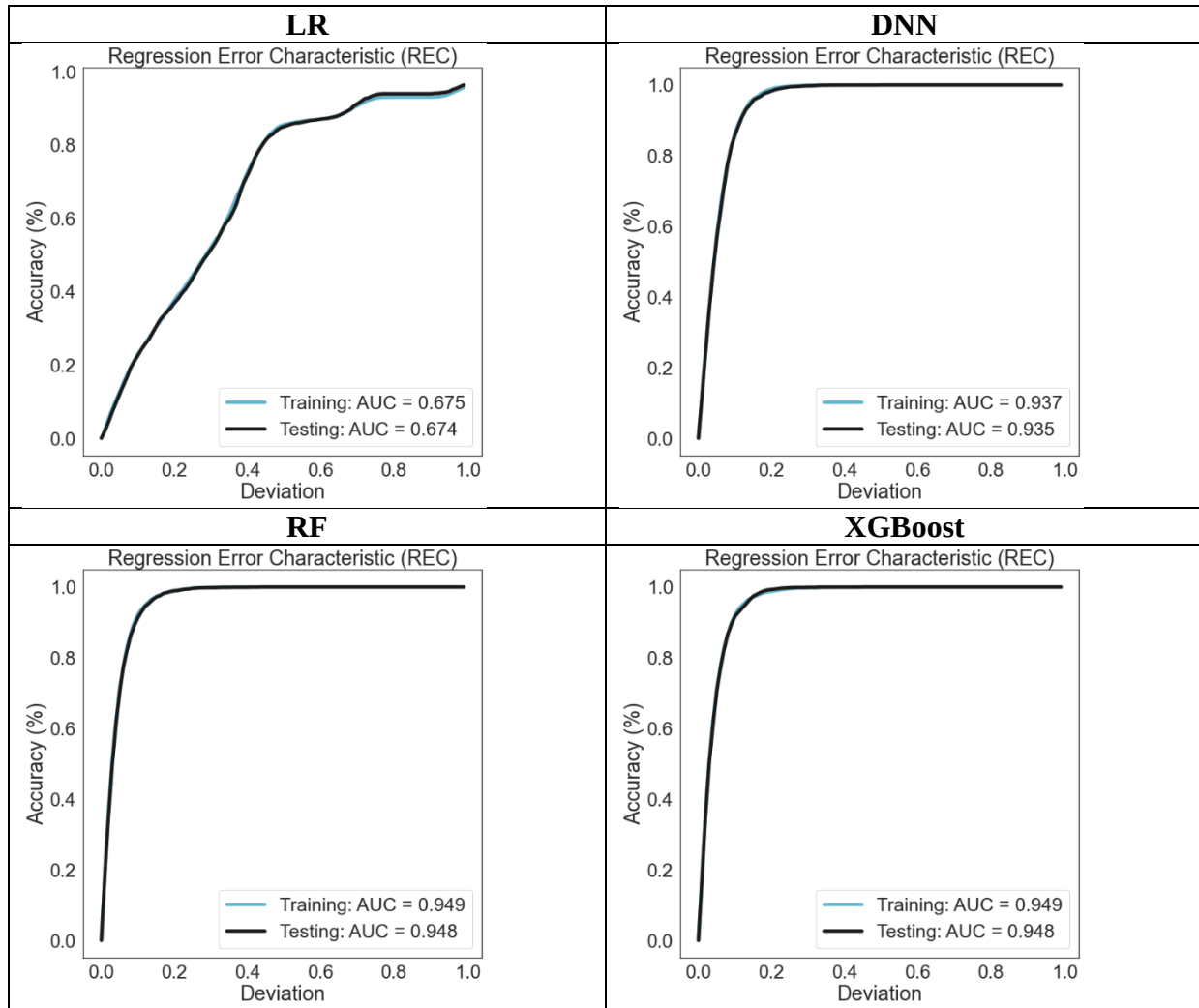


Figure 5-3 REC Curves of Delay Models for the Training and Testing Sets

Thus, the above results clearly illustrate the superiority of the XGBoost model [158]. The XGBoost model captures the dynamic conditions of AV-based traffic at intersections. This is a vital component for several innovative applications of traffic operations and for controlling the development of future traffic networks. In this study, the XGBoost model was selected to develop an ML model that can accurately represent the AV traffic environment for the

optimization process in the proposed optimization framework because of its lower computational complexity, greater flexibility, fast execution, and higher prediction performance.

B. Prediction Validation

Validation analysis was conducted to demonstrate the adequacy and robustness of the prediction model. The actual delay values of the randomly selected new points of the main inputs (not included in the test set) were measured using the simulation platform. These data points have entirely different values of the AV implementation rate and cycle length from the original training and testing sets. The resulting values were compared with the predicted delay values obtained using the XGBoost model. Table 5-2 lists the obtained values of delays for different traffic scenarios; the results showed that the average MPE was 7.58%, and it indicates that the prediction model is a highly validated model that can be used to appropriately predict the delay under different conditions.

Table 5-2 Actual and Predicted Delay Values for XGBoost Model Validation

Volume level	AV (%)	Cycle length (s)	Actual delay (s)	Predicted delay (s)	Error (%)
Low	50	37	13.30	12.55	5.64
	90	55	17.26	15.83	8.17
	10	73	22.90	22.07	3.62
	90	37	12.47	11.47	8.02
	10	55	18.66	17.61	5.63
	75	73	21.77	20.96	3.72
	50	55	20.40	19.80	2.94
	85	46	17.14	17.16	0.12

Moderate	15	65	24.31	24.70	1.58
	85	37	16.49	17.84	7.57
	15	55	22.51	21.47	4.62
	25	73	25.64	24.70	3.67
High	50	150	62.51	67.77	7.76
	70	78	55.63	50.90	8.50
	5	180	84.12	90.27	6.81
	60	218	76.89	75.51	1.79
	5	132	90.66	95.54	5.11
	100	110	41.05	39.80	3.04

C. Explainability Analysis of the Model

Three independent features were considered as inputs for delay prediction. SHAP analysis was performed to evaluate the importance of these features on prediction performance and enhance model interpretability. SHAP was proposed by Lundberg and Lee, and it is based on cooperative game theory [162]. The SHAP analysis has recently been used by many researchers in the field of traffic prediction ([164],[174]). The prediction results were explained by calculating the contribution of individual variables to the prediction performance using the SHAP analysis. If we consider each observation as a cooperative game played, the SHAP value (Shapley) of each feature represents the contribution of a player in the game, with a positive value indicating a positive impact on the success of the game, and a negative value indicating the opposite. In this study, SHAP values were used to reflect the negative or positive effects of each feature on the model output (i.e., delay). The positive SHAP values indicated an increase in delay, whereas negative values indicated a decrease. An SHAP value of zero indicated no impact on the delay.

Further, this analysis can be used to establish the relative feature importance ranking of the input variables using the mean absolute SHAP values. The obtained results of the SHAP analysis are based on the prediction results of the XGBoost model, as shown in Figure 5-4.

Figure 5-4 (a) shows the overall importance of each feature based on the average absolute SHAP values. All three features significantly contributed to the delay prediction; however, the traffic volume showed the highest impact, where the mean SHAP value was approximately 30.0, whereas the AV rate and cycle length showed almost similar impacts with a mean SHAP value of 6.0. Figure 5-4 (b) shows another form of an explainability analysis, in which the SHAP value is used for local explainability. In this figure, the ordinate represents features and is ranked according to their importance; the color represents the magnitude of the feature value. The abscissa shows the corresponding SHAP value of each sample, which is indicated by the dots. The results indicate that the traffic volume feature had a significant positive effect on delay only at higher volume conditions; however, moderate and lower volume conditions had negative impacts (i.e., decreasing delay). This finding is compatible with scientific knowledge of the positive correlation between the traffic volume and the resulting delay; this correlation is strong under congested traffic conditions. The analysis of the AV rate shows that the SHAP value decreases with an increase in the AV% rate; this indicates a negative correlation between them. For example, under conditions of low AV implementation rates such as 10% and 25%, there is a significant positive effect on the AV rate on the predicted delay, whereas at an AV rate of 50%, the SHAP values are almost close to zero, which indicate no impact. The result analysis of the conditions with high rates indicate a negative impact on the predicted delay; the positive impacts found at the lower rates are attributed to the stochastic nature of the driving performance of the

RVs compared to that of the AVs, which results in high delays. This finding also confirms the significant impacts of the AV implementation rate on expected traffic delays.

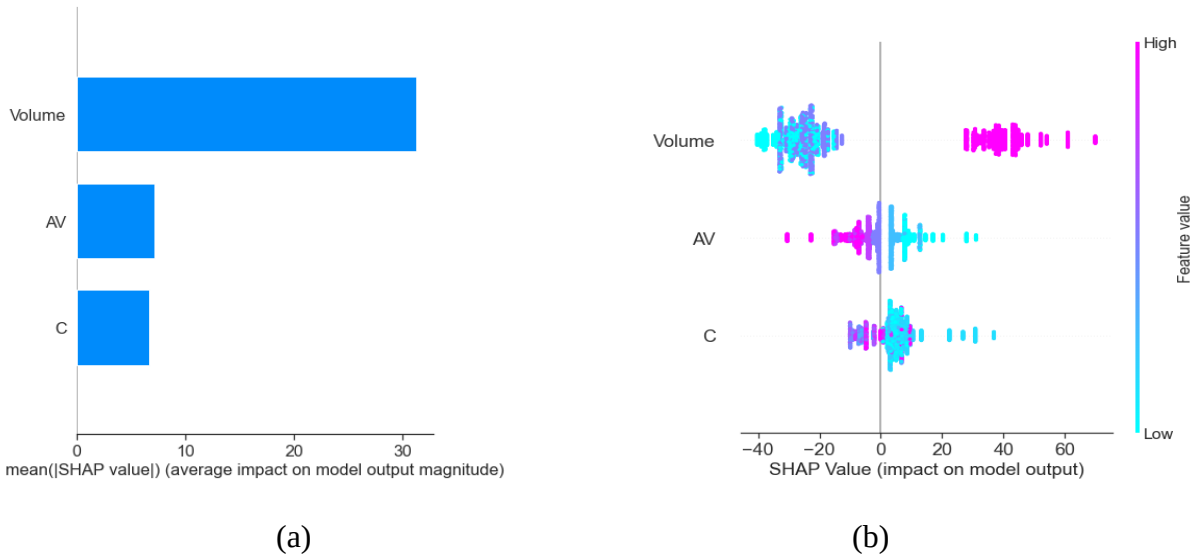


Figure 5-4 Explainability Analysis of the XGBoost Model: a) Features Ranking Based on Absolute Mean SHAP Values, and b) Summary Plot of the Features for Interpreting the Impact of Input Features on the Intersection Delay

D. Impact of the AV Implementation Rate on the Intersection Delay

We measured the prediction accuracy using the XGBoost model to further investigate the impact of the AV implementation rate on the resulting prediction performance; we considered five subsets of the original data set, where each set included all observations with similar AV rates (AV %) regardless of volume and cycle length conditions. Table 5-3 presents the results obtained using different performance measures. The analysis of the results clearly shows the positive effect of AV implementation on the resulting accuracies. There is a gradual improvement in the accuracy of the model with an increase in the AV rate. As an example, the MPE value considering all of the observations of 0% AV was found to be 0.0714; however, when considering all observations of 75% AV, the MPE value decreased to 0.0576, which indicates a 19.33% improvement in the resulting accuracy of the model. The improvement results from the

deterministic driving behavior of the AVs, and this reduces variations in the actual delay values. Findings obtained herein confirm the results of the SHAP analysis and they are aligned with the different findings of the AV rate importance in the literature [43]. The improved prediction performance caused by the AV implementation can be useful for enhancing the efficiency of many ITSs that involve different prediction-based components.

Table 5-3 Prediction Performances at Different AV Rates

AV (%)	MAE	RMSE	MPE	R²
0	4.642	8.258	0.071	0.969
25	3.447	6.411	0.062	0.970
50	3.040	5.619	0.063	0.967
75	2.289	4.673	0.058	0.963
100	1.591	3.024	0.050	0.979

5.3.2 Optimization Results

In the first part of this sub-section, the results of the optimization performance of the algorithms are presented and discussed; the second part presents the sensitivity analysis considering the impacts of the AV implementation on the signal optimization under different traffic volume conditions

A. Optimization Performance

The obtained objective function was evaluated in terms of convergence rate, processing time, and solution quality for each algorithm. The algorithms were optimized in a Python environment using the Opytimizer library. The optimizations were performed to obtain the optimum input variables (i.e., cycle length) considering the AV implementation rate and traffic volume; this

leads to the minimum delay. The population converged to the optimum fitness between two and five iterations for the three algorithms (EPO, GWO, and PSO), which provides the flexibility of terminating them after five iterations. The resulting optimization performance of the three algorithms is compared to a traditional optimization method built using the empirical equation developed by the TRL considering critical-lane traffic volumes [89]; this is referred to herein as the TRL method. Figure 5-5 shows the optimized cycle length values of the optimization methods at different volume levels and AV rates.

The three algorithms successfully optimized the cycle length, which minimized the fitness of the objective function. At the low volume level, the algorithms performed similarly and produced similar optimum values for most cases; however, at the moderate and high volume levels, the performance differed in terms of solution quality. At the moderate level, there are slight differences, with a slight superiority of the PSO except in the scenario with an AV rate of 50%, where it produced the highest value. At the high level, the differences in the values obtained by the algorithms were clearer compared to those at the moderate level. The PSO produced the minimum cycle length values at the 0, 50%, and 100% AV rates, whereas the EPO produced the minimum value at 75%. The time required by the algorithms in terms of the processing time for the optimization process differed. The convergence times were found to be 0.971, 1.957, and 1.022 s for EPO, GWO, and PSO, respectively; thus, EPO was the fastest algorithm. The processing time of the optimization is important for designing effective adaptive-based TSC systems [173]. Although the applied algorithms show comparable optimization results in terms of solution quality, the resulting solutions need to be validated further to evaluate the corresponding real effect on the signalized intersection performance. The required validation was

conducted in this study, and the obtained results are presented and discussed in Sub-section 5.3.3.

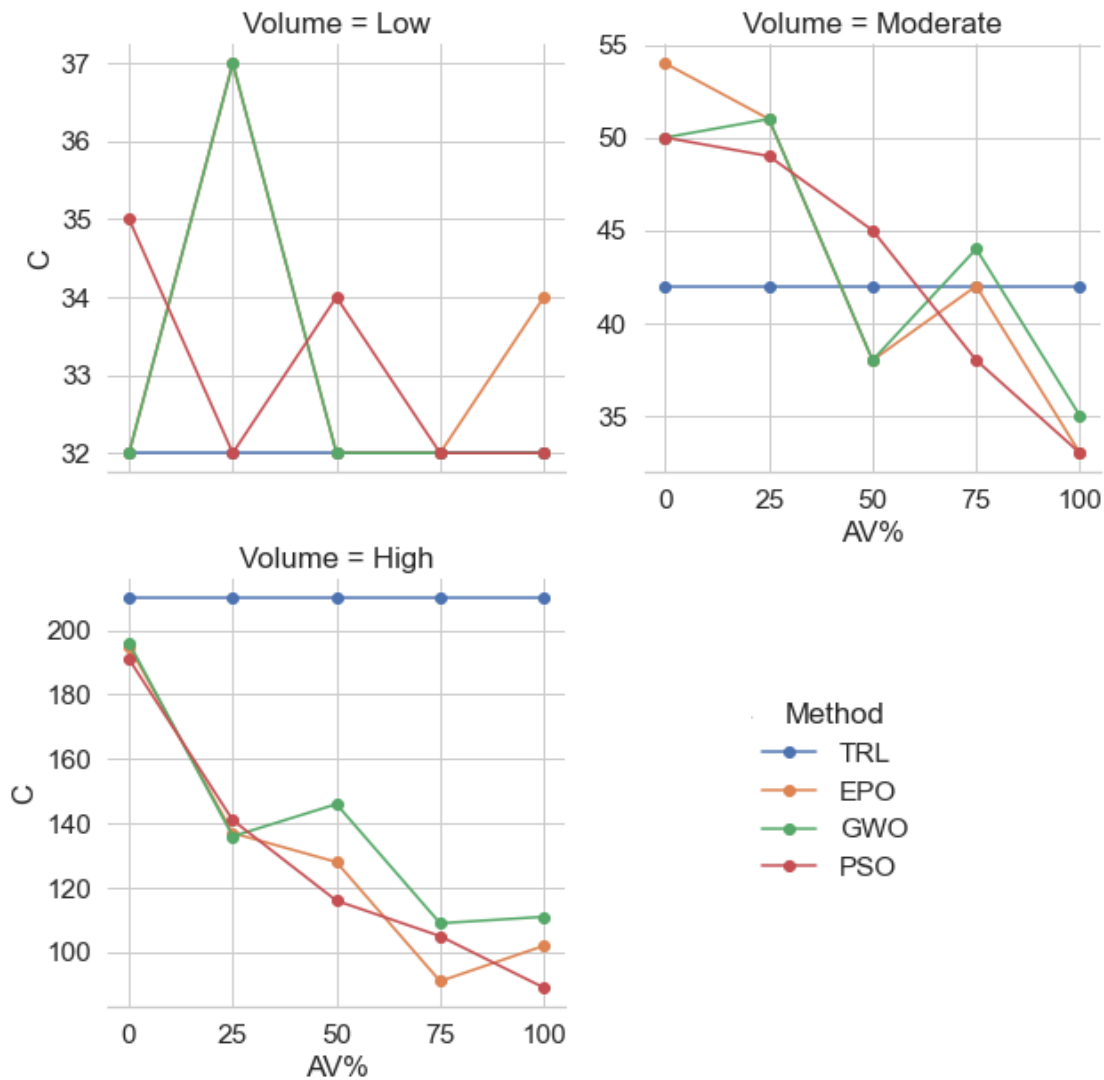


Figure 5-5 Optimized Cycle Length Values of the Optimization Methods at Different Volume Levels and AV Rates

B. Sensitivity Analysis

The sensitivity analyses conducted here are based on the optimization results obtained by the PSO. The results confirm the significant effects of the AV implementation on the cycle length optimization compared to that of the base conditions (full RV-based traffic); however, the level

of the improved solutions is based on the traffic volume level. As expected, the AV implementation did not affect the cycle length optimization at low volume levels. The optimization is controlled by the number of vehicles, and the positive impacts of AV implementation are hidden because of the low traffic volume. The minimum allowable cycle length ($C = 32$ s) was determined to be the optimum value for the AV rate. However, at the moderate level, there was a notable reduction in the optimized cycle length at higher AV rates. For example, the optimized value was found to be 50 s with full RV-based traffic, but it decreased to 38 s when the AV rate reached 75%; this indicates an improvement of 24%. AV implementation significantly affects signal optimization at the high level. For example, the optimized cycle length was 191 s when there were no AVs; however, the optimized values were 116 s and 89 s when the AV rates reached 50% and 100%; this indicated a reduction of approximately 39% and 53%, respectively.

The results clearly indicate that the level of optimization improvement is also controlled by the AV implementation rate. At moderate and high levels, even lower rates of AVs can reduce the required cycle length, which helps minimize the resulting delay. For example, at a high level compared to the base conditions, an AV implementation rate of 25% can reduce the cycle length by approximately 30%. In general, the resulting trends indicated a negative correlation between the AV rate and the resulting optimized values. This finding confirms the positive impact of the AV rate on the expected improvement of the traffic flow system ([52],[83],[12],[75],[25],[28],[32],[41],[4]).

5.3.3 Results Validation

A comparative analysis was conducted to validate the resulting optimization performance using simulation-based experiments conducted in Vissim to demonstrate the feasibility of the proposed

framework. A fixed-based TSC time plan was designed to control the signalized intersection, and the control performance was evaluated using the vehicle delay as a performance measure. Different plans were designed for each scenario based on the obtained optimum values of the cycle length (C) (s) of the optimization methods (EPO, GWO, and PSO); they were compared to traditional plans whose cycle length values were optimized using the TRL optimization method [89]. Simulation scenarios were designed to cover three traffic volume levels and five AV implementation rates. The setup of the simulation and network was similar to that used in the data generation explained earlier. Table 5-4 shows the resulting delay values (s) of the four plans for different tested scenarios.

Table 5-4 Delay Results of the Applied Methods at Different Scenarios of the Volume Level and AV Implementation Rates

Volume level	AV%	TRL		EPO		GWO		PSO	
		C (s)	Delay (s)	C (s)	Delay (s)	C (s)	Delay (s)	C (s)	Delay (s)
Low	0	32	13.444	32	13.444	32	13.444	35	14.119
	25	32	12.868	37	13.800	37	13.800	32	12.868
	50	32	12.312	32	12.312	32	12.312	34	12.766
	75	32	11.713	32	11.713	32	11.713	32	11.713
	100	32	11.029	34	11.661	32	11.029	32	11.029
Moderate	0	42	24.248	54	24.255	50	24.343	50	24.343
	25	42	21.447	51	21.529	51	21.529	49	22.210
	50	42	19.071	38	19.911	38	19.911	45	19.771
	75	42	17.214	42	17.214	44	18.005	38	17.501
	100	42	15.868	33	15.463	35	15.814	33	15.463
	0	210	90.081	195	90.079	196	87.618	191	91.101

High	25	210	82.405	137	76.045	136	80.153	141	74.783
	50	210	76.301	128	64.843	146	64.408	116	62.882
	75	210	71.044	91	50.875	109	50.190	105	52.440
	100	210	68.109	102	40.076	111	41.399	89	39.957

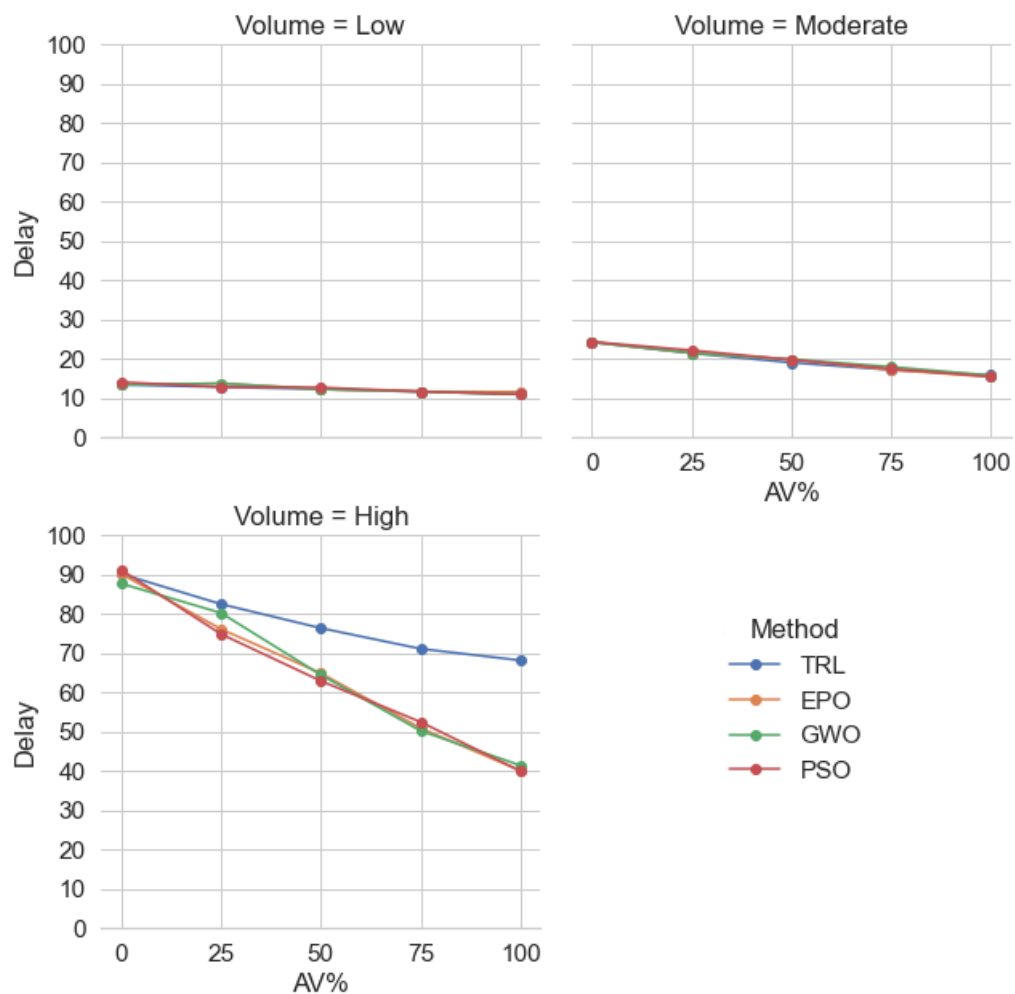


Figure 5-6 Resulting Delay Trends of each Method for Different Volume Levels and AV Rates

Figure 5-6 shows that all four methods performed almost similarly under the fixed AV rate conditions at a low volume level. The proposed optimization framework did not improve the signalized intersection performance, regardless of the optimization algorithm. The optimum cycle length of the TRL method produced minimum delays for any AV rate. The results indicate at low volume level when using the optimized values of the cycle length; the delay decreases slightly with an increase in the AV%. For example, the delay decreased by almost 18% when the AV% increased from 0 to 100%; however, the LOS remained at B for all tested scenarios at this volume level regardless of the AV rate. At a moderate volume level, the optimized signal plans by the TRL method outperformed the other methods, except for the scenario of full AV-based traffic where the optimization framework using the EPO and PSO method produced a minimum delay value. The full implementation of the AVs reduced the required cycle length from 42 to 33 s; this indicates that the significant effects of the AV implementation at moderate volume conditions on the signal optimization will be noticed only in full AV-based traffic. A comparison of the performances of the three algorithms considering the corresponding resulting delays indicate the slight superiority of the EPO method. For the moderate level, the results also confirm the negative correlation between the AV rate and delay; however, the correlation is stronger. For example, the delay decreased by approximately 36% when the AV rate increased from 0 to 100%. At moderate volumes, the LOS improved from C to B when the AV rate reached 50%. Unlike the low and moderate levels, the results of the high-volume level indicate the superiority of the proposed framework performance compared to the TRL method. The resulting delays of the optimized plans using the proposed framework were lower than those of the TRL method regardless of the AV rate. Further, the effects of the AV implementation rate on signal optimization, and therefore, on the resulting delays, were more significant compared to

those for the moderate level. A comparison of the performances of the three algorithms indicated noticeable variations between the resulting delays. GWO and PSO performed slightly better than EPO; however, PSO produced better results in the 25, 50%, and 100% scenarios, and it can be considered the best optimization method because of its fast processing capability. The results at the high level indicate a significant reduction in the delay values with an increase in the AV rate. The delays decreased by approximately 31% and 56% when the AV% increased from 0% to 50% and 100%, respectively. Thus, the LOS improved from F under the base conditions to E and D at AV rates of 50% and 100%, respectively; this confirms the positive impact of AV implementation on signalized intersection performance under congested traffic volume conditions.

The proposed optimization framework proved to be effective in optimizing signal plans under congested traffic volume conditions of mixed autonomous traffic. The positive effects of the AVs and the smart optimization performance of the heuristic algorithms were utilized successfully to minimize the delay at signalized intersections. The results obtained here confirm the valuable impact of the improved driving behavior of the AVs on signalized intersection performance. The examples of such behavior include shorter perception, reaction, start-up, and headway times, in addition to maintaining the desired speed, acceleration, deceleration, and lane changing. Incorporating these impacts with the effective optimization of the signal plans can help enhance saturation flow rates, and thus achieve an increased capacity of signalized intersections with an AV-based traffic environment.

5.4 Summary of Chapter 5

In this chapter, a future TSC problem of AV-based traffic was solved by developing a novel technique. An intelligent-based optimization framework for TSC under mixed AV-based traffic is proposed, developed and evaluated. The framework utilizes state-of-the-art ML approaches to represent and design different components of the optimization process of cycle length while considering delay minimization as the control objective.

The analysis of the prediction results revealed the significance of the AV implementation rate, traffic volume, and cycle length in determining the effects of AV on the signalized intersection performance. Approaches for the prediction of traffic flow conditions in future traffic should consider these features to accurately define the traffic status, and therefore, to design and operate effective traffic control systems. A positive correlation was observed between the AV implementation rate and the accuracy of delay prediction. Among the tested prediction models in this study, XGBoost slightly outperformed the others in terms of traffic delay prediction with respect to the prediction quality and processing time.

Compared to full RV-based traffic, the effect of AV implementation and its corresponding rate is critical under moderate and congested traffic volume conditions where the effects are more significant. At high volumes, traffic signal optimization is significantly controlled by the driving behavior of the vehicles, which is represented by the AV implementation rate, in addition to other factors such as the performance of the optimization method. The positive effects of the AVs on cycle length optimization are evident even at lower implementation rates of AVs.

Although the AV implementation can improve the intersection performance at low and moderate traffic volumes, the proposed framework does not improve the optimization performance

compared to the traditional optimization method. However, under congested volume conditions, the obtained results indicate that the proposed optimization framework can effectively improve the optimization performance of the cycle length, as well as the signalized intersection performance. Compared to full RV-based traffic, the implementation rates of 25%, 50%, and 100% can decrease optimized cycle lengths by 26%, 39%, and 53%, respectively, which can result in delay reductions of approximately 18%, 31%, and 56%, respectively. The proposed framework can capture and utilize the positive impacts of the improved driving and unique capabilities of the AVs on the solution quality of the optimization performance at congested volumes. Therefore, the level of expected improvements in the proposed framework increases gradually with an increase in the AV implementation rate. A comparison of the performance of the tested optimization algorithms shows varying results under high-volume conditions. The EPO and PSO show comparable processing times; however, considering the validated impacts of the produced solutions, and the PSO can be considered the optimum algorithm that can effectively enhance the performance of the proposed framework.

The application of fixed-based TSC methods will be inadequate because the traffic composition of urban networks is rarely uniform; therefore, signal timing needs to be adaptively adjusted based on the instantaneous traffic state. The results indicate the potential effectiveness of the proposed framework for adjusting signal plans in an adaptive-based manner. The proposed framework shows remarkable capabilities when responding to the dynamically changing environment of future AV-based traffic.

CHAPTER 6

CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

Considering mixed AV-based traffic environment, this research has conducted four main studies as follows: comprehensive literature review on the AV implementation impacts on traffic flow characteristics, simulation-based investigation of the AV impacts on the performance of signalized intersection, comprehensive literature review on the signalized intersection control and development of traffic signal optimization framework using ML. The main conclusions obtained from these studies are discussed in the preceding sub-sections below.

6.1.1 Comprehensive Literature Review on the AV Implementation Impacts on Traffic Flow Characteristics

There are limited numbers of efforts that have been made to investigate the impacts of the partial AV implementation. Also, most of the related studies have focused on the impacts of the partial automation levels of AVs. The conducted review concluded that, compared to full environment of RVs; the implementation of AVs may offer several potential positive impacts that may improve the overall efficiency of traffic system. Even partial implementation of different types of AVs, mainly the CAV, may increase the traffic capacity, improve the traffic flow stability and increase throughput. However, those are based on some important factors including the implementation rate, AV characteristics, modeling and operational settings of the AVs and the level of the traffic volume in addition to the impacts of human driving behavior. In addition to

that, it was concluded that it is clear that the actual impacts of the implementation of the AVs on mixed traffic still needs more investigations, mainly at network level.

6.1.2 Simulation-Based Investigation of the AV Impacts on the Performance of Signalized Intersection

Compared to full RV traffic, the implementation of different AV models provides significant performance improvements by reducing the vehicle delay, stopped delay, and queue length at a signalized intersection under different traffic volume conditions. Those reductions could reduce pollution, increase safety, and improve the efficiency of road networks. Compared to full RV-based traffic, the improvement increases with the increase in the AV implementation rate, and becomes significant at higher implementation rates (50% and above). The comparisons made between different AV models confirmed the encouragement of CAV implementation instead of non-connected AVs in order to maximize the AV efficiency. To increase the efficiency of the AV adoption in the near future, the obtained findings of the investigation can be used to design analytical models that incorporate mixed traffic environments in an urban transportation network. These models can be used to improve the efficiency of signalized intersection control by analyzing the relationships between different AV characteristics and traffic signal performance under different traffic conditions.

6.1.3 Comprehensive Literature Review on the Signalized Intersection Control under AV-Based Traffic

The intelligent incorporation of the AV implementation can increase the efficiency of signalized intersection control. However, most of the expected positive impacts of the AVs that may be utilized to propose autonomous-based methods may assume to happen in case of full traffic of

the AVs. Considering mixed traffic environment, the real application of most proposed methods will be based on different assumptions, requirements, and constraints related to the network environment, including the traffic composition, connectivity, road infrastructures, intersection, and functional design, and the driving behavior of the vehicles. The review concluded that the TSC methods in the future should be designed and applied considering the actual capabilities of AVs and RVs with minor modifications or requirements of the existing infrastructure. In the transition period to the full AV environment, the significant improvements in ML approaches should be used to develop reliable adaptive TSC-based methods that can effectively accommodate the potential positive impacts of the AVs without compromising the safety and level of service in the RVs.

6.1.4 Development of Traffic Signal Optimization Framework Using ML

The impact of the AV implementation rate confirms the significance of the driving behavior of the vehicles on the optimization performance. The increase of the AV implementation rate in traffic networks could improve the accuracy of traffic flow prediction, and therefore improve the robustness and reliability of different ITSs such as adaptive-based TSC systems. The proposed optimization framework in this research can effectively improve the signalized intersection performance at congested volumes. The level of expected improvements increases gradually with an increase in the AV implementation rate. Assuming that AVs are completely self-driving and that their settings are programmed based on effective traffic, the encouraging results obtained from the proposed framework indicate the proposed technique intelligently utilizes the potential positive impacts of AVs for enhancing the efficiency of the optimization performance of the cycle length. Thus, the proposed framework can be effectively utilized and applied to design an adaptive-based TSC system. The application of such a system will be completely reliable and

familiar to both AVs and RVs, which consider their actual characteristics and capabilities and offers an intelligent and safety measure for an inherent-based solution. Therefore, the proposed system involves the appropriate generalization for controlling any existing signalized intersections under the different conditions of mixed-based autonomous traffic. Moreover, it is a cost-effective system that can be applied simply without the requirements of connectivity or major costly modifications of vehicular traffic infrastructure.

6.2 Recommendations

To provide a holistic lens on the interpretation of AV impacts and the development of the AV implementation for the future actual practice and further research interests, the following recommendations are made after taking the observations of this research into account:

- There are uncertainties about the net impacts of the full level of AVs on the traffic flow under mixed traffic conditions. Further investigation efforts are needed to evaluate the impacts of lane changing modeling of different types of AV. Moreover, further investigations are needed to investigate the interaction effects of human driving behavior under mixed traffic environment considering full AV level.
- The findings from the conducted investigation of the AV implementation impacts in this research are based on a single isolated signalized intersection. Consequently, in future studies, the impacts should be evaluated considering different urban network levels, including multiple signalized and non-signalized intersections, as well as evaluation of other important parameters such as the road capacity and traffic safety.
- In terms of TSC, further studies should be conducted to analyze the relationships between different AVs characteristics and signal plan optimization. It is recommended to

investigate the performance of the proposed optimization framework using other ML-based prediction models and heuristics-based optimization algorithms to obtain more general conclusions. Future studies should include the development of multi-objective optimization frameworks that aim to utilize the impacts of AVs on environmental concerns, such as energy consumption and air pollution.

- The most significant obstacle to AV implementation is the acceptance of autonomous driving technologies by human, rather than technical challenges. Although AVs can address several problems associated with RVs, their positive impacts will remain unrealized until they are accepted and trusted by the public. Therefore, a high level of trust must be cultivated to ensure the acceptance and widespread use of AVs. The safety of AVs is the biggest concern for most people. Although some studies have indicated that AVs can improve safety under mixed traffic conditions, further studies are required to highlight this aspect and increase driver acceptance.

Finally, the different outcomes of this dissertation are beneficial for AV manufacturers, traffic community and policy makers in the future of AV's development and implementation. The obtained outcomes can help transportation planners, traffic authorities, and engineers to discover and understand the potential operational impacts of AVs and to enhance future control of the signalized intersection under mixed AV traffic environment.

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EDUCATION

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PhD Degree in Transportation Engineering, **GPA: 3.81/4.00**

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M.Sc. Degree in Transportation Engineering, **GPA: 3.54/4.00**

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WORK EXPERIENCE

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Civil and Environmental Engineering Department, King Fahd University of Petroleum and Minerals (KFUPM), Saudi Arabia

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Lecturer

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- Teaching transportation related courses such as: Surveying, Transportation Engineering, Traffic Engineering and Pavement Engineering
- Supervising undergraduate students during field training and design projects
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Teaching Assistant

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- Teaching and assisting students during different civil engineering labs
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RESEARCH INTERESTS

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PUBLICATIONS

1. M. Al-Turki, M. T. Kashifi, N. T. Ratroun and S. M. Rahman, “Traffic Signal Optimization Framework Using Interpretable Machine Learning Technique under Heterogeneous-Autonomy Traffic Environment,” *Physica A: Statistical Mechanics and its Applications*, January 2023, **under review**.
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