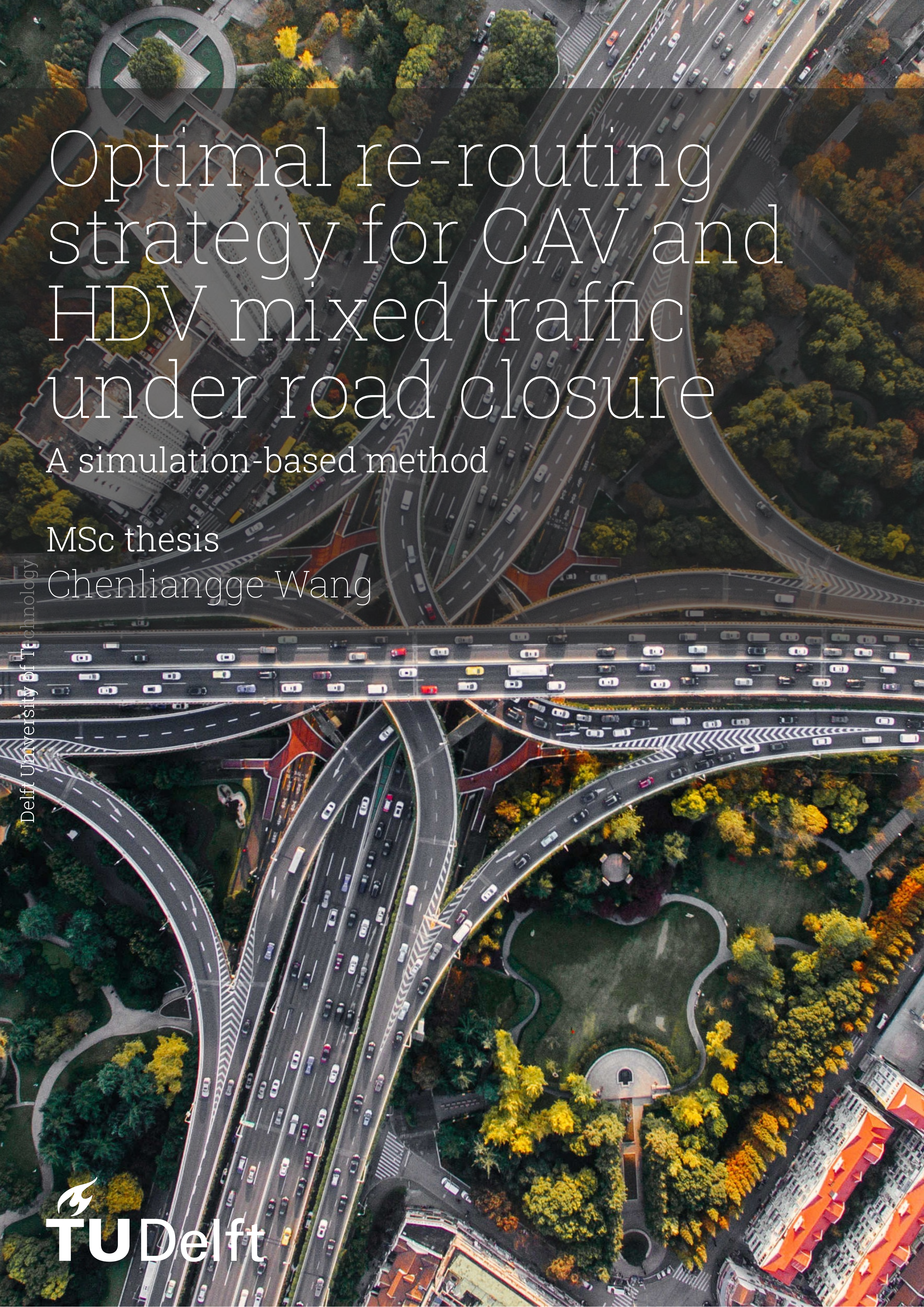

Optimal re-routing strategy for CAV and HDV mixed traffic under road closure

A simulation-based method

MSc thesis

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Delft University of Technology

Optimal re-routing strategy for CAV and HDV mixed traffic under road closure

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by

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to obtain the degree of Master of Science
in Civil Engineering with Track Transport & Planning
at Delft University of Technology

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Cover: Road aerial photography of concrete roads intersection of Shanghai

Preface

As I began to write these words, I realized that this journey is finally coming to an end. I had imagined this moment countless times before, but now that it is actually approaching, I find myself less excited than expected and more reflective on how much I have changed and grown over the past three years. This journey has given me far more than just a thesis.

First and foremost, I would like to sincerely thank the members of my graduation committee. My chairperson, Simeon, brainstormed this topic with me, respected my ideas, suggested many intriguing directions, and ultimately designed this new topic based on my interests. His patience and trust have been invaluable, and I am deeply grateful. Secondly, I want to thank my second supervisor, Maaike, who provided me with meaningful guidance throughout our interactions. She was always quick to identify unnoticed but crucial issues in my thesis, helping me understand and gain deeper insights into my research. Lastly, my daily mentor, Behzad, offered me many useful tools and documents and shared his experiences to help me overcome practical challenges. His selfless support has touched me deeply.

My family has always given me unconditional support and love. Although the outside world can sometimes be incomprehensible to you, you are always curious about my life, wishing me to be happy, and infecting me with the most positive thoughts when I am down, which is important to keep me going until now.

To my friends, both near and far, I am incredibly fortunate to have had you with me through this journey. Thank you for listening to my emotions, offering words of encouragement, and comforting hugs. I know we are going through a similar confusion and I wish we all the best in being brave, breaking the shackles and starting a new story.

For myself, with the initial intention of learning something new, I embarked on this journey through a series of uncertainties, difficulties, and ups and downs. I am glad to have found some answers along the way. Much like the academic process, I have been constantly reflecting on myself and the life I want to lead. I keep asking questions, thinking deeply, breaking down and disproving my thoughts, and thinking again, trying to find an answer to the meaning of life. I am glad that after those, my inner voice grows clearer in the cacophony of noise around me. And that, above all, is the most important takeaway for me.

Chenliangge Wang
The Hague, May 2024

Summary

Against the backdrop of the increasing maturity of connected automatic driving technologies and the gradually expanding market share of CAVs, this thesis explores the optimal traffic management strategies to cope with road closures in the context of Connected and Automated Vehicles (CAVs) and Intelligent Transportation Systems (ITS).

A rerouting strategy is designed based on the rerouting behaviour of vehicles when road closure occurs in life, the control parameters include the control of the CAV's automatic rerouting period, rerouting probability, HDV Knowledge of the time of lane closure, as well as their rerouting probability, as shown in Table 1. The aim of this study is to find the optimal combination of these five parameters. Four levels of CAV penetration (20%, 40%, 60%, and 80%) are considered with the objective of minimizing the total travel time on a mixed CAV and human-driven vehicle (HDV) traffic flow network. The main question is **What is the optimal rerouting strategy for CAV and HDV mixed traffic when road closure happens?** and in the process of answering this question, the effects of CAV penetration, individual rerouting parameters and different road closure locations are considered and analyzed.

Table 1: Rerouting parameters in rerouting strategy

Rerouting parameter	**Notation**	**Description**
CAV rerouting pre-period	re_{ppe}	The period for CAV to (re)route before departure
CAV rerouting period	re_{pe}	At each rerouting period CAV recalculates the shortest travel times during trips
CAV rerouting probability	re_{prob}	The probability of a CAV chooses to change route at each rerouting period
Rerouter time threshold	Re_{tTh}	The time before the rerouter to receive road closure information and take effect
Rerouter rerouting probability	Re_{prob}	The probability of a CAV choose to change route when passing the rerouter

In this thesis, a simulation-based approach is used to model the traffic flow applying both micro and meso scale models. Then, the simulation is conducted for the predefined scenarios, then the sensitivity analysis of each relevant parameter is performed using a one-factor-at-a-time approach to understand the impact of each parameter on the network traffic condition. Finally, Bayesian optimisation is used to find the optimal rerouting strategy within a certain search range and number of times, where the results obtained from the sensitivity analysis are used to determine the parameter search space.

The grid network and the Sioux Falls network are simulated respectively and the

relatively optimal rerouting strategies are found for them. The grid network can be regarded as a local area on the network, while the results of Sioux Falls, as a larger network, can provide some basis for city-level traffic management. Figure 1 and Figure 2 shows network structure and modelled road closure locations.

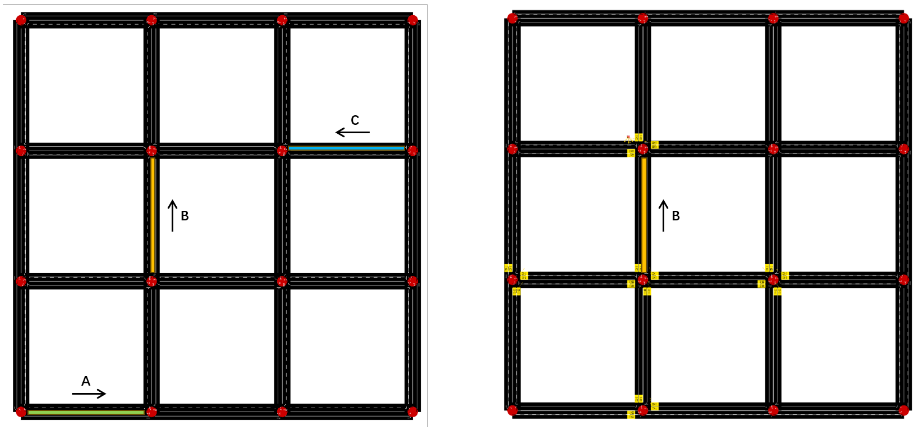

Figure 1: The locations of closed lanes (left) and the placement of rerouters for closure B (right) in the grid network

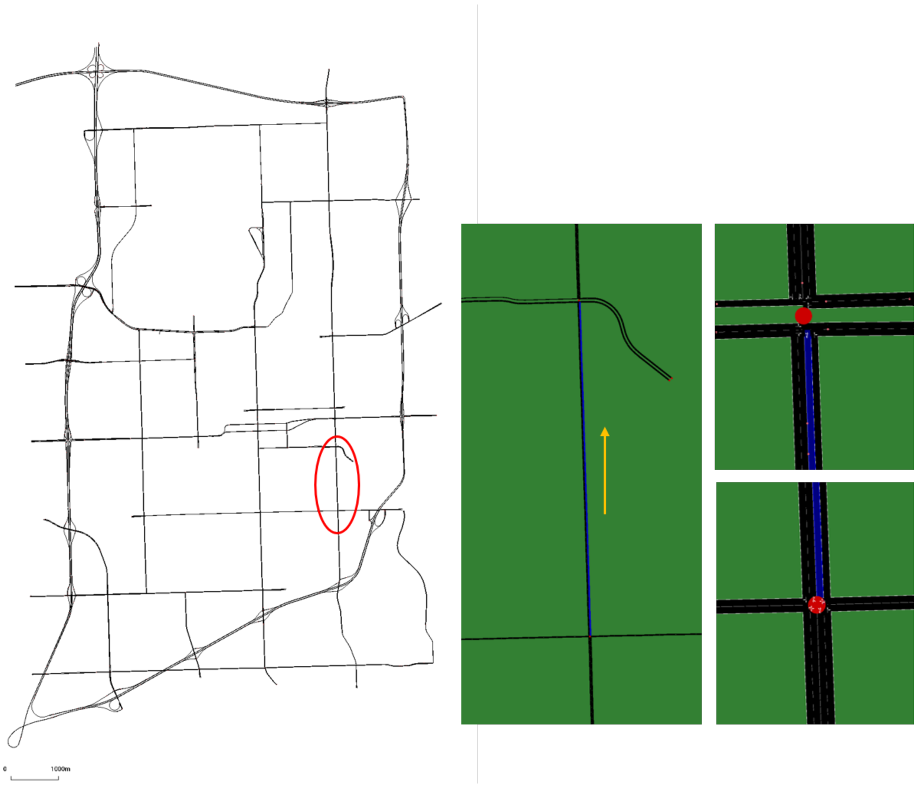

Figure 2: The location of closed road in Sioux Falls network

The key findings of this thesis include (1) CAV penetration increases bring reductions in TTT and TWT and increase in TTD to the network, overall, the traffic flow movement improves and severe congestion decreases, and network conditions improve significantly during the growth phases of 20%-40% and 60%-80%; (2) the importance of each rerouting parameter varies for different networks and at different penetration rates, and the results fluctuate significantly between different test values, with no single increasing and decreasing trend; (3) road closures at entrances and exits located at intersections are more critical and require targeted rerouting strategies; the traffic demand distribution has a significant impact on it; (4) Bayesian optimization can find the optimal rerouting strategy in a finite amount of time, where the specific strategy and the improvement effect varies for different networks and levels of demand.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
TM	Traffic Management
TMS	Traffic Management System
TMC	Traffic Management Center
CV	Connected Vehicle
CAV	Connected Automatic Vehicle
HDV	Human Driving Vehicle
PR	Penetration Rate
RSU	Road Side Snit
UE	User Equilibrium
SO	System Optimal
MTT	Marginal Travel Times
BO	Bayesian Optimization
TTT	Total Travel Time
TWT	Total Waiting Time
TTD	Total Travel Distance
O-D	Origin and Destination
TA	Traffic Assignment

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1
Introduction

Efficient traffic management can relieve traffic congestion, reduce fuel consumption, and improve traffic safety. Connected automated vehicles (CAV), as a new traffic mode, are considered among the top ten disruptive technologies that are expected to change the landscape of transportation over the next decade (Manyika et al., 2013; Matin and Dia, 2022). With the advancement of communication and automation technologies, a coexistence of traditional human-driven vehicles (HDVs), connected vehicles (CVs), and connected and automated vehicles (CAVs) is anticipated on urban roads in the near future(J. Li et al., 2023). On the one hand, the participation of CAVs is expected to contribute to solving, easing, or avoiding congestion (Lee and Park, 2013); on the other hand, the CAV and HDVs mixed traffic triggers challenges in traffic management problems.

1.1. Research background

1.1.1. Introduction of CAVs

CAVs are vehicles that utilize both connectivity and automated technologies to assist or even replace humans in driving tasks, which is achieved through the use of sophisticated sensor technology, on-board and remote processing capabilities, GPS, and telecommunications systems (“Connected and autonomous vehicles - Driverless cars and the journey to making motorised transport safer and healthier”, n.d.). Specifically, advanced in-vehicle sensors can help CAVs to perceive themselves and their surrounding environment and can be used for Advanced Driver Assistance Systems (ADAS), such as Lane Keep Assistant (LKA), Forward Collision Warning (FCW), Autonomous Cruise Control (ACC), and a part of autonomous driving (Guerrero-Ibáñez et al., 2018; “What is ADAS?”, n.d.). Additionally, CAVs utilize wireless V2X, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Pedestrian (V2P), etc., communication technologies to exchange traffic condition information with other road users, infrastructure, or even all elements of their surrounding environment (Sarker et al., 2020).

With the assistance of those intelligent systems, CAVs are expected to have a positive impact on traffic management and benefit urban mobility, traffic safety, and environmental protection (Campisi et al., 2021; Fagnant and Kockelman, 2015; Khoury et al., 2019; Matin and Dia, 2022). Recent studies show that CAVs can improve traffic efficiency by reducing travel time/delay while improving average speed where the cooperative ability of CAVs plays a more significant role in achieving these improvements than their autonomous function alone (Khoury et al., 2019; B. Liu et al., 2019; Puylaert et al., 2018). Furthermore, the increased penetration rate of CAVs is promising in improving traffic capacity by allowing for reduced headway between vehicles in a platoon due to the shorter reaction time of CAVs (Chang et al., 2020). In addition, the capabilities of the CAV platoon have been shown to have the potential to reduce fuel consumption and pollution emissions by allowing smoother speed/acceleration, as well as reducing air drag (Jin et al., 2014; Matin and Dia, 2022; Tsugawa et al., 2011; Wadud et al., 2016). Last but not least, CAVs have the potential to substantially reduce crashes and improve traffic safety in developed countries by mitigating or eliminating human errors (Jadaan et al., 2018,Arvin et al., 2020), given the fact that a significant proportion of traffic accidents are attributable to human factors such as alcohol consumption, distraction, and drug use (Fagnant and Kockelman, 2015).

However, despite research showing the promising benefits of CAVs for urban traffic, uncertainties remain regarding their impact when considering more realistic factors. One concern is that the use of CAVs could potentially exacerbate congestion by increasing the number of car trips. This could occur not only because people may assign a lower value to their time when using CAVs, making CAVs more attractive, but also because they could facilitate travel for non-drivers, such as the elderly and disabled (Fagnant and Kockelman, 2015; Gokasar et al., 2023; Puylaert et al., 2018). Additionally, it is important to note that human-driven vehicles (HDVs) still dominate the market, and it may take a long time for CAVs to achieve a penetration rate of 100% (Bamdad Mehrabani et al., 2023). Consequently, multiclass traffic flows are expected to persist in the coming years or decades. Moreover, while a greater adoption of CAVs can lead to long-term benefits, predictive models suggest potential mid-term fluctuations in costs and congestion (Medina-Tapia and Robust, 2019). Given this context, traffic management strategies for CAVs need further development, with addressing the challenges of managing multiclass traffic being a key priority.

1.1.2. Intelligent traffic management system

The objective of traffic management is to enhance the capacity of the infrastructure and decrease congestion levels (Djahel et al., 2014). This can be achieved by obtaining traffic-related data, identifying traffic hazards, and subsequently controlling traffic flow and improving traffic conditions (De Souza et al., 2017).To support it, a collection of applications and management tools collaborate to integrate communication, sensing, and processing technologies, known collectively as a Traffic Management System (TMS) (Djahel et al., 2014). One of the building blocks that composes TMS is Vehicular Ad Hoc Networks (VANETs), which support data exchange among vehicles, roadside units (RSUs), and Traffic Management Centers (TMCs) (De Souza et al., 2017). Within VANETs, vehicles are considered mobile nodes with On-Board Units (OBUs) that are capable of aggregating traffic data from different built-in sensors (such as GPS, speedometer, and odometer) and sending them to the TMC or sharing among its neighbors to be exploited (De Souza et al., 2017). CAVs could act as the desired actuators for TMSs to control trafficGokasar et al., 2023. As a reference, Figure 1.1 demonstrates a conceptual framework for an traffic management system.

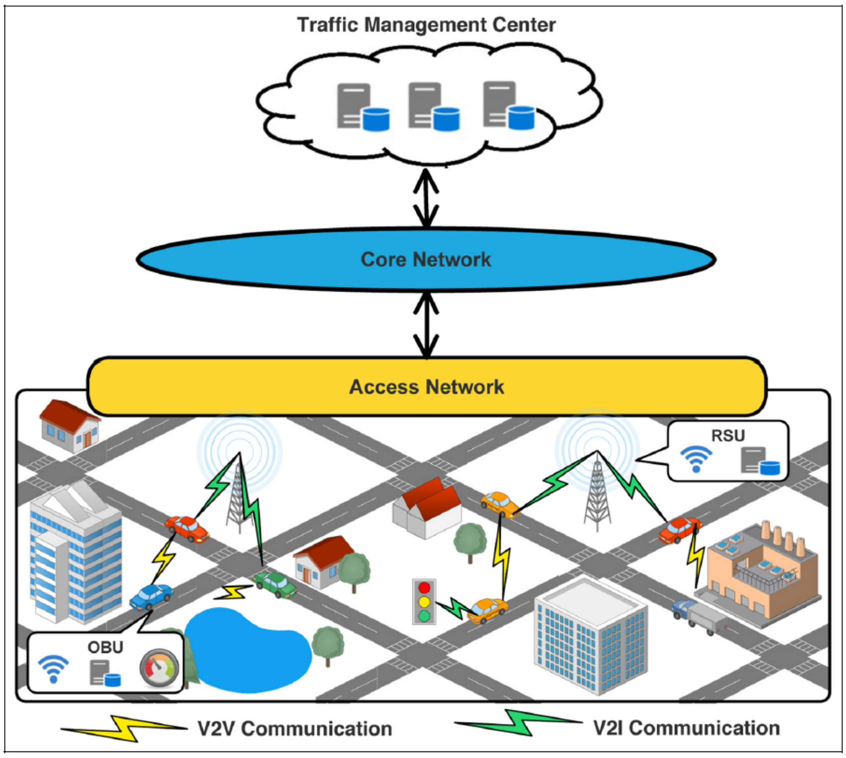


Figure 1.1: Overall TMS architecture presenting the major entities (De Souza et al., 2017)

Optimal management and control of traffic in urban networks is an important requirement for city authorities seeking efficient, safe and sustainable transportation. In addition, transport policymakers are required to achieve an increasingly wide range of objectives, such as prioritizing public transport, improving conditions for vulnerable road users, real-time traffic information; emergency and incident management and restricting traffic in sensitive areas (Papageorgiou et al., 2007).

As a response to these issues, Urban Traffic Management and Control (UTMC) systems have been introduced in many cities around the world to provide the tools to support efficient and effective network management to meet needs of current and future traffic problems (Papageorgiou et al., 2007). UTMC systems are designed to allow the different applications used within modern traffic management systems to communicate and share information with each other. It allows previously disparate data from multiple sources such as Automatic Number Plate Recognition (ANPR) cameras, Variable Message Signs (VMS), car parks, traffic signals, air quality monitoring stations and meteorological data, to be amalgamated into a central console or database. The idea behind UTMC is to maximise road network potential to create a more robust and intelligent system that can be used to meet current and future management requirements. figure 1.2 shows a conceptual diagram of Intelligent Traffic Management System.

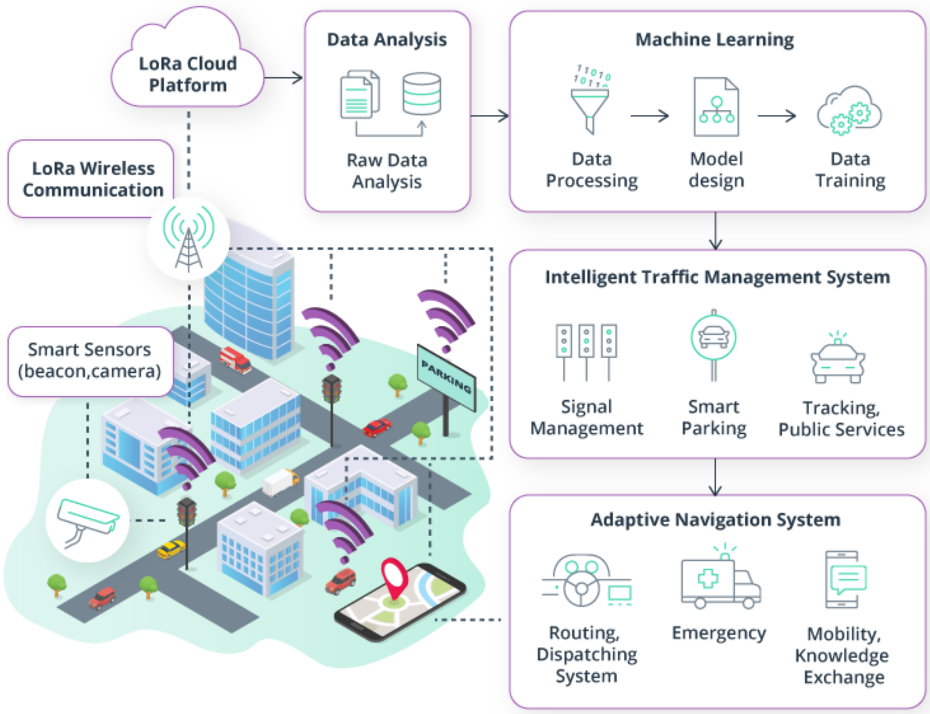


Figure 1.2: The conceptual diagram of Intelligent Traffic Management System (Seo and Singh, 2018)

In addition to the traffic congestion problem, in contemporary traffic management, incident response and mitigation have become important tasks for traffic control center operators. Although tools to monitor real-time traffic performance have been rapidly developed and deployed in recent years, the decision-making tools to guide or assist in determining the best response have not yet been developed (Burghout et al., 2010).

1.2. Problem statement

1.2.1. Research objective

Road closures are among the most common traffic incidents that affect traffic efficiency. Events such as car accidents, vehicle breakdowns, and extreme weather conditions can lead to partial or complete road or lane closures, reducing road capacity and often resulting in severe traffic congestion and increased emissions. Therefore, incident response and mitigation have become critical tasks for Traffic Control Center operators, requiring proactive measures from the Traffic Management Control Center to manage traffic flow. One essential task is to notify vehicles of road closures so that they can reroute before encountering the closed road. However, one of the possible situations is the closure of one or more lanes while others remain open, which poses a significant challenge for traffic management. In this situation, the road still retains some capacity, and not all vehicles need to reroute to avoid the closed lanes. This raises the question: how can the rerouting behavior of vehicles be controlled to optimize the road network's efficiency under these circumstances? This paper aims to address this question.

The actions taken by vehicles are influenced by the time and place at which they receive information. Traditionally, HDVs are notified of road closures through broadcasts or directional signs. However, with the advent of CAVs and vehicle-to-everything (V2X) communication systems, vehicles can now receive real-time traffic updates and broadcast warnings to other vehicles. Consequently, the methods for managing traffic differ between CAVs and HDVs. For CAVs, traffic management involves controlling the frequency of information updates and determining the percentage of CAVs that should take action after each information exchange. For HDVs, it focuses more on the coverage range of broadcasts or the location of traffic information display screens, as well as the timing of these information displays. In this thesis, we aim to investigate how these two types of traffic management can cooperate to control the rerouting behavior of vehicles, thereby achieving a better road network situation in mixed traffic conditions. This control strategy is referred to as the rerouting strategy in this thesis.

Therefore, this study aims to design an experiment to find the optimal rerouting strategy for a given network under lane closure incidents minimizing the impact of traffic incidents on traffic conditions. The rerouting strategy is a traffic flow management strategy determined by the TMC that includes the number and frequency of CAV message exchanges, the probability that a vehicle will be rerouted, and the location and time at which the HDV can receive the message.

1.2.2. Research questions

This study aims to find the optimal rerouting strategies under road closure and considers four CAV penetration rates. The main research question posed in this study is:

- **What is the optimal rerouting strategy for CAV and HDV mixed traffic when road closure happens?**

In order to answer the main research question above, the following four sub-questions are presented.

1. To what extent does the penetration rate of CAVs affect traffic conditions under road closure? and how can this impact be quantified and assessed?
2. To what extent does each rerouting parameter affect traffic flow separately? Which parameter is most important?
3. How do road closures affect traffic conditions when they occur at different loca-

tions? Which road closure locations are more critical?

4. How can the optimal rerouting strategy be determined for a network? What is the optimal rerouting strategy for the selected network and what is its performance in responding to road closures?

First of all, in addition to the rerouting parameters, the CAV PR itself is a significant factor that affects traffic conditions. For example, higher CAV penetration can lead to a faster equilibrium of the traffic flow and reduce congestion by avoiding selfish routing (Bamdad Mehrabani et al., 2023). Therefore, to objectively and comprehensively quantify the performance of the optimal rerouting strategies, the effect of the CAV PR will be measured separately in the first stage. This leads us to sub-question 1.

To answer sub-question 1, we simulate mixed traffic flows with different CAV PRs (20%, 40%, 60%, 80%) under any road closures applying the predetermined reference rerouting strategy. Indicators including total travel time (TTT), total travel distance (TTD), and total waiting time (TWT) will be analyzed. Sub-question 1 can be answered by comparing the difference between the results of different CAV PRs.

Answering sub-questions 2-3 will provide a better understanding of the impact of each parameter and the location of the different closed roads. These sub-questions can be addressed through the results of the one-factor-at-a-time sensitivity analysis. In this thesis, sensitivity analyses for the same parameters and test ranges/intervals were performed on road networks with different CAV PRs and road closure locations, where total travel time (TTT) is the main indicator to analyze. Sub-question 2 can be answered by analyzing the sensitivity and effective interval of each parameter, and sub-question 3 can be answered by comparing the results across the tested closure locations.

To answer the 4th sub-question, the methodology for finding the optimal rerouting strategy will be discussed. The advantages of using the Bayesian optimization method for this problem will be illustrated, and the performance of the optimal strategy found through Bayesian optimization will be analyzed in terms of Total Travel Time (TTT), Total Travel Distance (TTD), Total Waiting Time (TWT), as well as the traffic condition distribution. Additionally, the distribution of traffic conditions across the network will be examined. Finally, the results of applying the optimal strategy will be compared with those of a reference rerouting strategy.

In a nutshell, the five questions can be assigned to the following research steps: (1) Perform the traffic simulation for the network with different CAV penetration rates of reference rerouting strategy, (2) perform the sensitivity analysis of each parameter, and (3) search for the optimal rerouting strategy for different scenarios in the network. The research steps described above will be conducted on two networks. First, experimental tests will be conducted on a small grid network with a simple road structure to ensure the validity of the experiment, and then a case study will be conducted on the Sioux Falls network.

1.2.3. Research outline

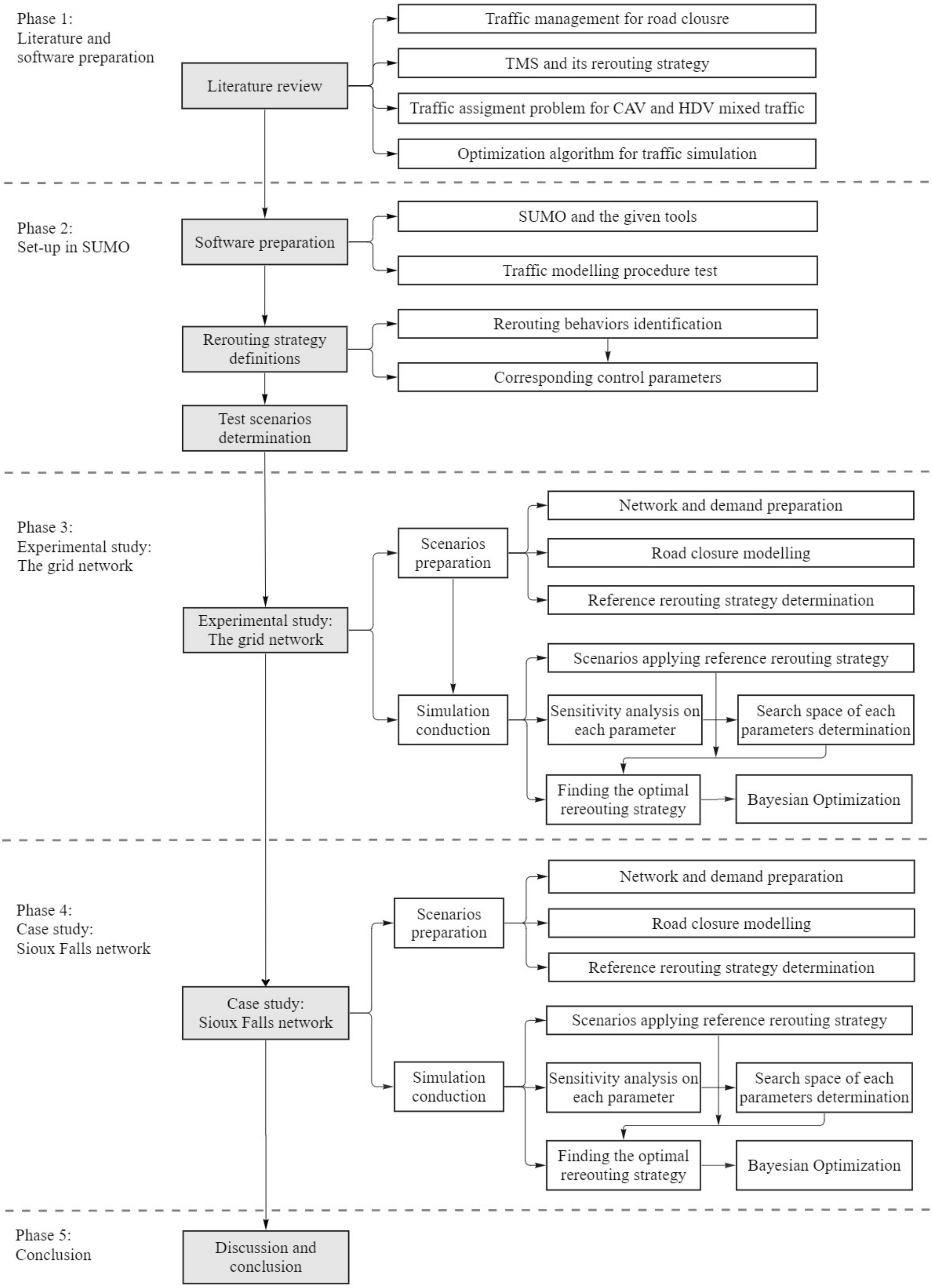


Figure 1.3: The conceptual framework of research plan

The work plan, see Figure 1.3, details a structured method for investigating traffic rerouting strategies through simulation, with a focus on sensitivity analysis to understand the impact of each parameter and then optimize the rerouting strategy for different scenarios.

The initial phase involves a comprehensive literature review to gather existing knowledge on simulation-based traffic management, sensitivity analysis in traffic simulations, and optimization algorithms. Alongside the theoretical groundwork, software tools like SUMO are prepared for practical application. Following the preparatory phase, the SUMO simulation environment is configured, which encompasses the establishment of basic settings, formulation of rerouting strategies, and the definition of various test scenarios. This preparation is pivotal for ensuring accurate and effective simulation runs.

The practical application begins in the third phase, where the previously defined strategies and scenarios are tested on a simplified grid network. This phase is critical for assessing the feasibility of the designed experiment and includes a detailed sensitivity analysis to understand the influence of different parameters across various scenarios. During this phase, the network, traffic, and demand are first prepared, and the reference rerouting strategy is determined and applied as the baseline. Then, sensitivity analysis is conducted for each parameter. Additionally, efforts are made to identify the optimal search space for each parameter in the optimization algorithm to find the most efficient rerouting strategy that minimizes total travel time. The results of using the reference rerouting strategy and using the optimal rerouting strategy found by Bayesian optimization methods are compared to illustrate the effectiveness of Bayesian optimization.

In the fourth phase, the study expands to include a case study of the Sioux Falls network, which is more complex than the simple grid network. The simulation process is replicated for the Sioux Falls network.

The final phase involves a thorough discussion and conclusion, synthesizing the results from the simulations to draw insightful conclusions. This last stage aims to encapsulate the findings and present them in a format that underscores the practical applications and theoretical contributions of the study.

1.3. Thesis structure

The remainder of this thesis is organized as follows: Chapter 2 discusses the literature review and identified research gaps. Chapter 3 details the methodology used in this thesis, including how to perform traffic simulation, the application of micro-model and mesoscale simulation, and an introduction to Bayesian optimization. Chapters 4 and 5 detail the experimental procedures and numerical results of the grid network and Sioux Falls network, respectively, and organize and interpret the simulation results. The results and methodology of this thesis are discussed in Chapter 6, followed by conclusions in Chapter 7.

2
Literature review

2.1. Traffic management strategies for road incident

In recent years, a large number of scholars have begun to study how to use CAV to manage traffic incidents, but most of them focused on traffic congestion, and the most usual solution is to dynamically control traffic lights through prediction of traffic on the network to control traffic flow. For example, Lilhore et al., 2022 and Satkunarajah and Puvanendran, 2023 proposed different models of traffic management system to constantly update traffic signal schedules; the former depends on the volume of traffic and the estimated movement from nearby crossings based on the machine learning method, allowing vehicles to travel when the light is green; and the latter is calculated by calculating the duration of activating the Green signal based on the density of vehicles on each road.

In addition to the traffic congestion problem, some scholars have begun to study how to use the advantages of CAVs to cope with road incidents and minimize their impact. In Huang et al., 2023's research, The CAV can judge the obstacles and adjust its trajectory to improve safety when there is a car accident or roadblock at the intersection under the control of the traffic management system. Mesoscopically, Long et al., 2011 uses the spatial topology of traffic jam propagation and introduces the concept of vehicle movement prohibition that is often used in real urban networks. They proposed four control strategies, and combinations of these control strategies were explored. The impact of these control strategies on traffic congestion and congestion delay changes is evaluated. In the sphere of traffic simulation for incident management, the PERDIKT project, funded by the Swedish National Road Administration, serves as a notable example of advancing mesoscopic modeling capabilities, as discussed in recent literature (Burghout et al., 2010). The project sought to extend the functionality of the mesoscopic simulation model MEZZO. Scholarly discussions highlight the project's focus on refining driver behavior response algorithms within the model, particularly in reaction to traffic incidents and dissemination of information. Critical modeling components underwent a series of tests and the implementation of a sophisticated incident response logic within MEZZO was appraised on the Södermalm subnetwork.

2.2. TMS with rerouting strategies

Recent research has proved that real-time traffic flow data and road travel time can be determined based on data reported by vehicles or road-side sensors (Work et al., 2008, Mohan et al., 2008, De Souza et al., 2016,). Based on this, scholars have proposed many traffic management systems in which the communication function between RSUs and vehicles can be used to realize dynamic route guidance for vehicles to improve traffic conditions (Pan et al., 2012, Brennand et al., 2015,de Souza et al., 2015, de Souza et al., 2016). The qualitative overview of the solution of TMS and rerouting strategy is displayed in Table 2.1 and Table 2.2. The focus of these TMS systems is to reduce traffic congestion, relying primarily on periodic congestion detection and consequent periodic vehicle rerouting.

Pan et al., 2012 posed some significant achievements in rerouting, including five traffic rerouting strategies suitable for dynamic traffic scenarios. First, Dynamic Shortest Paths (DSP) proposes a path with the shortest travel time, but this algorithm has the shortcoming of potentially shifting the congestion to another location. To solve this issue, the Random k Shortest Paths (RkSP) scheme is proposed, in which a path from k shortest paths is randomly selected and assigned to vehicles. The goal of this algorithm is to avoid switching congestion from one point to another by balancing the rerouted traffic among several paths. Third, Entropy Balanced k Shortest Paths (EBkSP) strategy takes into account the impact of each of the k paths on future traffic density, and improves RkSP by introducing 'urgency' to rank vehicles for rerouting in order. The results show that in the test scenarios, the average travel time is reduced by 36% for DSP, 41% for RkSP, and 45% for EBkSP. Most of the literature that has appeared since has improved on Pan et al., 2012. For example, de Souza et al., 2015 proposes cooperative re-routing, i.e., planning globally optimal routes for all vehicles, instead of traditional route planning, in which the best route for each vehicle.

Furthermore, most of these studies focused on the range of RSUs, with most assuming that vehicles within the communication range of RSUs would guide new routes, and in b only re-navigating vehicles that were about to pass through congested areas. However, each RSU can only collect local traffic information and does not know the global information of the network, and if a vehicle's route spans the area of multiple RSUs, the vehicle's route will be split into several parts for navigation, which can potentially result in multiple unnecessary rerouting behaviors that increase travel time. In addition, most of the literature assumes that all vehicles receive information from RSUs and that they have a 100% acceptance rate of new routes. However, the effect of different compliance rates is discussed in Pan et al., 2012. They found that at higher compliance rates instead lead to network condition degrades, which suggests that after detecting congestion, most of the vehicles may receive the same road, which results in new congestion.

Table 2.1: Qualitative comparison of re-routing strategy in traffic management systems

Solutions	Goal of rerouting	Design		Scenario	
		V2V	V2I	Network & size	CAV PR
DSP (Pan et al., 2012)	Avoid traffic congestion		x	Manhattan, $75km^2$; Newark,$24.82km^2$^2	20%-100%
RkSP (Pan et al., 2012)	Avoid traffic congestion		x	Manhattan, $75km^2$; Newark,$24.82km^2$^2	20%-100%
EBkSP (Pan et al., 2012)	Avoid traffic congestion		x	Manhattan, $75km^2$; Newark,$24.82km^2$	20%-100%
Brennand (Brennand et al., 2015)	Avoid traffic congestion		x	Cologne, $400km^2$	100%
CHIMBA (De Souza et al., 2016)	Avoid traffic congestion		x	Manhattan, $5km^2$ ^2	100%
SCORPION (de Souza et al., 2015)	Avoid traffic congestion		x	Manhattan, $5km^2$	100%
ICARUS (de Souza et al., 2016)	Avoid traffic congestion	x	x	Manhattan, $4km^2$2	100%

Table 2.2: Continue - Qualitative comparison of re-routing strategy in traffic management systems

Solutions	rerouting strategy					
	Shortest path	Traffic balance	Coorpoerative re-routing	Rerouting vehicle selection	Reouting period	Compliance rate
DSP	x			Vehicles from incoming segments, the range is decided by a parameter L	[150s, 750s]	[0.2,1]
RkSP		x		Vehicles from incoming segments, the range is decided by a parameter L	[150s, 750s]	[0.2,1]
EBkSP		x		Vehicles from incoming segments, the range is decided by a parameter L, introducing an urgency policy	[150s, 750s]	[0.2,1]
Brennand		x		All vehicles within the radius of RSUs	180, 300, 600s	1
CHIMBA		x		All vehicles within the radius of RSUs	15, 30, 60, 120s	1
SCORPION		x	x	All vehicles within the radius of RSUs	300s	1
ICARUS		x		Path-based, vehicles in AoI	150, 300, 600s	1

2.3. Traffic assignment for CAV and HDV mixed traffic

2.3.1. The Wardorp's principle

Traffic assignment (TA) is a process of allocating the traffic flow on the network by assuming all of them follow certain behavioral principles (Mehrabani et al., 2022), for example, all vehicles seek the shortest path for their own, which is called User Equilibrium (UE) in the Wardorp's first principle (Wardrop, 1952). At the same time, Wardorp also proposed a second behavior principle called System Optimal(SO), in which the users seek the route to reach the shortest total travel time of the whole system (Wardrop, 1952). Consequently, the guided route for a vehicle might be different following different principles.

In terms of assumptions of previous studies on CAV route choice behavior, some researchers assume that CAVs will follow SO routines (Aziz, 2019, Bagloee et al., 2017, Chen et al., 2020,Guo et al., 2021, R. Li et al., 2018, Mansourianfar et al., 2021, Ngoduy et al., 2021, K. Zhang and Nie, 2018), while others believe that CAVs will follow UE principles (Bahrami and Roorda, 2020, Samimi Abianeh et al., 2020,J. Wang et al., 2019, Xie and Liu, 2022). Also, some studies model the deterministic route choice behavior of CAVs (G. Wang et al., 2020, J. Wang et al., 2021J, J. Wang et al., 2019), and some others assume the stochastic route choice behavior for CAVs (Xie and Liu, 2022, F. Zhang et al., 2020).

Based on an assumption of the routing principle, traffic flow will be assigned to the network. There are two primary categories of traffic assignment methods: static traffic assignment (STA) and dynamic traffic assignment (DTA) (Saw et al., 2015). Static traffic assignment is utilized for strategic transportation planning, where traffic demand remains constant with respect to time. On the other hand, dynamic traffic assignment deals with varying traffic demand over time, where the arrival and departure times at a particular link may differ (Mehrabani et al., 2022).

2.3.2. Analytic-based and simulation-based method

To solve the dynamic traffic assignment problem, two methods named analytical-based method and simulation-based method are used frequently in literature. Analytical models of DTA use analytical formulations to predict the propagation of traffic in a network (known as network loading), for example, based on the cell transmission model (Ziliaskopoulos, 2000) or the link transmission model (Yperman, 2007). Simulation-based traffic assignment models use a traffic simulator to perform the traffic flow propagation and interactions with time and space (e.g., vehicle movements), which are based on micro/meso traffic flow simulation models Saw et al., 2015. However, most of the existing works for traffic assignment for CAVs are based on an analytical model (J. Liu et al., 2020, Ngoduy et al., 2021, Shen et al., 2006, Shen and Zhang, 2009, Tajtehranifard et al., 2018, Wie et al., 1990) and very few studies utilize a simulation-based model in microscopic or mesoscopic scale (Hu et al., 2018, Mansourianfar et al., 2021, Peeta and

Mahmassani, 1995, Sbayti et al., 2007, I. Yang and Jayakrishnan, 2012).

2.4. Micro-Meso-Macro scale traffic simulation

For the implementation of traffic management solutions, accurate knowledge of the traffic conditions and dynamics is necessary. Traffic simulation frameworks provide a helpful tool to answer complex research questions, to evaluate or to test traffic management strategies and their impacts. The traffic simulation tools can mainly be divided into four different groups Krauß, 1998: 1) Macroscopic: average vehicle dynamics like traffic density are simulated; 2) Microscopic: each vehicle and its dynamics are modeled individually; 3) Mesoscopic: a mixture of macroscopic and microscopic model; 4) Submicroscopic: each vehicle and also functions inside the vehicle are explicitly simulated e.g. gear shift. The advantage of macroscopic models are normally its fast execution speed. However the detailed simulation of microscopic or submicroscopic models are more precise especially when emissions or individual routes should be simulated (Lopez et al., 2018).

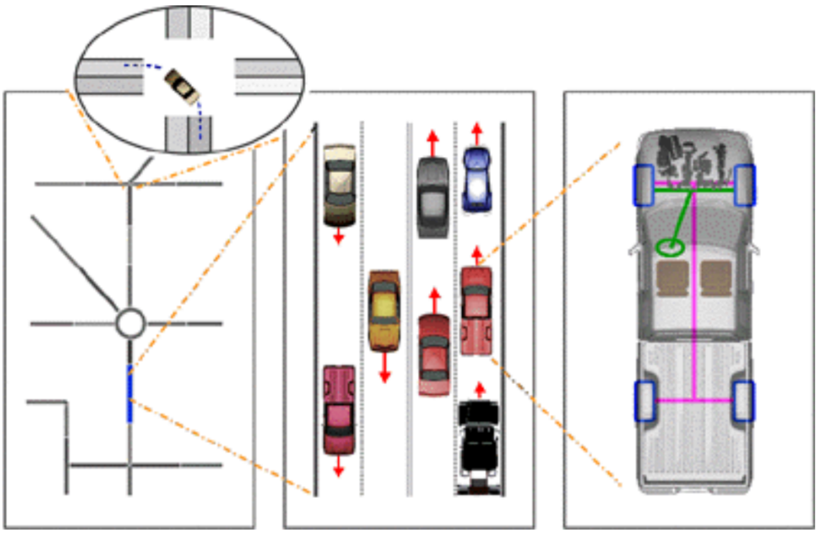


Figure 2.1: The different simulation granularities; from left to right: macroscopic, microscopic, sub-microscopic (within the circle: mesoscopic) (Alvarez Lopez et al., 2018)

The superior performance of the simulation-based dynamic traffic assignment (SBDTA) model (Ameli et al., 2020) has been demonstrated in previous studies. The simulation of urban mobility (SUMO), as an open-source, is one of the most frequently used simulators, which is a highly portable microscopic traffic simulation package that can handle large-scale networks and also can conduct traffic simulations on the mesoscopic scale (Bamdad Mehrabani et al., 2023). In recent years, some researchers have developed a traffic assignment algorithm for some open-source simulators (Bamdad Mehrabani et al., 2021, Bamdad Mehrabani et al., 2023) and now the algorithms for DSO and CAV and HDV mixed traffic flow are available.

2.5. Simulation Optimization method and application

Traditionally, simulation and optimization were regarded as distinct or even alternative methodologies within the field of operational research. However, advancements in computational power have facilitated the emergence of methodologies that integrate both approaches(Figueira and Almada-Lobo, 2014). Simulation-based methodologies have begun to incorporate optimization techniques for tuning model inputs, also known as controllable parameter settings. Conversely, optimization-based methodologies have started to leverage simulation for parameter computation, such as in queuing systems, or for sampling scenarios in mathematical programming models. In recent years there are literatures that give an introduction and evaluation of different types of simulation optimization problems and their common solution methods (Amaran et al., 2016; Figueira and Almada-Lobo, 2014. There are also a number of articles that have begun to use simulation optimization to solve real-world problems, especially in the industrial, medical, and transportation fields, and some researchers also developed the optimization algorithm adapted to their question.(X.-S. Yang and Deb, 2010; Yeomans, 2007).

The three major streams of simulation–optimization research are Solution Evaluation (SE), Analytical Model Enhancement (AME) and Solution Generation (SG) approaches. In Figueira and Almada-Lobo, 2014's research, the researchers have provided a detailed description of these three simulation optimization problems as well as a discussion of commonly used solution algorithms. In general, the SE problem consists of developing a comprehensive simulation model to represent the system and use that model to evaluate the performance of various solutions, and the research in this paper falls into this category, as the input set of control parameters needs to be evaluated based on the simulation results of traffic simulation software.

In the field of transportation and logistics, articles have begun to use simulation optimization methods to find optimal solutions. For example, X.-S. Yang and Deb, 2010 developed a new meta-heuristic optimization algorithm called cuckoo search (CS) and applied it to solve engineering design optimization problems, including the design of springs and welded beam structures. The optimal solutions obtained by the CS algorithm are far superior to those obtained by an efficient particle swarm optimizer; Osorio and Bierlaire, 2010 proposed a meta-model that integrates information from a simulator with an analytical queuing network model and applied it to the problem of signalization control in the Swiss city of Lausanne.

The problem involved in this thesis is also a problem mixed discrete optimization and , which is concerned with finding optimal settings for variables that can only take discrete valuesAmaran et al., 2016. The use of random search algorithms is popular when solving optimization problems with large or infinite solution spaces, annealing, genetic algorithms, nested partitions(e.g., Shi and Ólafsson2000), ant colony optimization and so on. Algorithms for SO are diverse, and their applicability may be highly dependent on the particular application (Amaran et al., 2016), it is difficult to judge how well or how poorly a particular optimization algorithm is applicable, Abdalhaq and Baker, 2014 from the perspective of calibration results, the adaptability of metaheuristic class algorithms commonly used in transportation engineering is compare, including Genetic Algorithm (GA), Tabu Search (TS), Particle Swarm Optimization (PS) and Simultaneous Perturbation for Stochastic Approximation algorithm (SPSA). They concluded that for problems acquiring the calibration process, PS and TS appear to be better than GA and SPSA. PS seems to be a promising optimization technique. It has also been shown that Bayesian optimization has a great advantage in solving black-box problems where simulation time is costly and gradients cannot be computed. A more specific literature review is in the following section.

With regard to rates of convergence, SO algorithms are generally inefficient and convergence rates are typically very slow.Amaran et al., 2016. As described in some detail by Fu (1994), the best possible convergence rates for SO algorithms are generally $O(1/\sqrt{k})$, where k is the number of samples. This is true from the central limit theorem that tells us the rate at which the best possible estimator converges to the true expected function value at a point. This implies that though one would ideally incorporate rigorous termination criteria in algorithm implementations, most practical applications have a fixed simulation or function evaluation budget that is reached first. Fu, 1994. In the discrete case, Xu et al., 2010 outlines criteria for local convergence, defining a point as locally optimal when it surpasses its 2m +1 neighboring solutions in terms of improvement. Globally convergent algorithms aim to find the global optimal solution, but this necessitates evaluating all feasible solutions, which is practically unfeasible due to infinite observations. Instead, a convergence property that allows for a practical stopping criterion may be more sensible (Hong and Nelson, 2009).

2.6. A review on optimization algorithm

Optimization algorithms are crucial for solving complex problems across various fields. One widely used algorithm is Gradient Descent, which iteratively adjusts parameters to minimize a given function. It's essential in machine learning for training models by finding the optimal weights (Goodfellow et al., 2016). Simulated Annealing is another popular method, inspired by the annealing process in metallurgy. It explores the solution space by accepting worse solutions at the beginning to avoid local minima, gradually reducing this tendency as the ”temperature” lowers (Kirkpatrick et al., 1983). Genetic Algorithms mimic the process of natural selection, using crossover and mutation to evolve solutions over generations, making them effective for complex optimization problems (Golberg, 1989). Particle Swarm Optimization (PSO) involves particles moving through the solution space, influenced by their own and their neighbors' best-known positions, which is particularly useful for continuous optimization problems (Eberhart and Kennedy, 1995). Lastly, Bayesian Optimization uses probabilistic models to select the most promising solutions to evaluate next, balancing exploration and exploitation, making it ideal for expensive-to-evaluate functions (Brochu et al., 2010). These algorithms offer diverse approaches to tackling optimization problems, each with unique strengths and applications.

The following table Table 2.3 summarizes the advantages and disadvantages of each algorithm and the scope of application.

Table 2.3

Algorithm	Pros	Cons	Suitable Scenarios
Gradient Descent (GD)	Fast convergence for differentiable functions, widely used in machine learning	Requires gradient computation,can get stuck in local minima	Large-scale machine learning, convex optimization problems
Genetic Algorithms (GA)	Good for global optimization, does not require gradient information	Computationally expensive, convergence can be slow	Complex, multimodal, discrete optimization problems
Simulated Annealing (SA)	Capable of escaping local minima, simple and flexible	Slow convergence, many parameters to tune	Optimization problems with many local minima
Particle Swarm Optimization (PSO)	Easy to implement, good for continuous optimization, parallelizable	Can get stuck in local minima, may require many iterations	Continuous, nonlinear, and multimodal optimization problems
Bayesian Optimization (BO)	Efficient for expensive functions, handles noisy evaluations, provides uncertainty estimates	Computationally intensive, less effective for high-dimensional spaces	Hyperparameter tuning in machine learning, expensive black-box functions

In summary, each optimization algorithm has its strengths and weaknesses. The choice of algorithm depends on the specific characteristics of the optimization problem, such as the nature of the objective function (differentiable or not), the presence of multiple local optima, and the computational resources available. Gradient descent and its variants are powerful for large-scale machine learning tasks, while genetic algorithms and simulated annealing offer robust solutions for complex, multimodal problems. Particle swarm optimization strikes a balance for continuous, nonlinear optimization, and Bayesian optimization excels in scenarios where function evaluations are expensive.

2.7. Research gap

First, as there is a limited amount of literature utilizing simulation-based traffic assignment models, and to fill this gap, this dissertation will conduct a simulation-based dynamic traffic assignment for CAV and HDV mixed traffic, and assume that the former follows UE and the latter seeks SO. This thesis applies microscopic and mesoscopic simulation to model individual driving behaviors and save computation time.

Second, the existing proposed rerouting strategies focus more on solving the traffic congestion problem, there is still a blank in the research of rerouting strategies to cope with the road closure event. In this thesis, we will simulate the traffic situation in the case of road closure and find an optimal rerouting strategy for it.

Considering the issue of traffic balance, in other words, to avoid all vehicles being assigned to the same shortest route and causing additional congestion, current studies introduce different algorithms of the shortest path assignment. However, in this study, instead of adding any new constraints on communication range and rerouting vehicles selection, we introduce CAVs on the network, which can receive the global information periodically and seek for SO principle when selecting routes, as a consequence, allowing an automatic traffic balance during the simulation.

Additionally, much of the existing literature on optimizing re-routing strategies only considers the ideal scenario of 100% CAV penetration, which may take decades to achieve. In contrast, this paper aims to investigate the evolving impact of CAVs on the network by simulating scenarios with varying penetration rates. The findings could provide valuable insights for traffic management in cities in the near future.

Moreover, Bayesian optimization is well-suited for black-box problems with large solution spaces and no gradient function, making it widely used in microsimulation. However, within the authors' knowledge, there is no relevant literature that applies it to optimize input variables for transportation simulation; therefore, this study aims to explore the application of Bayesian optimization method in simulation, examine its effectiveness and analyze the performance of the results.

3
Methodology

This section will clarify the research framework for the entire study, delineating the methodology used in each phase. This encompasses defining the re-routing strategy, executing traffic simulations in SUMO, simulating road closures, and applying optimal algorithms to ascertain the most effective rerouting strategy.

3.1. Overall methodology

This thesis is a simulation-based study on traffic management of rerouting strategy. The simulation is performed on SUMO(Simulation of Urban MObility) [1], which is an open source, highly portable, microscopic and continuous traffic simulation package designed to handle large networks. It allows for intermodal simulation including pedestrians and comes with a large set of tools for scenario creation. The sensitivity analysis used a one-factor-at-a-time approach and finally the optimal rerouting strategy (combination of parameters) was found by applying Bayesian optimization.

Figure 3.1 shows a general overview of the research methodology of this thesis, with the main steps of the study in the middle part. Firstly, the scenario to be tested is defined, including the network and traffic demand; then the reference rerouting parameters are determined; then the parameters in the CAV travel file and the file for the road closure are updated according to the defined parameters, so that all the required files are prepared. Next, the sensitivity analysis of each parameter is carried out, and the specific process is shown in the box on the left, the one-factor-at-one-time approach is adopted, adjusting one parameter at a time and updating the previous travel file or road closure file, after which the traffic simulation is carried out and the kpi is collected until all the adjustments are completed. After completing the sensitivity analysis, the application of Bayesian optimization will be performed. The Bayesian optimization solution space and other attributes are adjusted according to the conclusion learned from the sensitivity-based analysis. After each Bayesian optimization picks the solution

[1] https://sumo.dlr.de/docs/index.html

set, the relevant parameters will be updated and the traffic simulation will be performed again. Each parameter set and TTT as the target value will be recorded and evaluated for the next search point selection. The above process is looped until all iterations are completed. The solution of the iteration with the smallest TTT among all the iterations will be the optimal solution (routing strategy).

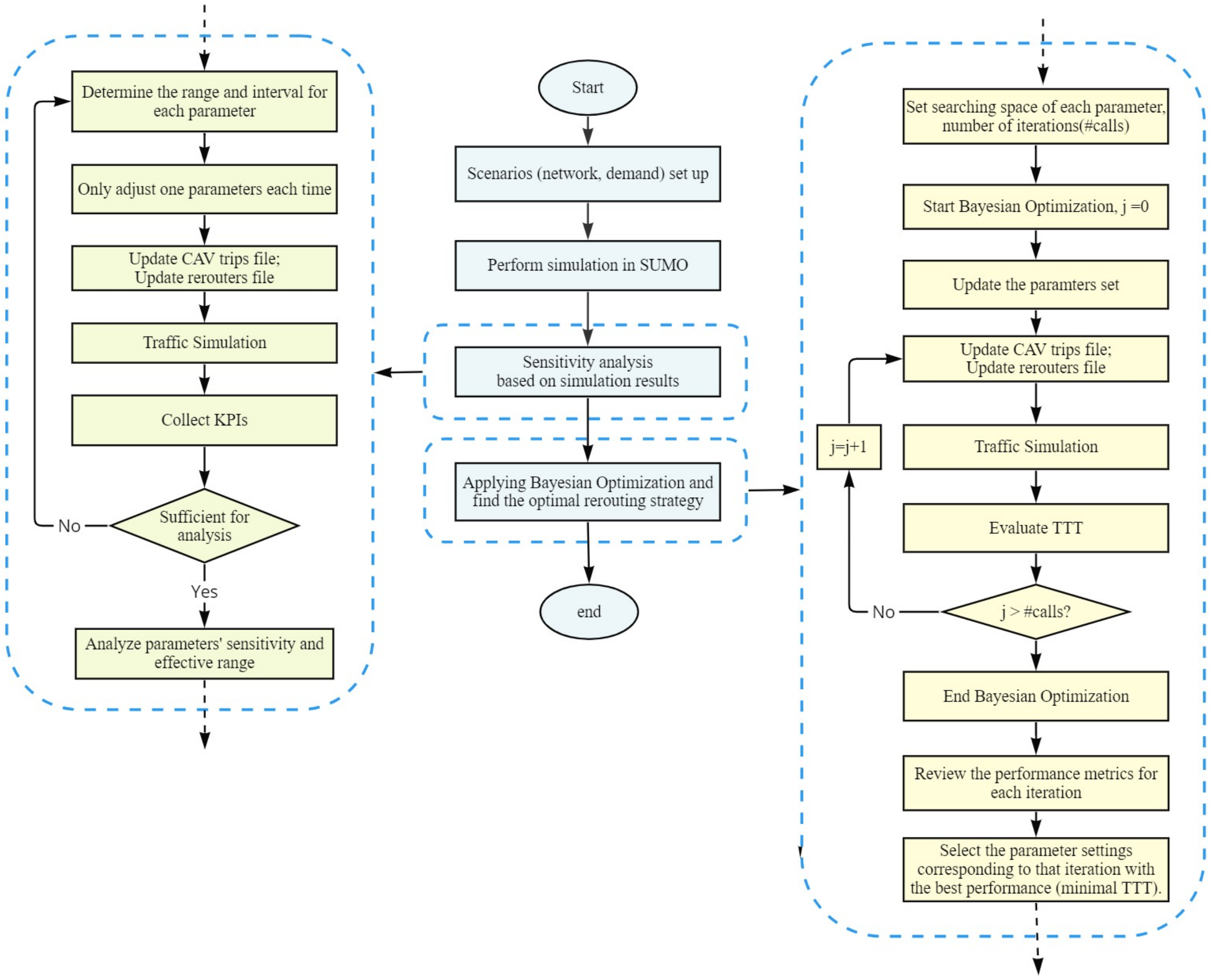


Figure 3.1: The conceptual framework of the designed experiment

Figure 3.2 illustrates the framework of the process of traffic simulation. The implementation can be divided into four steps: First, initial traffic demand; second, performing the path-selection procedure; then carrying out the traffic simulation in SUMO iteratively until equilibrium, in each iteration, the vehicles/trips are dynamically loaded on the network and the travel time on each link is computed, allowing the reroute of CAVs during their trips; and the last step is put the road closure on the network, where the convergent iteration will be chosen and HDVs' routes are fixed until passing the edge with rerouter, while CAVs can still change route during simulation. The total travel time is collected as the key performance indicator.

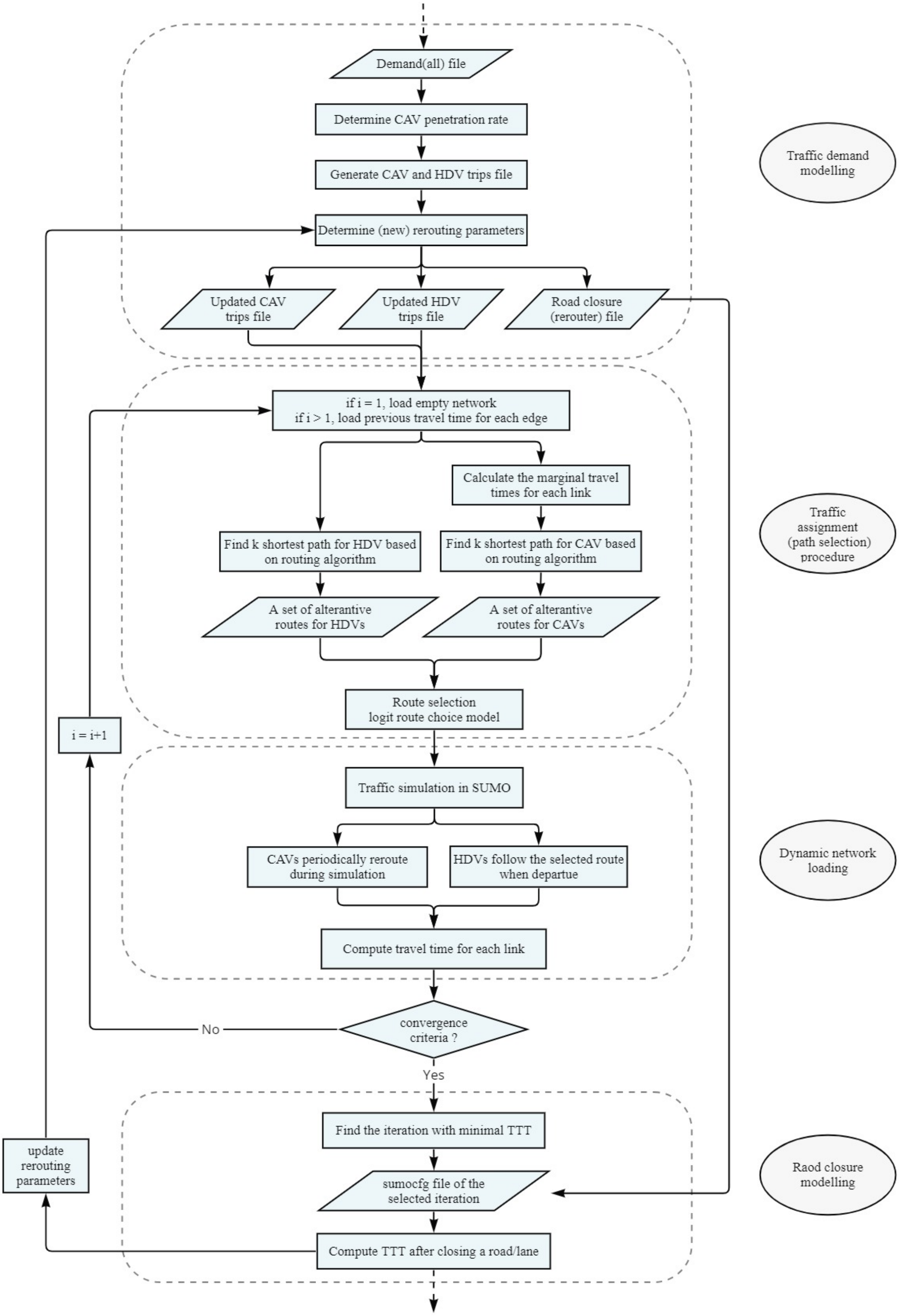


Figure 3.2: The research framework of simulating a road closure on the network

3.2. Rerouting strategy definition

When a road disruption occurs, the Traffic Management Control Center (TMCC) will take measures to reroute traffic flow to avoid road closures and, at the same time, avoid congestion to ensure the flow experiences the least travel delay. In the network with multi-class traffic consisting of CAVs and HDVs, this can be achieved through controlling the rerouting behaviors of CAVs and HDVs, including the time of receiving updated information and the probability of changing route every time receiving it.

Based on the introduction provided in previous sections, two types of rerouting occur on the network when a road closure occurs: periodic rerouting behavior, exclusive to CAVs, and another rerouting behavior that applies to all vehicles that they will re-decide the route when passing through an edge with a rerouter. These two behaviors can be controlled in a control center of a Traffic Assignment System, e.g. how often the CAVs exchange information, how many CAVs will change route after each exchange, and where and when HDVs will know that there is a road closure ahead of them, etc. Therefore, the period and probability of rerouting, as well as the react time of reroutes are the most important parameters to be determined. The notation and description of the key parameters are displayed in Table 3.1.

Following is a more detailed description of all parameters in Table 3.1 and their functions in traffic simulation. Parameter re_{ppe}, re_{pe} and re_{prob} together determine the rerouting behavior of CAVs. re_{ppe} denotes the parameter, used to model the ability of the CAV to receive traffic information from the TMC before departure. This helps the CAV to determine its initial route upon departure. Each exchange of information includes the traffic conditions (travel time) on each link as well as the availability of roads, and one shortest route will be stored. If a road/lane closure occurs on the network, the TMC will send this information to the CAV at the next information update. For example, if re_{ppe} is 60s, the information exchange/receive period for not-depart CAVs is every 60 seconds, and the road closure occurs at 500s, and the first CAVs to know the lane closure will be the first CAV depart after 540s. Rerouting behavior after departing is determined by re_{pe} and re_{prob}. re_{pe} represents the information-exchange period for CAVs during their trips, for each time the shortest route will be updated, together with re_{prob}, the probability of CAVs to change route after each time of updating the route, they determine the frequency of updating travel time and the number of CAVs to change routes every time updating. Parameters Re_{tTh} and Re_{prob} control the action of the rerouter, which can be viewed as a traffic information display on the roadside and can therefore notify HDVs that are unable to exchange information about the road conditions ahead. In this study, it publishes information about road/lane Closure. Re_{tTh} is the response time for the router to display the latest information on road/lane availability, if Re_{prob} is 60s, it means that the information will be displayed 60 seconds after the road/lane closure occurs.

This determined set of parameters shown above is called the rerouting strategy. TMC needs to determine the best combination of all parameters, so-called the optimal rerouting strategy, to minimize the total travel time on the network after closing a road/lane.

Table 3.1: Rerouting parameters in rerouting strategy

Rerouting parameter	Notation	Description
CAV rerouting pre-period	re_{ppe}	The period for CAV to (re)route before departure
CAV rerouting period	re_{pe}	At each rerouting period CAV recalculates the shortest travel times during trips
CAV rerouting probability	re_{prob}	The probability of a CAV chooses to change route at each rerouting period
Rerouter time threshold	Re_{tTh}	The time before the rerouter to receive road closure information and take effect
Rerouter rerouting probability	Re_{prob}	The probability of a CAV choose to change route when passing the rerouter

3.3. CAVs and HDVs mixed traffic modelling

This section describes how to define mixed CAV and HDV traffic in SUMO. In this study, the CAVs and HDVs mixed traffic is simulated at micro and meso levels and different driving behaviors are distinguished, including car following behavior, lane changing behavior, and queuing behavior. In addition, In addition, CAVs have the ability to periodically re-routes while traveling.

3.3.1. Microscopic simulation

The movement of vehicles is modelled using car-following and lane-changing models on the microscale in SUMO.

Firstly, CAVs and HDVs are assigned distinct car-following behaviors in this study to simulate the automation feature of CAVs. The fundamental idea behind modeling the longitudinal movement of CAVs is that they follow the same car-following model as HDVs, with modifications to simulate the full automation features of CAVs. Due to automation technologies, CAVs have a shorter reaction time, allowing them to maintain a smaller headway distance compared to HDVs. It is assumed that CAVs have a shorter time headway, a smaller minimum gap, and faster acceleration than HDVs. Additionally, CAVs can avoid collisions if the leading vehicle begins braking within their acceleration limits Karbasi et al., 2023; Lu et al., 2020. In alignment with the previous research of Mehrabani et al., 2023, in this study, both CAVs and HDVs follow the Krauß model (Krauß et al., 1997) as the car-following model, and some parameters are modified for CAV. The parameters in the Krauß model for CAVs and HDVs are listed in Table 3.2.

The LC2013 lane-changing model, as applied in the SUMO traffic simulation, governs the lateral movement of vehicles (Lopez et al., 2018). In this model the key parameter is lcAssertive, indicating a vehicle's willingness to accept smaller gaps in the target lane, with higher lcAssertive value means a more aggressive attitude toward shorter gaps, fa-

Table 3.2: Parameters of car-follow model for CAVs and HDVs

Indicator	accel	decel	em.decel.	max.V	sigma	tau	minGap
HDVs	3.5	4.5	8	27.7	0.5	0.9	1.5
CAVs	3.8	4.5	8	27.7	0.0	0.6	0.5

*accel: the acceleration ability of vehicles (m/s^2).
*decel: the deceleration ability of vehicles (m/s^2).
*em.decel: the maximum deceleration ability of vehicles in case of emergency (m/s^2).
*sigma: driver imperfection (between 0 and 1).
*tau: the desired (minimum) time headway (s) of the driver.
*minGap: the offset of the leading vehicle when standing in a jam (m).

cilitating lane changes with smaller gaps (Alvarez Lopez et al., 2018). The lcAssertive value is set to 0.7 for CAVs and 1.3 for HDVs, reflecting the different lane-changing behaviors of these vehicle types. More details on selecting car-following and lane-changing parameters for CAVs can be found in Bamdad Mehrabani et al., 2023; Karbasi et al., 2023.

3.3.2. Mesoscopic simulation

The mesoscopic model in SUMO is derived from the research by Eissfeldt, 2004. This model organizes vehicles into traffic queues, similar to the cell transmission model proposed by Daganzo (1995). Vehicles are generally released from these queues in the order they entered, adhering to the first-in-first-out (FIFO) principle (Amini et al., 2019). The model determines the travel time for a vehicle to leave the queue by considering the traffic state in the current and subsequent queues, the minimum travel time, and the traffic signal phase (e.g., red, green, yellow). There are four possible traffic state combinations between consecutive segments: (1) a vehicle travels from a free segment to another free segment, (2) a vehicle travels from a free segment to a congested segment, (3) a vehicle travels from a congested segment to a free segment, and (4) a vehicle travels from a congested segment to another congested segment(Alvarez Lopez et al., 2018). For each combination, the minimum headway between vehicles is calculated using the parameter τ, which acts as a multiplier to set these minimum headways.

Specifically, CAVs and HDVs are differentiated based on their platooning model parameters, with each type of vehicle using a different minimum forward speed (τ) value. CAVs are assumed to be able to follow vehicles more efficiently between consecutive road segments compared to HDVs, and therefore CAVs are assumed to have lower values of the parameter (Bamdad Mehrabani et al., 2023). In Behzad's study, for the first time, the parameter was calibrated for both CAVs and HDVs, and two scale-consistent fundamental diagrams (FDs) were obtained, which ensured the consistency of the meso- and microsimulation results. After calibrating and comparing the micro- and mesoscale FDs, the authors found a τ value of 1.06 for HDV and 0.79 for CAV. This paper uses the same demonstrations and parameters as in the author's study, see For more information on the parameterization process see Bamdad Mehrabani et al., 2023.

Besides, all vehicles are characterized by the same size in this study. The focus is solely on the flow of passenger traffic (there are no trucks or buses present on the network), and the physical characteristics of the vehicles are not the essential feature to capture; therefore, an average size is established for all vehicles. The physical attributes of the vehicles are shown in Table 3.3

Table 3.3: Physical attributes for all vehicles

Parameter	Length	Width	height
values (m)	5	1.8	1.5

3.3.3. Rerouting behavior

In addition to driving behavior, communication ability is a crucial feature of CAVs. This capability enables CAVs to consistently receive real-time information on network traffic conditions, including travel times on each link, enabling them to dynamically seek shorter routes based on updated traffic information to reach their destination. Consequently, CAVs can more quickly adapt to traffic issues, such as congestion jams or unexpected changes in the network. In this study, the action of continually seeking the shortest routes is referred to as 'Rerouting'.

In SUMO, to enable the rerouting ability of a vehicle, a "Rerouting Device" has to be equipped on it, which allows them to periodically collect the average travel time in the network for each edge and update the shortest paths, hereby reselecting their route. More specifically, during traffic simulation, CAVs receive the present edge weights (travel speed, and hence travel time) both before they are about to be inserted into the network and every certain period after starting their trip, consequently, keeping updating the alternative routes. If a route is found to be shorter than the current one, they will change their route to the updated shortest route. However, vehicles without such devices (HDVs) will only get the edge weight on the network once (before they are inserted into the network). They will always run on the originally selected route.

With such rerouting ability, the traffic condition on the network will come to equilibrium faster. However, the effectiveness will be influenced by the frequency of updating edge weights and rerouting activities. SUMO provides a set of parameters to configure the percentage of vehicles to be equipped on the device, how often the rerouting decisions will be made, and how the estimation of travel times is calculated from current and recent knowledge (Alvarez Lopez et al., 2018), all rerouting parameters included in this study and their description are shown in 3.4. Moreover, it is important to mention that apart from periodic rerouting, the rerouting behavior can be active immediately when the vehicles pass the edge where a **'Rerouter'** is installed. The definition and application will be clarified in section 3.5.

Table 3.4: Automatic rerouting parameters and the description

Parameter	Type	Description
Rerouting probability	Float	The probability for a vehicle to have a routing device
Rerouting period	String	The period for re-routing during trips
Rerouting pre-period	String	The period for rerouting before departing
Rerouting adaptation interval	Int	The interval for updating the edge weights
Rerouting adaptation steps	Int	The number of steps for averaging edge weight
Rerouting with TAZ*	Bool	Use TAZ as the start and end point of trips

*TAZ: The traffic assignment zones

3.3.4. Demand generation in SUMO

To generate specific demand for this study, the random trip generator tool (*randomTrips.py* [2]) and a demand splitting tool (*DemandGenerator.py*[3]) are utilized. In SUMO, it is possible to manually define or randomly generate traffic demand for a given network, represented by a list of edges in the *net.xml* file, with depart time and origin-destination information. In this study, demand is randomly generated using *randomTrips.py*, resulting in a list of trips saved as a *trips.xml* file. Once the initial demand is established, a demand generator (*DemandGenerator.py*) is employed to categorize trips into CAVs and HDVs based on a given penetration rate, each with specified attributes, and then save them into separate files (*trips.trips.xml* and *trips.trips.CAV.xml*). Additionally, rerouting parameters can be manually modified in the file.

3.4. Route selection procedure

With the given network (*net.xml* files) and traffic flow (*trips.xml*, or *trips.trips.xml* and *trips.trips.CAV.xml*), the simulation could determine the routes of vehicles to reach their destination. This procedure to determine suitable routes that take into account travel time in a traffic-loaded network is called traffic assignment (Alvarez Lopez et al., 2018).

In SUMO, a dynamic traffic assignment is applied through an iterative procedure by using tool *duaIterate.py* [4] (for HDVs or CAVs) or *duaIterateMix.py* [5] (for HDV and CAV mixed traffic). At each iteration, a routing algorithm (Dijkstra, Astar, or Contraction Hierarchies (CH)) is employed to determine a set of alternative routes. The specific algorithm could be selected through *–routing-algorithm*). For this study, Dijkstra's Algorithm is used on the test network, and Contraction Hierarchies (CH) is applied on the real-world network.

[2]Provided by SUMO
[3]Supported by Behzad
[4]Provided by SUMO
[5]Provided by SUMO

During the alternative route determination procedure, HDVs and CAVs seek the User Equilibrium (UE) principle and the System Optimal (SO) principle, respectively, the former uses the weighted link travel time in previous iterations to calculate the k-shortest paths, while the latter uses the link marginal travel time (MTT) (activated by *–marginal-cost and –marginal-cost.exp*). In order to simulate the traffic flow more realistically and to introduce a certain amount of randomness, each time the shortest path is recalculated, a random path is added to the set of alternative paths. After the alternative routes are determined, the Logit model (by setting *–logit*) is used to calculate their usage probability to select the optimal one. Finally, the selected path of each vehicle (known as *trips.rou.xml* file) is collected and used by SUMO to perform the simulation. Consequently, the travel time of each link could be calculated, which is stored in the output file *edgedata.xml* and used by the next iteration step as an input file. Additionally, the number of iterations is definable by *–last-step* and/or *–convergence-iteration*, a swapping algorithm PSwap is used to determine the fraction of vehicles to reassignment. After obtaining the output data, a hybrid gap is computed for the travel time as the convergence criterion.

3.4.1. Calculation of marginal travel times

In the path selection procedure, HDVs select paths following the UE principle based on link travel times from the previous iteration, while CAVs follow the SO principle based on link marginal travel times (MTT). The MTT is defined as ”the marginal contribution of an additional traveler on the ath link to the TTT on $a - th$ link” (Sheffi, 1985). The link MTT can be calculated by global or local approximation, the latter calculating the path MTT by summing the corresponding link MTTs. For this study, a surrogate model is used to compute the local approximation of the path MTT proposed by Mehrabani et al., 2022. The calculation is shown below:

$$\bar{c}_a^i = c_a^{i-1} + f_a^{i-1} \frac{c_a^{i-1} - c_a^{i-2}}{f_a^{i-1} - f_a^{i-2}} \tag{3.1}$$

where,
$\bar{c}_a^i$ represents the surrogate MTT of link a at simulation step i
c_a^{i-1}, c_a^{i-2} represent the travel time, or cost, of link a at simulation steps i − 1 and i − 2
f_a^{i-1}, f_a^{i-2}represent the traffic flow of link a at simulation steps i − 1 and i − 2

The first component on the right-hand side of Equation (3.1) is the average travel time on link a, and the second component is the impact of an additional user on all other travelers. The sum of these two components makes up the MTT.

3.4.2. Route choice model

In SUMO, it is possible to choose different route choice models among available alternatives, which are Gawron, Logit, or Lohse. In this study, the logit model is selected as the route choice model.

The Logit route choice model is a widely used approach in transportation analysis for predicting the probability that a traveler will choose a particular route among a set of available routes. The model assumes that the utility of each route is a random variable with a specific distribution. The core idea is that each traveler aims to maximize their utility, which is often a function of travel time, cost, and other relevant factors. The probability of choosing a specific route depends on the relative utilities of all available routes.

In this study, the logit model is applied to each vehicle's set of alternative routes, $P_{j,i}^{r-s}$, in which the k-shortest paths for the subject vehicle are available. The travel times are considered as the cost for each alternative path. The travel time of each path is equal to the sum of the travel times of the corresponding links from the previous simulation. The logit model formulation is as follows:

$$Pr_{k,j}^{i} = \frac{\exp(-\theta c_k^i)}{\sum_{k=1}^{l} \exp(-\theta c_k^i)} \tag{3.2}$$

$$c_k^i = \sum_{a \in A} \delta_{a,k}^i c_a^i \tag{3.3}$$

$$\delta_{a,p}^i = \begin{cases} 1 & \text{if link } a \text{ is on path } k \\ 0 & \text{otherwise} \end{cases} \tag{3.4}$$

where $Pr_{k,j}^i$ is the probability of selecting path k by vehicle j in iteration i; c_k^i is the travel time (cost) of path k in iteration i; and θ is the logit model scale parameter. Given the multiple alternative routes with slightly different travel times, it may be reasonable to select a route other than the strictly shortest route (to avoid congestion on that route). Hence, the scale parameter θ assigns a probability for each route alternative. With a high value of theta, logit always selects the route with the least travel time, whereas with a low value of theta, logit selects all the routes with almost equal probability.

3.4.3. Swapping algorithm

Most studies using simulation-based traffic assignment methods employ a swapping algorithm to achieve optimal results and prevent oscillation. The key concept of swapping algorithms is that only a fraction of vehicles, rather than all, should change their path in each iteration. In this thesis, For the reassignment of a fraction of vehicles at each iteration, the Probabilistic Swapping (PSwap) algorithm is used instead of the traditional Method of Successive Average (MSA). The algorithm was proposed by Mehrabani et al., 2022 for solving the stochastic traffic assignment problem based on the logit route choice model. It has better performance compared to the traditional MSA algorithm. The swapping algorithm is as follows:

$$p_{j,i}^{*,r-s} = \begin{cases} p_{j,i}^{r-s} & \text{if } x \geq \rho_i \\ p_{j,i-1}^{*,r-s} & \text{if } x < \rho_i \end{cases} \tag{3.5}$$

The equation for $p^{*,r-s}_{j,i}$ encompasses several variables: $p^{r-s}_{j,i}$ indicates the path chosen by vehicle j in iteration i based on the current logit model, while $p^{*,r-s}_{j,i-1}$ refers to the final path selected by vehicle j in iteration $i-1$. Additionally, x is a random variable ranging from 0 to 1, and ρ_i represents the step size sequence for each iteration, which determines the likelihood of retaining the previous final selected path. The value of ρ_i is predetermined and calculated using the formula $\rho_i = \frac{i}{\gamma}$, where i is the iteration number and γ is a scale parameter that controls the speed of convergence. A lower value of γ results in quicker convergence but limits the number of explored alternative paths. Conversely, a higher value of γ slows the convergence but allows more alternative paths to be examined. For stochastic assignments, it is generally better to use higher γ values. However, in large or medium-scale networks, performing many iterations can be computationally intensive. In this study, γ is set to 10 for grid networks and 30 for Sioux Falls networks.

3.4.4. Convergence Criterion

To find the endpoint of the simulation, a convergence criterion is defined. Align with the research of Mansourianfar et al., 2021, Mehrabani et al., 2023, a hybrid gap function for the algorithm convergence is proposed, where the gap is the average difference between the average travel time and the least travel time of vehicles share the same O-D. The gap value is calculated for CAVs and HDVs separately and the convergence is considered when the average of them is stable and under a specified value.

$$Gap_{hdv}(i) = \frac{\sum_{h\in D_H}(\frac{\sum_{h\in H} tt^{o-d}_{j_h,i}}{\pi_H} - tt^{*,o-d}_{H,i})}{\theta_H} \tag{3.6}$$

$$Gap_{cav}(i) = \frac{\sum_{c\in D_C}(\frac{\sum_{c\in C} \overline{tt}^{o-d}_{j_c,i}}{\pi_C} - \overline{tt}^{*,o-d}_{C,i})}{\theta_C} \tag{3.7}$$

$$Hybird\ Gap(i) = Gap_{hdv}(i) * \frac{\theta_H}{\theta_H+\theta_C} + Gap_{cav}(i) * \frac{\theta_C}{\theta_H+\theta_C} \tag{3.8}$$

Following is the explanation for the formulas and notation above. First, in formula 3.6, $Gap_{hdv}(i)$ refers to the gap value for HDV trips in iteration i; $tt^{o-d}_{j_h,i}$ represents the travel time experienced by CAV j_h traveling from edge o heading to edge d in iteration i, while $tt^{*,o-d}_{H,i}$ represents the least travel time among all HDV trips from o to d. π_H donates the number of HDVs leaving i heading to j, and θ_H donates the total number of HDVs in simulation. It is clear that $\frac{\sum_{h\in H} tt^{o-d}_{j_h,i}}{\pi_H}$ refers to the average travel time of all pairs of OD taken by HDV trips in iteration i, and the gap to find is the difference between it and the travel time of the shortest trip. The formula 3.7 is similar to 3.6, but it is noticeable that for CAVs the gap is calculated using marginal travel times instead of travel times, represented by $\overline{tt}$. It is because CAVs seek for a system optimal, as a result, their experienced travel time will be equivalent to the average travel time on the links plus the marginal travel time, which is extra time contributed by the extra users. Therefore, the average travel time has no effect on the value of the gap here, whereas the difference in marginal travel time is the value that plays a role. The formula 3.8 shows that the hybrid gap is determined by two individual gaps and their respective proportion.

3.5. Road closure modeling

The type of disturbance modeled in this study is road closure, a traffic event that often occurs in life. In SUMO, a **rerouter** must be defined to simulate a road closure. The concept and application of the rerouter are introduced in the following sections.

To address the issue investigated in this study, the rerouter is conceptualized as an on-road unit capable of exchanging information with vehicles, forcing them to alter their route following the specified rules. In this study, the rerouter could inform vehicles of the road closures ahead and let them change routes to avoid the closed road. The rerouter could be placed on several edges(Alvarez Lopez et al., 2018).

The rerouter could be defined in an additional file (more explanations can be found in Alvarez Lopez et al., 2018). In this study, each rerouter is assigned to a specific location of road closure and is installed on one or multiple roads near it. The probability of rerouting a vehicle is set to 1, indicating that the rerouting device for all vehicles equipped with it will be immediately activated upon passing the rerouter. It is noticeable that the rerouter will change CAVs' destination if the destination edge is unavailable due to the road closure (by adding a line of the element *destProbReroute*). In this study, the alternative destinations are the incoming streets of the closed road, and the probability for all alternative streets is the same. For example, if street X can be approached through four streets and now is closed, the probability that each of those 4 streets is the new destination of CAVs going to X will be 0.25. In addition, The interval of road closure is usually set to be no longer than half of the simulation time.

The additional file of rerouter definition could be written manually or set through the visual network editor *netedit*. To address the research questions in this study, rerouters are set into the simulated network by adding the options of additional files (through setting *–addtional* or -+) when using traffic assignment tool *duaIterate.py*.

3.6. Bayesian Optimization and application

3.6.1. Bayesian Optimization

In this study, Bayesian Optimization (BO) is used to find the optimal rerouting strategy, and the Python library *skopt* is used to apply it. Bayesian optimization is an optimization method based on Bayes' theorem, which is widely used in many fields that require efficient search of optimal parameters. It achieves efficient global optimization by constructing a probabilistic model of the objective function and gradually updating and optimizing the parameter selection based on it. Scikit-Optimize [6], or skopt for short, is a Python library dedicated to solving function minimization problems, and this study implements the one *gp_minimize* to apply the Bayesian optimization based on Gaussian process regression.

In general, Bayesian Optimization is interested in solving:

$$x^* = \arg\min_x f(x) \tag{3.9}$$

Under the constraints that:
f is a black box for which no closed form is known (nor its gradients);
f is expensive to evaluate;
and evaluations of $y = f(x)$ may be noisy.

To optimize the objective function, BO operates iteratively and consists of the following steps, shown in Figure 3.3: (1) Model Construction: A probabilistic model, usually a Gaussian Process (GP), is constructed to represent the unknown objective function based on available data; (2) Acquisition Function: An acquisition function is used to decide where to sample next. This function balances exploration of the space where the model is uncertain and exploitation where the model predicts high values; (3) Sample Selection: The acquisition function is optimized to select the next point to sample, which is expected to offer the most information gain about the objective function; (4) Objective Evaluation: The actual objective function is evaluated at the chosen sample point; (5)Model Update: The probabilistic model is updated with the new sample point and corresponding function evaluation. The Iteration repeats from Steps 2 through 5 are repeated until a stopping criterion is met, like a maximum number of iterations or a satisfactory level of optimization. This loop allows for efficient optimization by using the model to infer likely beneficial sample points, reducing the number of costly evaluations of the actual function.

In this study, the objective function is:

$$minimize : TTT = N * (\overline{duration} + \overline{departdelay}) \tag{3.10}$$

TTT is the output of traffic simulation and is influenced by vehicles' behavior during the simulation, which is controlled by the rerouting strategy. The simulation in the large-scale network requires significant time costs, and there is no mathematical function to describe the relationship between rerouting parameters and the TTT. Moreover, there is a certain amount of randomness in the simulation process and the results may be noisy. Therefore, BO could be a suitable tool to solve the problem in this study.

[6] https://scikit-optimize.github.io/stable/auto_examples/bayesian-optimization.html

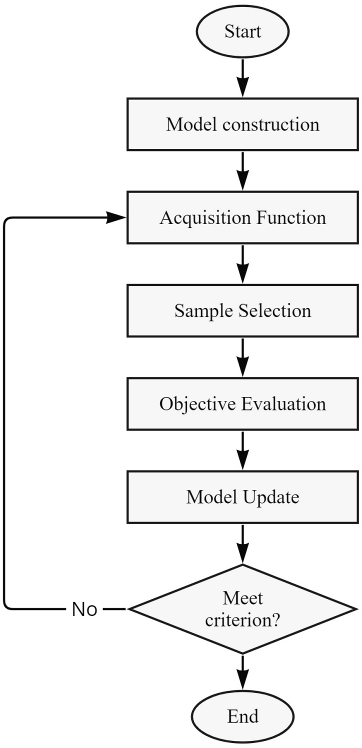


Figure 3.3: The Bayesian Optimization loop

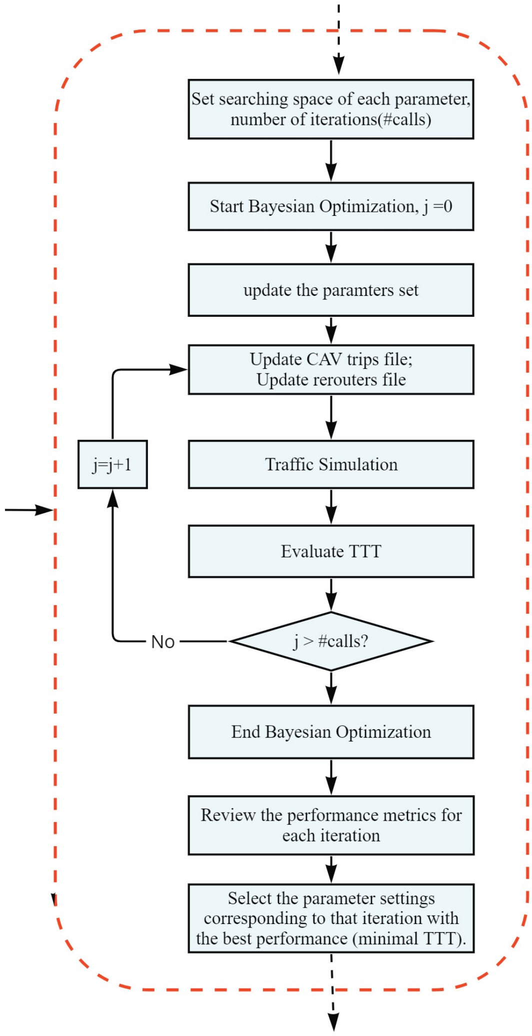


Figure 3.4: The steps of applying Bayesian Optimization

Figure 3.4 illustrates the process of applying BO in this study. The rerouting strategy (parameters) is the sample to select and TTT is the objective to minimize. Initially, the search space of rerouting strategy and parameters in BO such as the number of optimization iterations are defined. The BO process then begins, involving updating the rerouting parameter set for the simulation. After each update, the CAV trip and router configuration detail files are adjusted according to the new parameters. Note that it is important to make parameter changes on the original generated file and not to regenerate a new trips file, otherwise, the simulation results will not be comparable. Traffic simulation follows, allowing for the assessment of Total Travel Time (TTT) under the current parameters. Note that a converged iteration must be found before placing the road closure environment. The simulation results after placing the road closure will be collected. Then, The BO loop will continue until the predefined limit is reached. Upon completion, performance metrics from each iteration are reviewed. The final step involves selecting the iteration's parameters that resulted in the lowest TTT, thereby identifying the most effective rerouting strategy.

3.6.2. Hyper-parameters

In the *skopt* library, Bayesian optimization offers several hyperparameters that can be fine-tuned to enhance the optimization process. One key hyperparameter is n_calls, which specifies the number of evaluations of the objective function. Another is n_random_starts, determining the number of initial random points before the Bayesian model starts to predict. The acq_func hyperparameter, which stands for acquisition function, defaults to gp_hedge, a strategy that dynamically selects among multiple acquisition functions. The $base\_estimator$, defaulting to "GP" (Gaussian Process), defines the model used to approximate the objective function. Additionally, the xi and kappa parameters, used in the acquisition function, control the balance between exploration and exploitation, with default values of 0.01 and 1.96 respectively. These hyperparameters can be adjusted based on the problem's complexity and the need for exploration versus exploitation. Proper tuning of these settings can lead to more efficient convergence and better optimization results.

In this thesis, the following parameters are determined and adjusted:

Table 3.5: Hyper-parameters for Bayesian Optimization

Hyper-parameter	Value
$nrandomstarts$	depends on the n_{calls}
acq_{func}	gp_{hedge}"
$random_{state}$	1234
n_{calls}	depends on computation time

3.7. Key performance indicator

1. **Total travel time.** Total Travel Time (TTT) is one of the most important indicators to reflect the traffic condition on the network. This study aims to find an optimal rerouting strategy to respond to unexpected disruptions and the objective of the reroute strategy is to minimize the TTT on the network. With the support of the available statistic output (known as *stats.xml*) in SUMO, the total travel time could be calculated by the following formula:

$$TTT(i) = N(i) * (\overline{duration} + \overline{departdelay}) \tag{3.11}$$

Where,
$TTT(i)$ refers to the total travel time in the i-th iteration.
$N(i)$ is the number of trips that have been inserted on the network.
$\overline{duration}$ is the average travel time for all trips.
$\overline{departdelay}$ is the time that the vehicle had to wait before it could be inserted into the network.

2. **Total travel distance.** Apart from TTT, Total Travel distance (TTD) is also calculated to reflect traffic conditions. Due to the re-routing function of CAV, the vehicle will have the behavior of changing the route/detouring during the driving process, and the metric of TTD can be a good response to the degree of detouring of CAV, which helps us to analyze and understand the simulation results. With the support of the available statistic output (known as *stats.xml*) in SUMO, the total travel distance could be calculated by the following formula:

$$TTD(i) = N(i) * (\overline{routeLength}) \tag{3.12}$$

Where,
$TTD(i)$ refers to the total travel distance in the i-th iteration.
$N(i)$ is the number of trips that have been inserted on the network.
$\overline{routeLength}$ is the average travel distance of all trips.

3. **Total waiting time.** In SUMO, ”travel delay” is defined as the time lost due to traveling below the desired speed, which can be roughly regarded as the time when a vehicle encounters a traffic jam. When a vehicle’s speed is less than 0.1 m/s, it indicates that the vehicle has stopped and waited in place, and therefore the time during which the vehicle is traveling at a speed less than 0.1 m/s is defined as ”waiting time”. This time can reflect the congestion of the network to some extent and can further help in understanding and interpreting the simulation results when TTT and TTD are known. Similarly, the indicators of travel delay can be calculated by the following formulas using data in *stats.xml*:

$$TWT(i) = N(i) * (\overline{waitingTime}) \tag{3.13}$$

Where,
$TWT(i)$ refers to the total time in which the vehicle speed was below or equal to 0.1 m/s in the i-th iteration.
$N(i)$ is the number of trips that have been inserted on the network.
$\overline{waitingTime}$ is the average waiting time

4

Experimental test: The grid network

This section is the numerical results of rerouting parameters sensitivity analysis and the optimal rerouting strategy, for the grid network. To comprehend how HDVs, CAVs, and multi-class traffic flow influence traffic conditions during a road closure and find the optimal rerouting strategy for the grid network, 12 scenarios have been created covering four CAV penetration rates (20%, 40%, 60%, and 80%), and three different road closure locations. First, this section explains the process of determining reference parameters for the rerouting strategy. Second, a sensitivity analysis of all the parameters involved is performed. Third, based on the results of sensitivity analysis, determine the space of parameters in Bayesian Optimization to find the optimal rerouting strategy for different scenarios. The significance of individual parameters within the rerouting strategy is examined, based on the influence of the rerouting parameters on traffic conditions. Additionally, critical locations for road closures are deliberated upon.

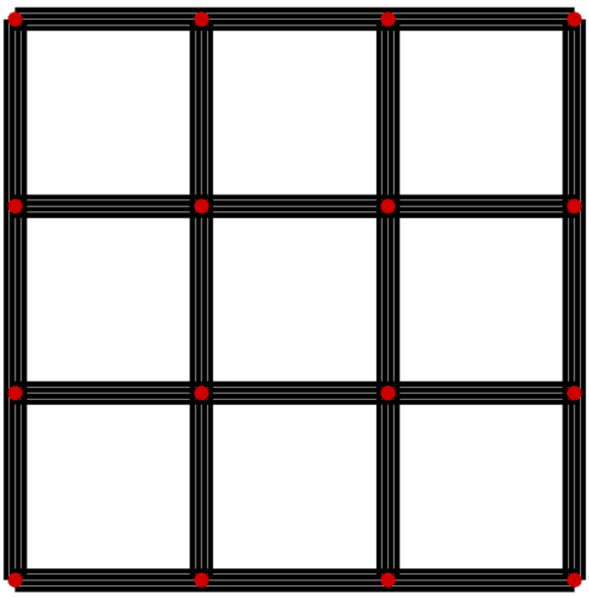


Figure 4.1: The 4x4 grid network

4.1. The grid network and traffic demand

To tackle the research problem in this section, a grid network is used to simulate the aforementioned scenarios for two primary reasons: 1. Use a simple network to save computation time; 2. The grid network encapsulates partial characteristics of real urban road networks, making conclusions drawn from this simulation more informative for the subsequent case study on the Sioux Falls network. A 4x4 gird network is created in *netedit* (using the tool *netgenerate*), as illustrated in Figure 4.1. The network comprises 48 edges and 16 intersections, with each edge having an equal length of 100 meters and consisting of two lanes. To simulate traffic for 20 minutes on the given grid network, 2000 trips are randomly generated (by using *randomTrip.py*) and uniformly inserted into the network following an insertion rate of 1 trip per 0.6 seconds.

4.2. The reference rerouting strategy

The reference rerouting strategy is established based on the traffic condition of the scenario with no CAV and no roadblock. The process of determining the re-routing parameters of the CAV and the re-router is described next, respectively.

4.2.1. Reference rerouting parameters for CAV

The reference rerouting parameter for this network is established based on traffic conditions in a scenario without CAVs and road closures. A statistical analysis of the duration (travel time) distribution of the trip is performed for all trips, the results are shown in Figure 4.2, and Table 4.1.

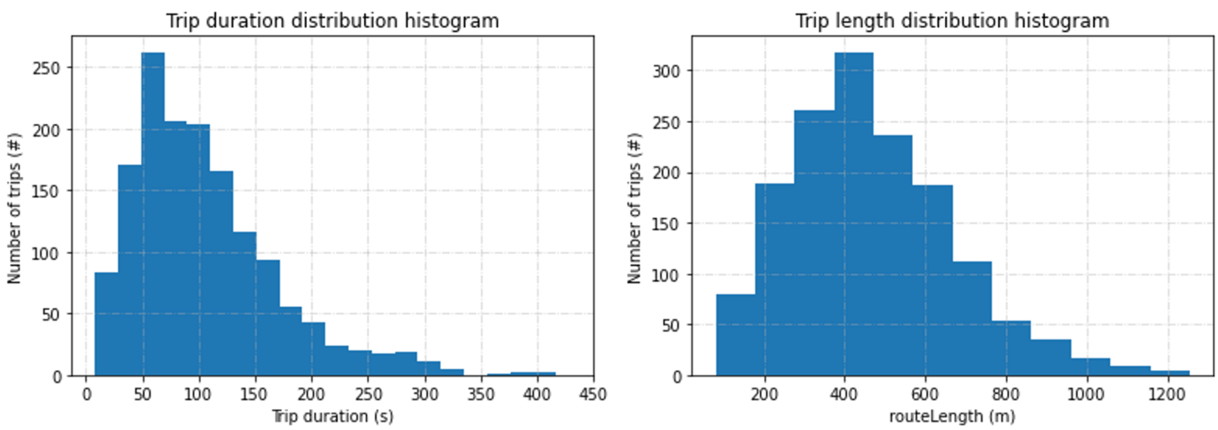


Figure 4.2: Travel time (left) and distance (right) distribution of trips on the grid network

Figure 4.2 illustrates that on the network when there is all HDV and no disruptions occur, most vehicles would experience 200-1200 meter trips in the grid network, among all trips, most vehicles have a travel time of 50-120 seconds, at the same time, there are extremely long trips that are over 300 seconds. In the reference rerouting strategy, it is expected that all CAVs will have at least 1 rerouting opportunity, therefore, knowing the minimal travel time is essential. However, the need for rerouting for trips traveling less than 200m (two streets) is not significant given the mechanism for changing travel routes and the size of this network. Therefore, only travel times for journeys over 200 meters are counted here, see Table 4.1. More detailed, in Table 4.1 shows the minimal travel time of all trips is 31s, and the average travel time is 81.9s.

Table 4.1: Statistic results of travel time of long-distance trips in non-CAV scenario

Indicator	Min.TT	Max.TT	Med.TT	Ave.TT
Value (s)	31.0	407.0	67.0	81.9

Therefore, the rerouting period is set to 30 seconds thus the majority of vehicles will have an opportunity to reroute during their trips; The rerouting pre-period is set to 1 second to allow all CAVs to receive the most updated traffic condition; The rerouting adaptation interval is set to 1, indicating that the edge weights on the network are updated at every time step during the simulation, facilitating data collection for further analysis. Apart from the above three parameters included in the rerouting strategy to investigate in this thesis, other rerouting parameters remain the fixed values in all simulations. The rerouting adaptation step is set to 1200, determined by the length of each iteration. The specific numerical values for the parameters can be found in Table 5.2 and Table 5.3.

Table 4.2: The reference rerouting parameter for CAV

Parameter	re_{ppe}	re_{pe}	re_{prob}
Value	1	30	0.5

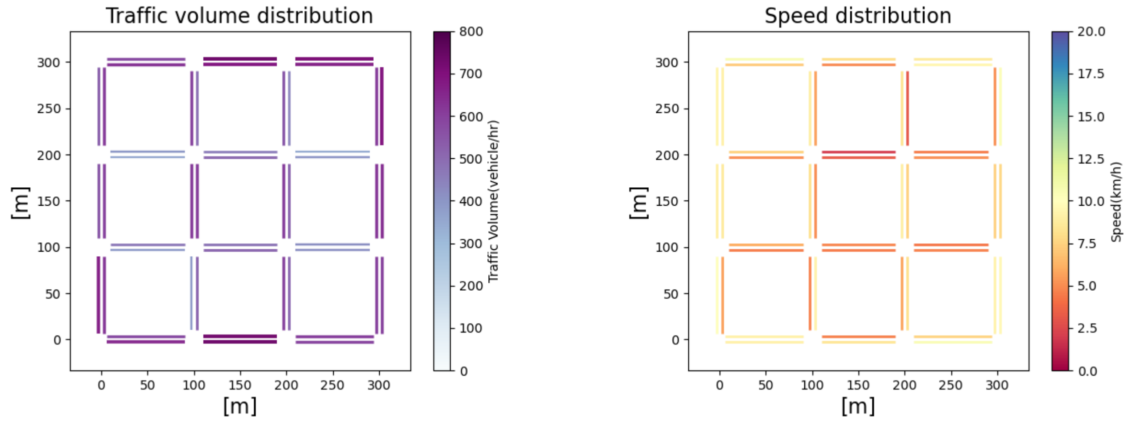
Table 4.3: Other (fixed) rerouting parameters for CAVs

Parameter	re_{AdIn}	re_{AdSt}
Value	1	1200

4.2.2. Reference rerouting parameters for rerouters

1. **The road closure location selection**

Figure 4.3 demonstrates the distribution of traffic volume (veh/hr) and travel speed (m/s) in the grid network. Figure 4.3a shows the distribution of traffic flows in the grid network. The colors range from light blue to dark purple, with darker colors representing higher traffic volume. It can be seen that at the edges of the grid and a few roads in the center the traffic flows are relatively higher. The speed map Figure 4.3b shows that congestion is mainly concentrated in the center of the network, with speeds as low as 5m/s, while speeds in the fringe area are 10-12.5m/s. Comparing the two graphs it can be seen that the edge areas are heavily loaded with traffic but move efficiently, however the centre area bears a lot of the congestion. There are two reasons for this result: 1. the distribution of demand on the network is uneven: the centre road has many departing and arriving vehicles, which are occupied by other vehicles at the same time, and the edge road has low demand, mostly from departing vehicles; 2. the structure of the network is too simple to provide alternative routes that can skip the centre.



(a) Traffic Volume distribution

(b) Speed distribution

Figure 4.3: The traffic volume and speed distribution of grid network - all-HDV scenario

Based on the above discussion, three road are selected for closure, as shown in the left figure Figure 4.4. For convenience, they are named Closure A, Closure B, and Closure C, respectively, from the left to the right. The three closures occur on an outgoing path of an L-junction, a T-junction, and a cross-intersection with relatively high usage. Each location is separately modelled and has the same closure duration. In terms of positioning the rerouter for the closed road, for this grid network, a 2-incoming path placement option is used, which is rerouters are placed in the two incoming paths before the closed road. The right sub-figure Figure 4.4 displays the locations of rerouters for Closure B.

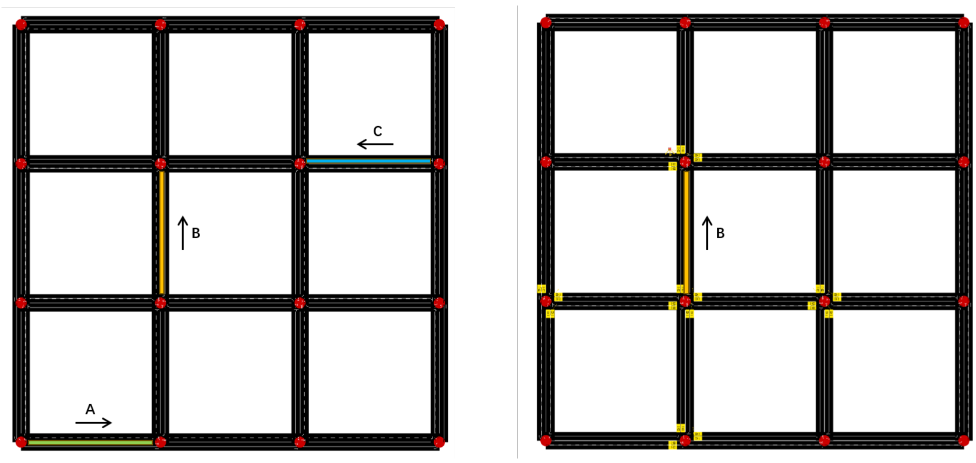


Figure 4.4: The locations of closed lanes (left) and the placement of rerouters for closure B (right)

2. **Reference rerouting parameters for rerouters**

Table 4.4 shows the reference parameters for the rerouters. The whole simulation lasts 1200s, and the lane closure occurs from 300s and dues for 10 minutes, ending at 900s. The rerouters' react time (Re_{tTh}), known as the time threshold, is set as 0 to simulate the quickest information providing; the rerouting probability for vehicles when passing the active rerouter is set as 0.5 taking into account the fact that only one of the lanes in a two-lane roadway is closed, and that there is still some traffic capacity. Therefore, the re-router will be active at 300 seconds and deactivated at 900 seconds, during which time 50% of the vehicles passing the edge will be informed of the lane closure ahead and forced to reroute.

Table 4.4: Parameter of rerouters' operation for the base scenarios

Parameter	Re_{tTh}	Re_{prob}
Value	0	0.5

4.3. The test scenarios defining

In order to find the optimal rerouting strategy during road closures at different locations under CAV heterogeneity, 12 scenarios involving four CAV penetrations (20%, 40%, 60%, and 80%) and 3 lane closure locations (A, B, C) are created for further analysis. The specific setup of each scenario is shown in Table 4.5. For all scenarios, the simulation lasts 1200s, and the lane closure occurs from 300s and dues for 10 minutes, ending at 900s. During the simulation, CAVs seek for SO while HDVs follow the UE. The reference value for each rerouting parameter strategy is shown in Table 4.8.

Table 4.5: The scenarios to simulate in the grid network

Scenario	CAVs' penetration rate	HDVs' penetration rate	Road closure id	Road closure druation	CAVs' routing principle	HDVs' routing principle
1	20	80	A	[300,900]	SO	UE
2	20	80	B			
3	20	80	C			
4	40	60	A			
5	40	60	B			
6	40	60	C			
7	60	40	A			
8	60	40	B			
9	60	40	C			
10	80	20	A			
11	80	20	B			
12	80	20	C			

Table 4.6: The reference value for all rerouting parameters

Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
Value	1	30	0.5	0	0.5

4.4. Rerouting parameters sensitivity analysis

The sensitivity analysis is conducted for 12 scenarios covering four penetration rates of CAV (20%, 40%, 60%, and 80%), and three locations of road closure mentioned in the previous section. More details of the 12 scenarios can be found in Table 4.5. The lane closure occurs from 300s and dues for 10 minutes, ending at 900s. CAVs seek for SO while HDVs follow the UE.

Five rerouting parameters mentioned in the previous section (re_{ppe}, re_{pe}, re_{prob}, Re_{tTh}, and Re_{prob}) are tested. The sensitivity analyzes were performed using the one-at-a-time analysis, i.e., one parameter was adjusted at a time, while the other parameters were kept constant, and the outputs were collected each time to observe the changes. The following are the results of the sensitivity analysis.

Table 4.7: Scenario setting for SA of rerouting parameters in the grid network

Test Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
re_{ppe}	[1,2,3...15]	30	0.5	0	0.5
re_{pe}	1	[1,30,60...300]	0.5	0	0.5
re_{prob}	1	30	[0.1,0.2...1.0]	0	0.5
Re_{tTh}	1	30	0.5	[0,10,20..120]	0.5
Re_{prob}	1	30	0.5	0	[0.1,0.2...1.0]

Table 4.7 shows the parameters setting to perform the sensitivity analysis for each parameter, and the results are shown in Figure 4.5. The range of CAVs' rerouting pre-period (re_{ppe}) is set as [1,15], the interval is 1 based on the simulation step, and other parameters are set as the reference values. In addition, it is worth mentioning that apart from the value in the table, a larger range of this parameter has been tested, however, because the change in output is less significant when the values are larger than 15 seconds, the range is narrowed down to 15 seconds for a better results display. As for the rerouting period re_{pe}, a broader range of [1,300] with intervals of 30 was tested. Considering that when the rerouting period is greater than 300, more than 90% of CAVs do not have the opportunity to re-route during traveling, which makes the rerouting capability ineffective, thus the upper boundary is set as 300. Based on the simulation step, the lowest value is set as 1. The rerouting probability of CAVs (re_{prob}) and vehicle passing rerouter (Re_{prob}) ranges from 0 to 1, and the sensitivity analysis is performed with an interval of 0.1. Last, the test range of rerouter's time threshold (Re_{tTh}, known as the react time) is determined as [0s,120s], 0-2 minutes, with an interval of 10s. Sensitivity analyses were performed

using the one-factor-at-a-time method, where each time a parameter was tested, the other parameters were kept at their reference values.

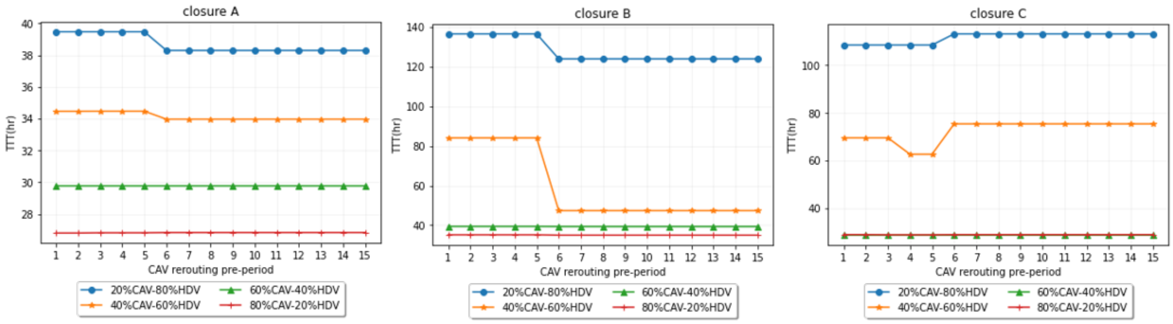
4.4.1. CAVs' rerouting pre-period

Figure 4.5a displays the simulation results of different re_{ppe} under different CAV penetration rates. From a general perspective, traffic conditions are not sensitive to the time at which the CAV receives updates on traffic conditions prior to departure at all CAVs' penetration rates, and after CAVs' penetration rate reaches 60%, re_{ppe} has no longer influence traffic condition, and among the three road closure locations, locations B and C show slightly greater sensitivity to fluctuations in re_{ppe}.

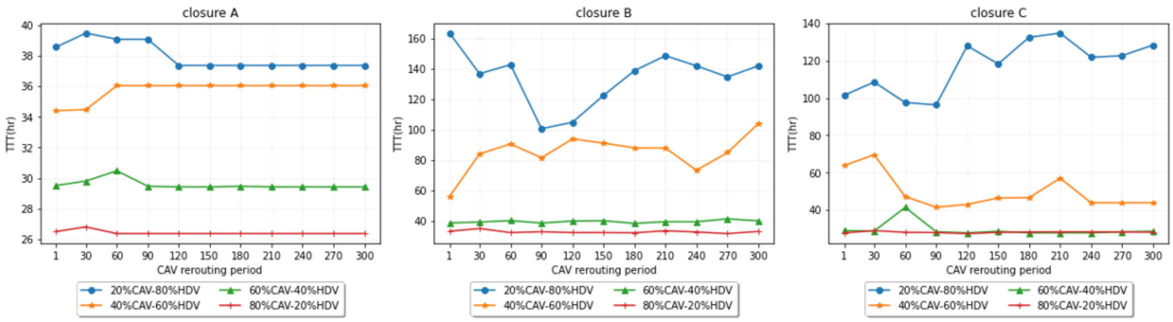
More specifically, a more frequent (re)route ability of CAVs before departure may not consistently benefit overall traffic conditions, particularly when the closed road is a heavily trafficked route. Take Closure B as an example, a longer pre-period brings to a lower TTT in all cases, in particular, when there is 40% CAV on the road, a pre-period longer than 5s leads to 30 hours less total travel time on the network. In the case of location C, the TTT has the highest sensitivity under the scenario of a 40% CAV penetration rate, where the optimal rerouting period before departure falls within the range of 3s to 6s, resulting in a TTT of approximately 61 hours. Notably, changes in TTT are predominantly observed when re_{ppe} falls within the range of 3s to 6s, once this period exceeds 7 seconds, adjusting this time will no longer affect the network conditions for all cases.

4.4.2. CAVs' rerouting period

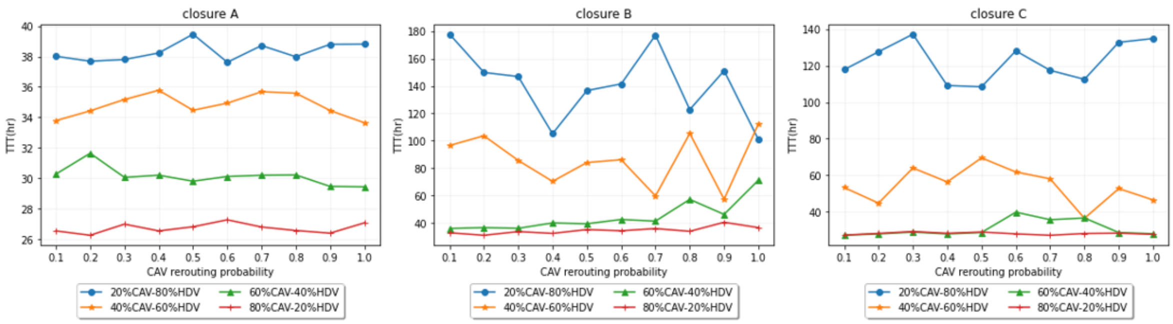
Figure 4.5b illustrates that CAVs' rerouting period sensitivity varies over different CAV PRs and road closures. When road closure occurs in A, the effectiveness interval of re_{pe} is [1s,150s], the change in re_{pe} causes a change in TTT from 0 to 2 hours. When lane B is closed, re_{pe} is more sensitive when CAV PRs are lower than 40%, for 20% CAV PR scenario, a dramatic drop in TTT happens when re_{pe} change from 60s to 90s, a re_{pe} longer than 120 leads a increasing TTT in the grid network. Therefore, exchange information every 90 seconds is the best for road closures to occur at locations B, resulting a TTT of 100 hours, As the percentage of CAVs increases to 40%: For Closure B, a shorter period is more beneficial for the traffic condition, and there is little change in the network TTT when re_{pe} changes from 30 to 210 seconds, which is around 90 hours. In the case of Closure C, the sensitivity of re_{pe} is affected by the PR of CAV. When there are 20% of the vehicles on the network are CAVs, shorter than 90 seconds of re_{pe} results in better traffic conditions with a TTT of about 100 hours. Conversely, when CAV penetration rises to 40%, the reduction in TTT is significant when the rerouting period of the CAV exceeds 60s, at the same time, the sensitivity to re_{pe} decreases significantly, and TTT is stable around 40 hours; when CAVs start to dominate the road traffic, TTT is less sensitive to CAVs' automatic rerouting period, 10s changes in re_{pe} often cause a fluctuation of 0h to 2h in TTT and TTT is approximately 25 hours in all cases.



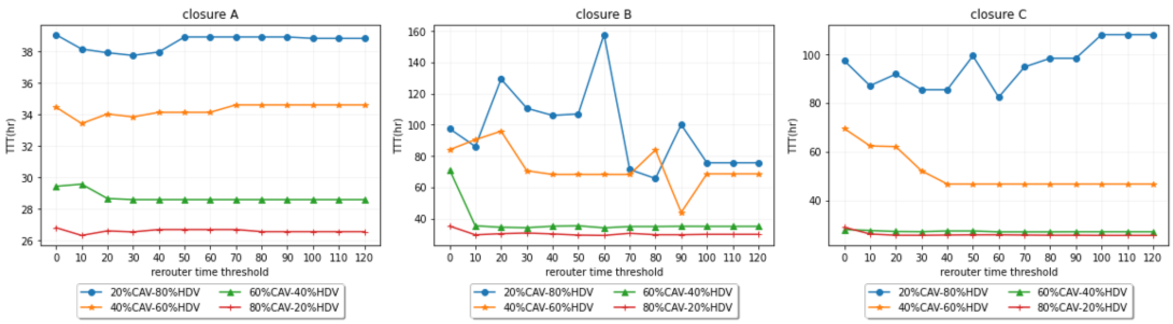
(a) CAVs' rerouting pre-period



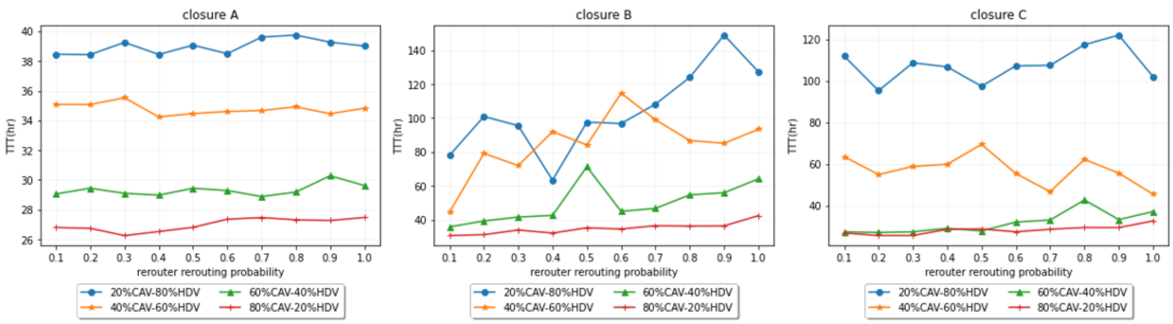
(b) CAVs' rerouting period



(c) CAVs' rerouting probability



(d) Rerouters' time threshold



(e) Rerouters' rerouting probability

Figure 4.5: Sensitivity analysis results of rerouting parameters in grid network

4.4.3. CAVs' rerouting probability

Figure 4.5c shows the sensitivity analysis results of parameter re_{prob}. Overall, traffic conditions are more sensitive to CAV rerouting probability when there is a lane closure at B, followed by C and A. Meanwhile, re_{prob} are less sensitive with the increasing CAV PRs.

For closure A, changes in re_{prob} does not cause significant fluctuations in TTT across all CAV PRs, with an average fluctuation range of about 2 hours. In addition, the average TTT drops by 4 hours with each 20% increase in CAV PR. For Closure B, traffic conditions are more sensitive to changes in re_{prob} under low CAV PR conditions, and different rerouting probabilities result in differences in TTT of up to 80 hours and 50 hours for 20% CAV and 40% CAV, respectively; when the CAV PR is up to 60% and 80%, TTT stays stable when re_{prob} is lower than 0.7 and increase slightly when re_{prob} trends to 1.0. Similarly, when lane C is closed, TTTs fluctuate more at scenarios of 20% and 40% CAV PR, with the maximum difference in TTTs due to different rerouting probabilities being about 30 hours, besides, it is noticeable that there is a significant drop in TTT when CAV PR increases from 20% to 40%, and the network condition under 60% and 80% CAV PR is basically the same, around 25 hours.

Furthermore, it can be found that with this default setting of other parameters, if the number of CAVs is less than the number of HDVs, Re_{prob} has a random effect on traffic conditions, but when the percentage of CAVs on the road is higher than 60%, the higher rerouting probability of CAV may instead negatively affect the TTT in the network, especially when closures occur on location B. Nevertheless, when a longer period or lower probability of CAVs' automatic rerouting is applied, the rerouting function of rerouters might be more significant.

4.4.4. Rerouters' time threshold

It is conceivable that when a lot of cars change lanes close to the closing lane, it is more likely to cause congestion on the surrounding roads. Moreover, when the traffic volume exceeds the capacity of its open road, the congestion will spread to the approaching road, and when the approaching road is also completely blocked with traffic, the rerouter will not work at this time. This assumption can be reflected in the results, see Figure 4.5d. In all scenarios, the longest react time for the rerouter to be effective is 100s, and for different locations and CAV PRs, the time differs. For example, when lane A is closed, the effective interval of Re_{tTh} under 20%, 40%, 60% and 80% CAV penetration rates are 50s, 60s, 20s, and 80s, respectively.

In most scenarios, the drop in TTT can be found when Re_{tTh} increases, especially when lane B is closed. Network with closure A experiences a stable traffic condition under all CAV PR; however, the TTT in the gird network with closure B changes markedly, and the react time shorter than 10s and longer than 100s leads to better traffic conditions; when Lane C is closed, the network condition under a 20% CAV penetration rate (PR) is better with a shorter router response time, whereas the traffic conditions under 40% and 60% CAV PRs improve with a longer router response time.

4.4.5. Rerouters' rerouting probability

Figure 4.5e inllustrates the sensitivity analysis results of parameter Re_{prob}. From an overall perspective, the sensitivity pattern varies across different road closure locations and CAV PRs, however, a common trend is that a higher rerouting probability for vehicles passing roads with rerouters tends to result in longer total travel times in the network, and this trend is most pronounced when lane B is closed, where the increase in Re_{prob} from 0.1 to 1.0 increases TTT by around 70 hours, 60 hours, 20 hours and 10 hours under 20%, 40%, 60%, and 80% CAV PR respectively. But there is an exception at 40% CAV scenario when closing a lane at location C, in which the higher probability leads to lower TTT on the network.

In addition, the traffic conditions are more sensitive to rerouter's rerouting probability When lane closure occurs at location B, followed by C and A. When lane closure B occurs, the grid network experiences a strong sensitivity under 20%-40%, resulting in a variation in TTT from 5 hours to 40 hours depending on the Re_{prob} value. However, the grid network under closure A shows an insignificant change in sensitivity of Re_{prob} with increases in CAV PRs, averagely, when the probability increases by 0.1, the TTT increases by 1 hour for all CAV PR. Under closure C, Re_{prob} sensitivity slightly increases: when CAV's penetration is 20%, an increase in the probability by 0.1 brings about an increase/decrease in the TTT of 10 hours on average, but when CAV's market share reaches 80%, the change in TTT reduces to 0.25 to 5 hours as the probability changes by 0.1.

4.4.6. Takeaways on sensitivity analysis

In this grid network, parameter re_{ppe} is less effective on traffic management when having a lane closure event. In theory, this parameter influences the initial routes chosen by CAVs. However, the opportunity to change routes during their trip is also crucial for CAVs in determining the route. re_{pe} is more effective when the CAV penetration rate is low, and across all CAV penetrations and closure locations. The sensitivities of the parameters re_{prob}, Re_{Th} and Re_{prob} show more significant differences in different cases. First, re_{prob} and Re_{prob} show similar patterns, which is that TTT has a marked increase when increasing the rerouting probability for scenarios with high CAV penetration rate; as for Re_{Th}, its sensitive ranges are narrowed down with the increasing number of CAVs. Consequently, in the subsequent optimization of the rerouting strategy, the search range of these three parameters will be narrowed on this basis.

The results of the grid network show that for all parameters, the impact decreases with increasing CAV penetrations; comparing CAV's automatic rerouting with rerouter's rerouting, the latter is more crucial in coping with lane closures in the grid networks, because lower TTTs are detected when adjusting the parameters of the rerouting parameters of routers. One of the reasons for this observation is the small number of streets in such a small network and the fact that, in case of a road closure, the congestion immediately spreads to multiple surrounding roads, which results in the cost of additional travel time caused by switching to a different route and detouring being too high for CAVs to find a shorter alternative route during their trips. Another reason is that the tests for the other parameters were performed with Re_{TTh} as the reference value (0), yet this value is proved to lead to higher TTT in subsequent analyses, therefore, if the response time of the rerouter is prolonged, the effect of the other parameters might be more pronounced. However, the results regarding rerouters' parameters suggest that a lower number of vehicles changing routes is usually the best strategy, or in other words, without reroutes, the TTT would instead be lower. These observation suggests two primary conclusions. Firstly, lane closures and rerouted vehicles significantly exacerbate congestion on surrounding paths, making it challenging for vehicles to find alternative routes even when informed of road closures in advance. Secondly, on this small-sized network, the additional travel time cost resulting from route changes and detours tends to outweigh waiting in line. Consequently, vehicles typically opt to remain on their current route.

Unexpectedly, it is found that B and C often show opposite trends when CAV penetration is low, e.g., with 40% CAV penetration, a shorter re_{pe} and a higher CAV switching rate are more beneficial to the network traffic conditions when lane B is closed, while the rerouter's lane switching function negatively affects the network; however, the situation is the same when closure C occurs the opposite. This is due to the fact that the control of the rerouter is more important when HDV domain the network, however street B is located in the center of the network and has excessive traffic demand, after closing a lane, HDVs change lanes as they approach the roadblock, however, due to their selfish routing, a large number of vehicles will choose the same shortest road, which will quickly cause additional congestion all around; however, for lane C, most of the vehicles pass by in order to get closer to the center of the network as a congested area, and due to the rerouting/detouring of some of the vehicles after the lane closure, it delays their approach to the center of the network, which to a certain extent serves to balance out the traffic flow on the network, so the role of the rerouter will have a positive impact.

4.5. Optimal rerouting strategy

This section is organized as follows: firstly, the simulation results of applying the reference rerouting strategy on the grid network are analyzed; then the process of applying BO to find the optimal rerouting strategy and the results are described, and finally the results of the optimal strategy and the reference strategy are compared and discussed.

4.5.1. Numerical results of applying reference rerouting strategy

The reference value for each rerouting parameter strategy is shown in Table 4.8, and the simulation results of all scenarios under the reference rerouting strategy are displayed in Table 4.9.

Table 4.8: The reference rerouting strategy for the grid network

Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
Value	1	30	0.5	0	0.5

Table 4.9: The simulation results of applying reference rerouting strategy

Scenario	TTT(hr)	TTD(km)	TWT(hr)
1	39.066	751.355	12.746
2	129.986	756.390	83.914
3	104.094	751.431	66.368
4	33.641	741.646	10.165
5	65.597	749.341	30.748
6	56.224	745.332	28.261
7	29.698	742.083	7.310
8	34.084	745.218	11.164
9	27.708	746.491	6.138
10	25.508	735.357	5.885
11	29.619	739.271	7.870
12	26.605	739.499	5.972

Table 4.9 shows the simulation results for scenarios 1-12 applying the reference rerouting strategy. In scenarios 1-12 CAV PRs increase from 20% to 80% and the closed lanes are A, B, and C respectively. Comparing across all scenarios, the TTT varied significantly, ranging from 25.508 hours (Scenario 10) to 129.986 hours (Scenario 2). Scenario 2 and 3 had significantly higher TTTs of 129.986 hours and 104.094 hours, which indicates that the reference rerouting strategy is not applicable to these scenarios, and further research is needed to find a more optimal rerouting strategy. Scenarios 10, 11, and 12, in which the CAV PR is 80%, had the lowest TTTs of 25.508, 29.619, and 26.605 hours, respectively. TTD varied less across scenarios, ranging from 735.357 km (Scenario 10) to 756.390 km (Scenario 2). Scenario 2 has the highest TTT and TTD of all the scenarios, and the TWT of 83 hours is more than half of the TTT, which indicates that vehicles in this scenario experience the most detour and congestion.

Moreover, it can be seen that the increase in CAV brings better network conditions to the network. As the CAV penetration increases, there is a significant decrease in TTT and TWT. Especially in the scenario where lanes B and C are closed, when CAV rises to 60%, the advantage of CAV is revealed and the TTT on the network is reduced by 80-90 hours compared to the 20% scenario.

At the same CAV penetration (comparing scenarios 1-3, 4-6, 7-9, and 10-12, respectively), there is a great difference in traffic conditions resulting from different lane closure locations, especially at low CAV penetration. Location B is the most critical location, as Lane B is located at the intersection in the center of the network and possesses high traffic demand, and traffic congestion is still difficult to alleviate even with Rerouter's notification control at CAV penetration rates below 50%. In later studies, more aggressive rerouting control of HDVs can be attempted by increasing the rerouting probability of the rerouter for scenarios with low CAV PR.

4.5.2. Optimal rerouting strategy using BO

In this section, the optimal reroute strategy for 12 scenarios shown in Table 4.5 is found using Bayesian Optimization (BO). Some attributes should be determined before carrying out $gp_{minimiza}$, shown in table 4.10 and Table 4.11.

The parameter setting for BO is shown in table 4.10. The number of iterations of BO is 30 and the goal is to minimize the TTT in the lattice network. The optimal rerouting strategy is the parameters set of the iteration with the lowest TTT within the 30 iterations. In order to find the best results faster, it is necessary to limit the search space of the parameter.

Table 4.10: The parameters of the Bayesian optimization algorithm for grid network

Scenario	n_{calls}	S1 (re_{ppe})	S2 (re_{pe})	S3(re_{prob})	S4(Re_{TTh})	S5(Re_{prob})
1-3	30	Integer[1,10]	Integer[1,180]	Real(0, 1)	Integer[0,120]	Real(0,1)
4-6	30	Integer[1,10]	Integer[1,180]	Real(0, 1)	Integer[60,120]	Real(0,1)
7-12	30	Integer[1,10]	Integer[1,180]	Real(0, 0.5)	Integer[10,90]	Real(0,0.5)

*n_{calls}: the total number of iterations performed by the Bayesian optimization algorithm
*S1: Search space of parameter re_{ppe}
*S2: Search space of parameter re_{pe}
*S3: Search space of parameter re_{prob}
*S4: Search space of parameter Re_{TTh}
*S5: Search space of parameter Re_{prob}

The search space of each parameter is determined based on the sensitivity analysis results, since the parameter sensitivities at each of the four levels of CAV penetration vary, different search space options were set up for each of them. For all scenarios, the parameter re_{ppe} is limited to 10 seconds and set to integer values between 1 and 10. and the space of re_{pe} is set from 1 to 180 as integer values. The differences are concentrated on parameters re_{prob}, Re_{TTh} and Re_{prob}. The search space of re_{prob} is between 0 and 1 in a continuous space for CAV penetration rate of 20%, 40%, and 80%; but is narrowed down to (0,0.5) for 60% scenario due to the clear trend shown in all closure locations in SA that the TTT increase with the increasing re_{prob}. As for parameter Re_{TTh}, its range in scenarios 4-6 is narrowed down to [60,120] because the significant drop in TTT is shown at point 40s in SA, and the range is expanded by 20 seconds to take account of the flexibility of change in results caused by changes in other parameters; in scenarios 7-9 and 10-12, a range of [10,90], 0s and the time and [90,120] is dropped; and only integers within these range are considered. As the same with re_{prob},

Re_{prob} is also a continuous parameter with a search space of (0,1) for low CAV penetration scenario (20%, 40%) and (0,0.5) for high CAV penetration scenario (60%, 80%).

Other settings when using $gp_{minimiza}$ is displayed in Table 4.11. For each time of optimization, the initial number of observations is 10, which means in the initial step, 10 parameter sets are first generated for the first evaluation.

Table 4.11: The initial setting of BO for the grid network - other settings

Attribute	n_{calls}	acq_{func}	$n_{randomStarts}$
value	100	gp_{hedge}	10

Table 4.12 displays the numerical results of the optimal reroute strategy for the 12 scenarios, with the corresponding simulation results of the TTT, TTD, and TWT. The results show that the parameters of the optimal rerouting strategy vary greatly from scenario to scenario, suggesting that for different traffic situations, the rerouting strategy needs to be adapted to obtain the best results. TTT values varied considerably between scenarios, ranging from a minimum of 24.811 hours to a maximum of 86.028 hours. Whilst TTD varied considerably, there was no significant difference in the total distance traveled, the TTD was relatively stable, varying between 733 and 753 km. The best case is Scenario 10, with 80% CAV uptake and Lane A closed, with the shortest TTT of 23.908 hours and the lowest TTD of 733.058km; the worst case is Scenario 3, with 20% CAV penetration on the network and lane C closed, with a TTT of 86. 028 hours, and traffic is completely blocked for 57.1 hours, which is more than half of the TTT.

Table 4.12: The optimal rerouting strategy for different scenarios on the grid network

Scenario	Optimal rerouting strategy					TTT(hr)	TTD(km)	TWT(hr)
	re_ppe	re_pe	re_prob	Re_tTh	Re_prob			
1	4	144	0.866	74	0.824	34.548	736.497	10.176
2	8	27	0.74	104	0.284	63.122	744.363	30.015
3	2	140	0.359	35	0.438	86.028	752.571	57.1
4	6	80	0.924	83	0.1	31.936	738.758	8.481
5	6	7	0.529	94	0.279	43.294	752.837	17.438
6	7	24	0.162	99	0.429	34.459	744.572	10.582
7	10	1	0.464	84	0.255	28.811	736.744	7.574
8	9	139	0.225	54	0.362	33.292	740.107	11.062
9	10	127	0.481	17	0.5	26.384	741.38	5.568
10	6	63	0.314	59	0.103	23.908	733.058	4.096
11	10	1	0.5	10	0.213	28.838	739.556	7.584
12	3	38	0.39	66	0.032	24.811	738.226	4.850

As CAV rises, the movement efficiency of network traffic flows increases. As CAV penetration increased, TTT and TWT gradually decreased, with the most pronounced at the rise from 20 to 40. Comparing Scenarios 1-3 and 4-6, Closures A, B, and C occurred with TTT reductions of 2.6, 20.1, and 51.5 hours, respectively, with more than a quarter of this coming from the reduction in TWT. Also overall, detours are decreasing, although when the CAV penetration rate increases to 40%, CAVs have to make more detours than when it is 20%, but there is a significant improvement in TTT and TWT, suggesting that the traffic flow is moving more efficiently.

In addition to the discussion above for the network as a whole, the results vary for different road closure locations. Among the three locations, lane closure at A has a relatively minor impact on the network, even when there is only 20% of trips are CAV trips, the network still experiences a smooth traffic flow, requiring fewer detours (TTD). For closures B and C, when the road traffic consists of more than 50% CAV trips, both closures result in similar TTD on the network. However, closure B tends to lead to more congestion, as reflected by the higher TWT. However, Closure C is more critical when CAV penetration is 20%, with a TTT of 86.028 hours for the optimal network condition, which is 23 hours higher than that for Closure B.

Comparing the results in Table 4.12 with the Bayesian-optimised search space in Table 4.10 reveals that: (1) the parameters re_{ppe} converged to the upper limit of the search space in most scenarios, which indicates that longer rerouting pre-period may be more beneficial in reducing the total traveling time; (2) the parameters re_{pe} and Re_{Th} have a wide range of values from 7 to 144 and from 10 to 104, respectively, suggesting that these two behaviours need to be adapted to specific scenarios; (3) in most scenarios, the value of CAVs' rerouting probability (re_{prob}) and rerouter's rerouting probability (Re_{prob}) are close to the upper limit of its search space, which imply that higher rerouting probabilities are favourable for improving traffic flow, the search space may narrow down in further research.

4.5.3. Results Comparison

Compared to the simulation results of the reference strategy, applying the optimal rerouting strategy obtained using Bayesian optimization leads to a great improvement in traffic conditions. The specific improvements in KPIs are shown in Table 4.13.

As can be seen from Table 4.13, the optimal rerouting strategy significantly improves the traffic condition in TTT, TTD and TWT in most scenarios. In particular, in scenario 2, all indicators show significant improvement, getting a TTT improvement of 66.9 hours, in which the number of hours in which vehicles experience full congestion is reduced by 53.9 hours. It indicates that the optimal strategy is very effective in this scenario. However, certain scenarios such as Scenarios 7 and 11, while showing an overall improvement, show a slightly negative impact on specific metrics (e.g., TWT and TTD), which may require further optimisation of the strategy or consideration of particular traffic dynamics in a given scenario. Overall, the data in the table suggests that the optimal replanning strategy is effective in improving traffic efficiency and mobility in most scenarios.

At CAV penetrations of 60% and 80%, the optimal policy only shows a slight improvement compared to the reference policy due to (1) the fact that the optimal policy is already a relatively good policy for this network, and (2) the rerouting strategy (SO) for CAVs balances and optimizes the network conditions at high CAV penetrations, so that even if the rerouting strategy changes, the vehicles do not need to change routes multiple times, and the path choices remain similar.

Table 4.13: Comparison in KPIs between reference and optimal rerouting strategy (grid network)

Scenario	TTT(hr)	TTD(km)	TWT(hr)
1	4.518	14.858	2.57
2	66.864	12.027	53.899
3	18.066	1.406	9.268
4	1.705	3.068	1.684
5	22.303	3.496	13.31
6	21.765	0.76	17.679
7	0.887	5.339	-0.264
8	0.792	5.111	0.102
9	1.324	5.211	0.57
10	1.6	2.299	1.789
11	0.781	-0.295	0.286
12	1.794	1.273	1.122

5

Case study: Sioux Falls network

The case study in this study employed the Sioux Falls network. Scenarios of four CAV penetration rates (20%, 40%, 60%, and 80%) are analyzed, and road closures at the same locations and times were simulated under these four scenarios. First, the reference parameters for the rerouting strategy are determined based on the non-CAV non-disruption network and then the search spaces for the key rerouting parameters are detected through a sensitivity analysis, based on which, the optimal rerouting strategies for all scenarios are found by carrying out the Bayesian Optimization.

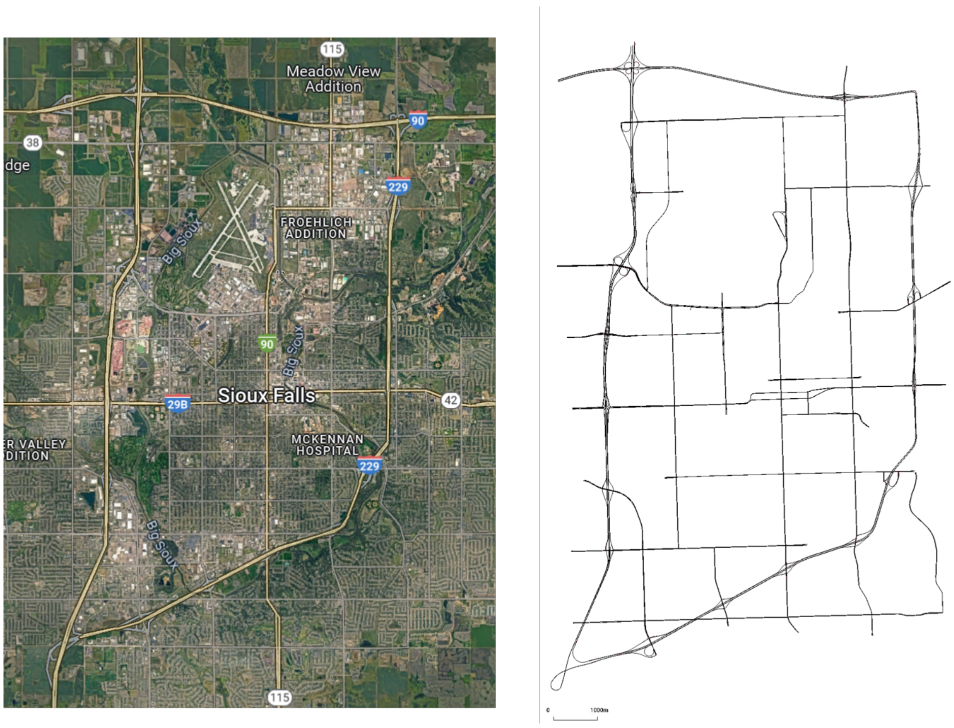


Figure 5.1: The Sioux Falls City (left) and its road network (Right)

5.1. Sioux Falls network

The Sioux Falls network is a widely recognized and used traffic network model within the transportation research community. It is based on the actual road network of Sioux Falls, South Dakota, but is often used as a hypothetical or virtual testing environment for traffic simulation studies. The Sioux Falls network shown in Figure 5.1 consists of 580 intersections, 33 types of roads, and 869 edges. The length of the edges ranges from 50 to 200 meters. Most of the main roads have two lanes, with a few three- and four-lane roads present, and most of the ramps are single-lane. Figure 5.2 shows the permissible speed distribution and stoplight locations for the Sioux Falls Network.

In the case study, 36000 vehicles were simulated in one hour, each assigned an origin and destination reflective of the demand patterns outlined in the seminal work by LeBlanc, Morlok, and Pierskalla from 1975 (LeBlanc et al., 1975). Aligned with Behzad's previous work, mesoscopic simulation was used for this case study. For further details on the meso-simulation model and the parameters used in mesoscopic simulation in SUMO, please refer to Bamdad Mehrabani et al., 2023 and Amini et al., 2019, and Mansourianfar et al., 2021, respectively. During the simulation, CAVs seek the SO principle with periodic rerouting, while HDVs follow the UE principle and drive on the route selected when departure.

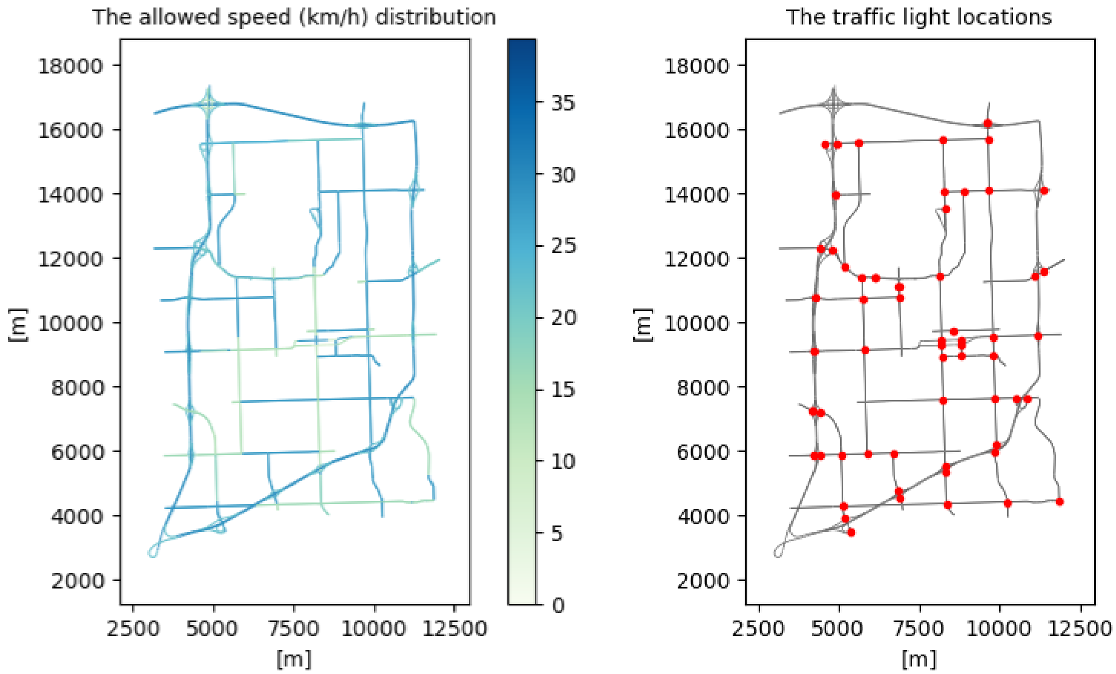


Figure 5.2: The allowed speeds and traffic light location in the Sioux Falls network

5.2. The reference rerouting strategy

The reference rerouting strategy is established based on the traffic condition of the scenario with no CAV and no roadblock. The process of determining the re-routing parameters of the CAV and the re-router on Sioux Falls netowrk is described next, respectively.

5.2.1. Reference rerouting parameters for CAV

The reference rerouting parameter for this network is determined based on traffic conditions in a scenario without CAVs and road closures. A statistical analysis of the duration (travel time) distribution of the trip is performed for all trips, the results are shown in Figure 5.3, and Table 5.1.

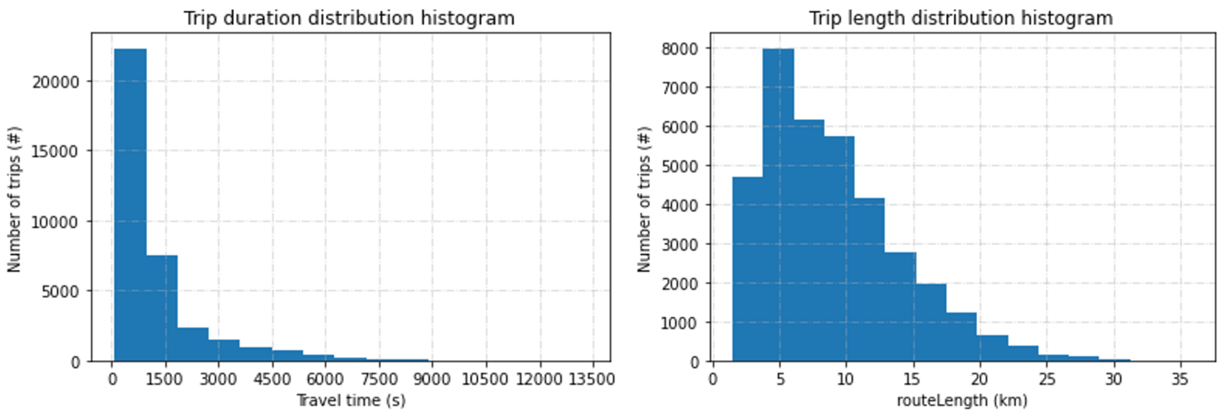


Figure 5.3: Travel time (left) and distance (right) distribution of trips on the Sioux network

Table 5.1: Statistic results of travel time in non-CAV scenario of Sioux Falls network

Indicator	Min.TT	Max.TT	Med.TT	Ave.TT
Value (s)	83.0	13310.0	787.0	1247.5

The histogram in Figure 5.3 shows the distribution of trip durations and distance across the network. The x-axis represents the duration / distance of the trip in seconds / km, while the y-axis represents the number of trips. Most trips are concentrated in the range of 0 to 1500 s, with a travel distance range form 1.5 km to 35km. indicating that a significant portion of travel times in the network are short. There is a rapid decline in the number of trips as the trip duration increases, which is typical for urban travel where shorter trips are more common. Table 5.1 provides a summary of travel time statistics. It lists indicators including the minimum (Min.TT), maximum (Max.TT), median (Med.TT), and average (Ave.TT) travel times in seconds. The minimum travel time recorded is 83 seconds, suggesting that there are very short trips or efficient routes within the network. The maximum travel time is substantially longer at 13310 seconds, indicating there could be long-distance trips or congestion causing delays. The median travel time, which is less sensitive to outliers than the average, is 787 seconds, offering a better representation of a typical trip within the network. The average (mean) travel time is 1247.5 seconds, about 20 minutes, skewed higher than the median due to long-duration trips. This analysis points to a varied range of trip durations within the Sioux Falls network, with most trips being relatively short, but with some longer trips that could be influencing the average travel time.

On the basis of the above analysis, to let most CAVs have the opportunity to reroute during their trips, the reference rerouting period for CAVs is set as 60s; the rerouting pre-period is set to 1 second to simulate that all CAVs receive the latest traffic conditions; and the rerouting probability is set to 0.5 instead of 1.0 because it may be more favorable to the network traffic conditions if not all vehicles change their routes every time they receive a message, which is also shown in the test results on the grid network. As for other parameters, the rerouting adaptation step length is adjusted to 3600 seconds aligning with the simulation time of each iteration; the rerouting adaptation interval is set to 1, which indicates that during the simulation process, the edge weights on the network will be updated at each time step, which makes it easy to collect the data for further analysis; The specific values of the parameters can be found in Table 5.2 and Table 5.3.

Table 5.2: The reference rerouting parameter for CAV (Sioux Falls network)

Parameter	re_{ppe}	re_{pe}	re_{prob}
Value	1	60	0.5

Table 5.3: Other (fixed) rerouting parameters for CAVs (Sioux Falls network)

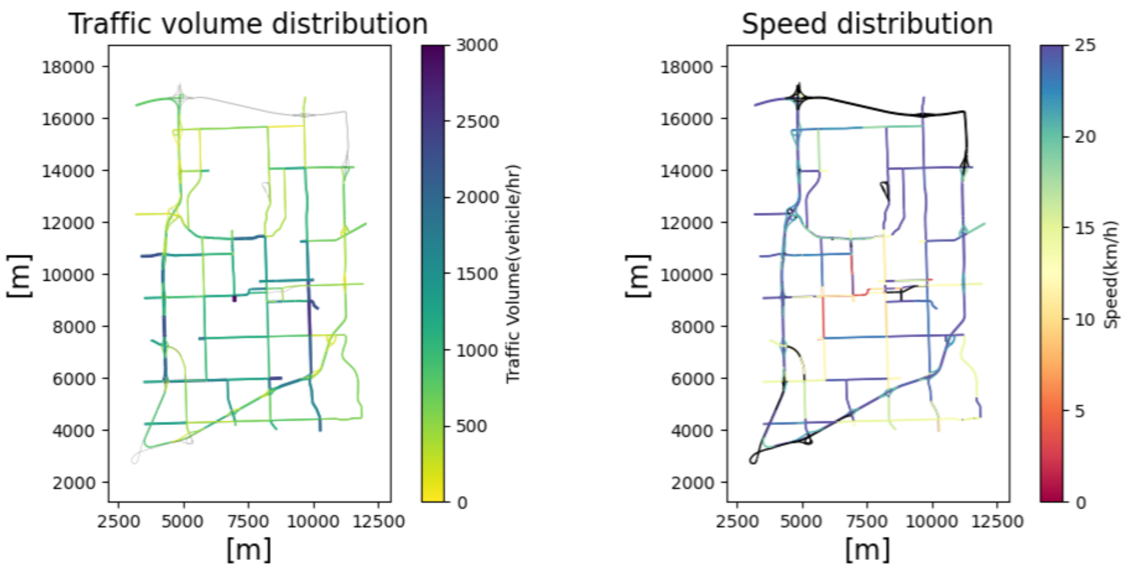
Parameter	re_{AdIn}	re_{AdSt}
Value	1	3600

5.2.2. Reference rerouting parameters for rerouters

The location of lane closure and its rerouters is determined as below.

1. **The road closure location selection**

Figure 5.4a depicts the volume on the Sioux Falls network in the all-HDV scenario, categorized based on both colors and width, where from blue to purple represents a traffic volume from 0 km/h to 3500km/h, and thicker links indicate higher traffic volume. It can be seen that most of the roads in the center of the Sioux Falls road network have traffic volumes between 1000 to 1,500 vehicles per hour, with the busiest roads seeing traffic volumes of 3,000 vehicles per hour, while the roads on the edge of the city pass less than 500 vehicles per hour. in the Sioux Falls network. Figure 5.4b shows the distribution of average speeds, The figure uses colored gradient bars, where the colors represent the average speeds of the different sections of the road, where the closer the color is to blue means higher speed, and the closer it is to red means lower speeds. Analyzing travel speed with the distribution in traffic volumes, it reveals that the network is not highly congested and vehicles can travel at 20-25km/h on most of the main roads. The congestion is mainly concentrated on one main road located in the center; the area to the south endures more congestion, with average speeds on most of the roads in the range of 5-15km/h. Meanwhile, some of the end side roads (ramps) are also in a more congested state due to the high volume of traffic but low road capacity.



(a) Traffic Volume distribution

(b) Speed distribution

Figure 5.4: The traffic volume and speed distribution of grid network - all-HDV scenario

Based on the traffic conditions of this network, we chose the inlet and outlet of one of the more congested intersections as the location of the road closure for testing. The exact location is shown in Figure 5.5. This is a two-lane main roadway running south to north, with the lane near the center to be closed later in the simulation. The rerouter to which it is adapted is placed on the 2 approaches that precede that road. The exact locations are shown in Figure 5.6.

2. **The reference rerouting parameters for rerouter**

Table 5.4 shows the reference parameters for the rerouters. The rerouters' react time (Re_{tTh}), known as the time threshold, is set as 0 to simulate the quickest information providing; the rerouting probability for vehicles when passing the active rerouter is set as 0.5 taking into account the fact that only one of the lanes in a two-lane roadway is closed, and that there is still some traffic capacity. Therefore, the re-router will be active at 900 seconds and deactivated at 2700 seconds, during which time 50% of the vehicles passing the edge will be informed of the lane closure ahead and forced to reroute.

Table 5.4: Parameter of rerouters' operation for the base scenarios

Parameter	RePr	Time threshold
Value	0.5	0

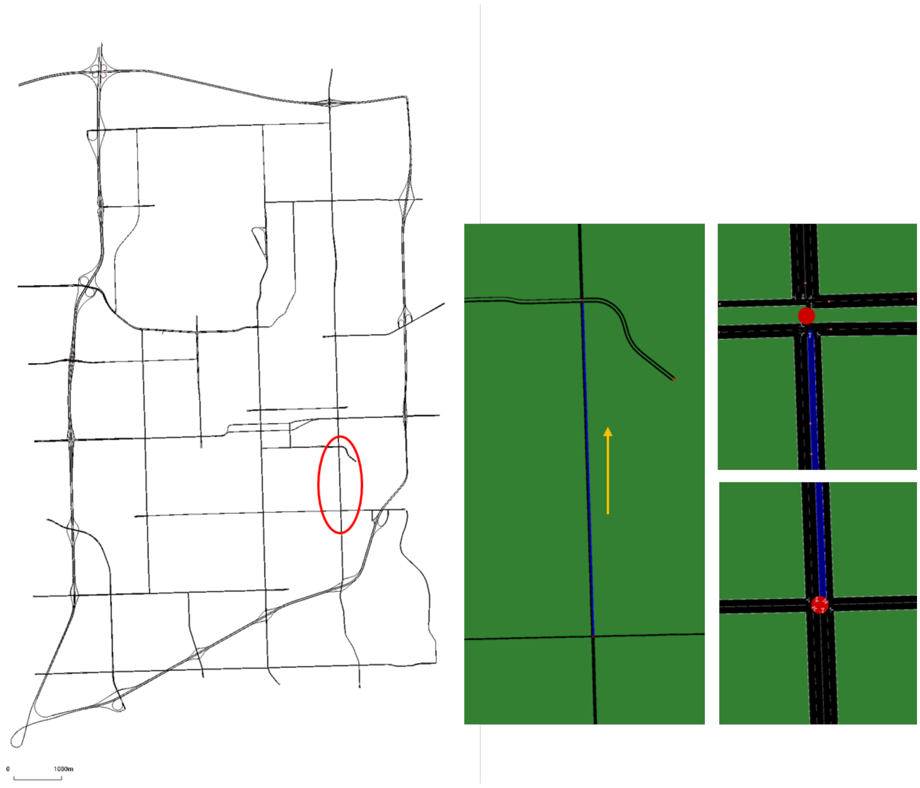


Figure 5.5: The location of closed road in the Sioux Falls network

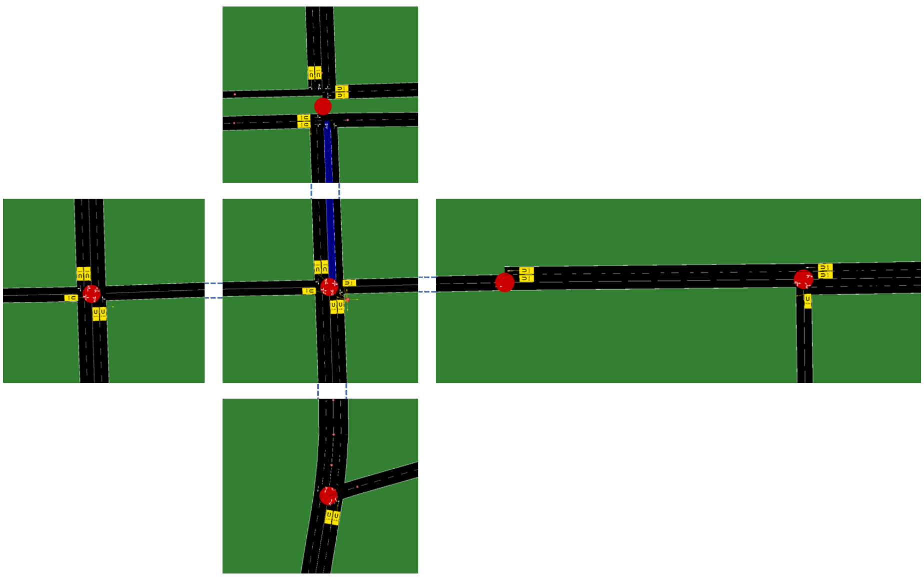


Figure 5.6: The location of rerouters in the Sioux Falls network

5.3. The test scenarios defining

In order to find the optimal rerouting strategy under CAV heterogeneity, four CAV penetration rates were tested (20%, 40%, 60%, and 80%), referred to as Scenarios 1-4. For all scenarios, the simulation lasts 1 hour, and the lane closure occurs from 900s and dues for 30 minutes, ending at 900s. During the simulation, CAVs seek for SO while HDVs follow the UE. The specific setup of each scenario is shown in Table 5.5. The reference value for each rerouting parameter strategy is shown in Table 5.6.

Table 5.5: The scenarios to simulate in the Sioux Falls network

Scenario	CAVs' penetration rate	HDVs' penetration rate	Road closure id	Road closure druation	CAVs' routing principle	HDVs' routing principle
1	20	80	X	[900,2700]	SO	UE
2	40	60	X			
3	60	40	X			
4	80	20	X			

Table 5.6: The reference rerouting strategy (Sioux Falls network)

Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
Value	1	60	0.5	0	0.5

5.4. Rerouting parameters sensitivity analysis

The sensitivity analysis is conducted for scenarios in Table 5.5. Table 5.7 shows the parameters for testing Re_{prob} sensitivity in falls network, re_{ppe} ranges from 1 to 150 with a 10 seconds interval and Parameter re_{pe} ranges from 1 to 600 and takes a larger time interval of 60 seconds, i.e. 1 minute; The probability of CAV to change route ranges re_{prob} and rerouter's rerouting probability Re_{prob} range from 0 to 1, and the sensitivity analysis is performed with an interval of 0.1. The react time of rerouter is set [0,300], with an interval of 30 seconds. The one-factor-at-one-time method employed this sensitivity analysis, where only one parameter is changed in each test and the other parameters remain at their reference values. Figure 5.7 shows the results of sensitivity analysis of all parameters based on the above setting.

Table 5.7: Scenario setting for testing impact of rerouting parameters

Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
re_{ppe}	[1,10,20...150]	60	0.5	0	0.5
re_{pe}	1	[1,60,120...600]	0.5	0	0.5
re_{prob}	1	60	[0.1,0.2...1.0]	0	0.5
Re_{tTh}	1	60	0.5	[0,30,60..300]	0.5
Re_{prob}	1	60	0.5	0	[0.1,0.2...1.0]

In the results presented in Figure 5.7, the x-axis of the graph is the value of the parameter and the y-axis is the value of the TTT, each graph contains the results of four scenarios, and the y-axis of each icon has a range of [25000,33000], which facilitates comparison between graphs.

Similar to the test results in the grid network, it can be observed that in the Sioux Falls network, the sensitivity of re_{ppe} is generally low. changes in re_{ppe} cause small TTT fluctuations (about 100 hours) at CAV penetrations of 20% and 60%; while at 40% and 80%, its effect on TTT is slightly larger, with network TTT differences at different re_{ppe} of up to 600 hours. It is worth noting that the sensitivity of re_{ppe} is highest when the CAV is 80%, and allowing the CAV to know the latest road information 30s-60s before departure can lead to a better network condition. However, at lower penetration rates, re_{ppe} has no significant effect. **This suggests that the ability to anticipate road information ahead of time has more potential to benefit trips on the network only when the majority of trips are made by CAVs. At low CAV penetration, initial route choice is even less important.**

Test results for re_{pe} show that CAV rerouting strategies are more sensitive at CAV penetrations of 40% and 60%, and that longer routing cycles lead to better network conditions in all scenarios. For CAV penetration of 20% and 40%, rerouting period lower than 420s has 500 hours - 1000 hours up and down fluctuation in TTT, 60s and 180s are the optimal periods for 20% penetration and 40% penetration, respectively; rerouting period longer than 420s negatively affects the network conditions. The network condition is negatively affected by a rerouting period of more than 420s. After CAV penetration exceeds 60%, shorter rerouting periods (180s or less) result in lower TTT.

The re_{prob} is the most sensitive of all parameters, with each 0.1 change in re_{prob} resulting in up to 1500 hours of TTT increase/decrease. At CAV penetration rates of 20%-60%, although the TTT fluctuated over a wide range at different re_{prob}, it was maintained at a level value on average, with no significant increasing or decreasing trend, and the lowest TTT appeared in the interval of 0.4-0.5. However, when the CAV penetration rate is at 80%, the TTT showed a clear increasing trend with re_{prob}. **This suggests that a better rerouting strategy is to reduce the number of rerouted vehicles when CAV's market share reaches 80%.**

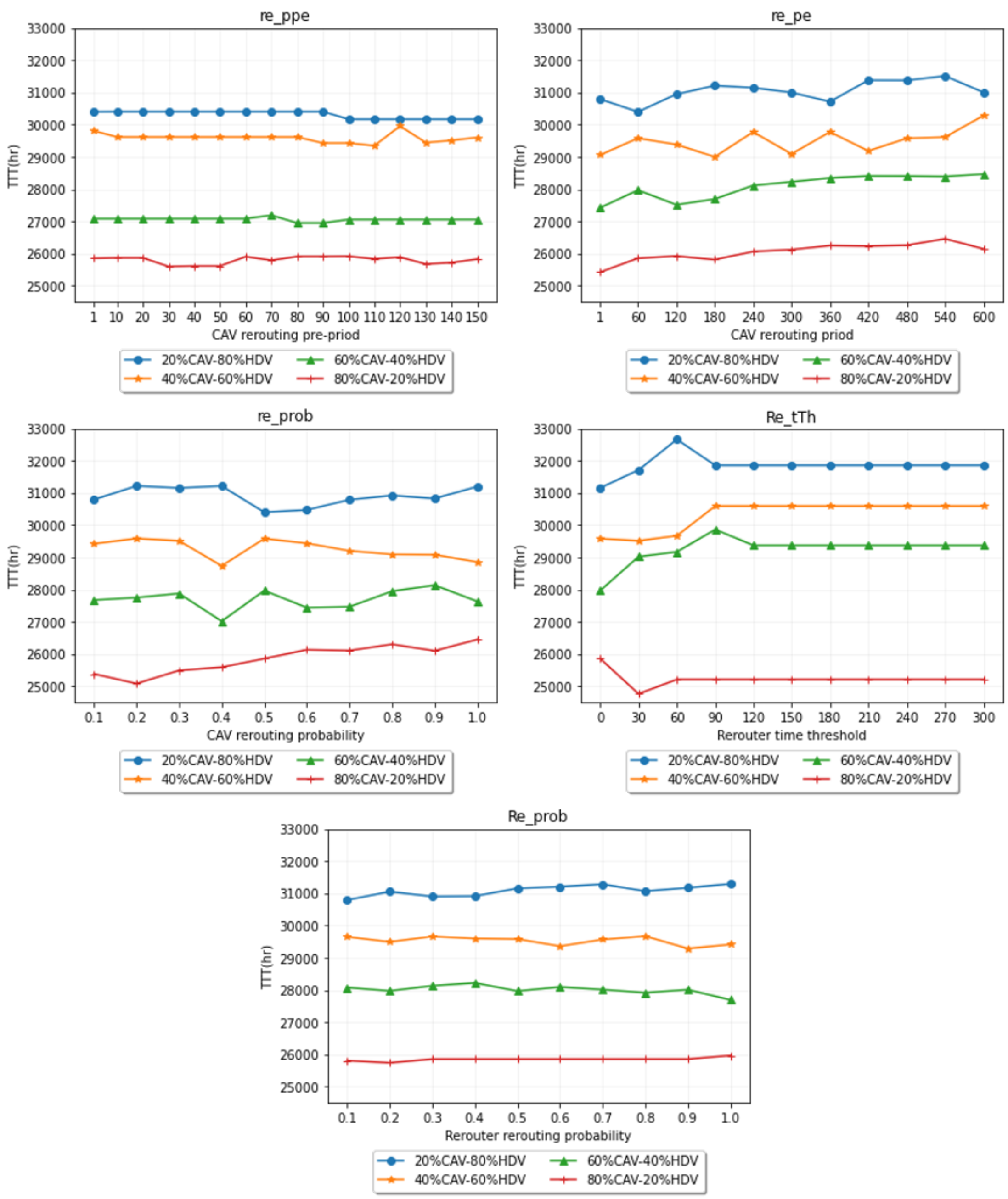


Figure 5.7: The impact of each parameter on TTT on the Sioux Falls network

The simulation results for Re_{tTh} is similar to those on the grid network. For Re_{tTh}, which is the maximum sensitivity interval of the rerouter is from 0 to 120 seconds. Moverover, shorter reaction time thresholds that are more favorable to the traffic conditions at CAVS penetrations of 20% - 60%. However, a Re_{tTh} of 60 seconds leads to the shortest TTT when CAV is 80%. In contrast, the Sioux Falls network is less sensitive to Re_{prob} compared to the grid network. At a CAV penetration of 20%, the TTT on the network increases slightly with Re_{prob} and the total gap is about 300 hours, on the contrary, at CAV penetrations of 20% and 60%, the TTT on the network decreases slightly with

Re_{prob}, and the total gap is about 500 hours. However, when the CAV penetration is 80%, the TTT does not change significantly and only experiences an increase of about 75 hours at points 0.3 and 1.0.

The above results show that on the Sioux Falls network, with 20%-60% CAV penetration, the network requires the rerouter to take more aggressive control, including faster response time, and higher rerouting probability. However, in the scenario of 80% CAV penetration, the rerouter no longer plays a significant role, this is due to the fact that when most of the trips on the network are by CAVs, they can be informed of lane closures in time, and thanks to their automatic rerouting capability, which already balances the traffic flow well, the passing of the remaining HDVs does not result in congestion near the closed road, therefore, the rerouter's regulation as well is no longer important.

In addition, it is worth noting that a CAV penetration of 60% is one of the more critical scenarios in the Sioux Falls network, where improper rerouting strategies can lead to extremely high latency in the network. For example, for all parameters tested at 60% penetration, the TTT was as low as 26,990hours (re_{prob}=0.4) and as high as 29,837hours (Re_{tTh}=90s), with as much as a 3,000-hour difference between different rerouting strategies.

5.5. The optimal rerouting strategy

This section is organized as follows: firstly, the simulation results of applying the reference rerouting strategy on the Sioux Falls network are analyzed; then the process of applying BO to find the optimal rerouting strategy and the results are described, and finally the results of the optimal strategy and the reference strategy are compared and discussed.

5.5.1. Numerical results of applying reference rerouting strategy

The reference value for each rerouting parameter strategy is shown in Table 5.8, and the simulation results of all scenarios under the reference rerouting strategy are displayed in Table 5.9.

In the Sioux Falls network, As CAV penetration increased, the TTT decreased from 31158.30 hours (scenario 4) to 25859.48 hours (scenario 1). For every 20% increase in CAV penetration, the TTT decreases by an average of about 2,000 hours, and the TTD increases by an average of about 100km, which indicates an increase in the average speed, and also reflects the role of the CAV in balancing the distribution of traffic flows.

Table 5.8: The reference rerouting strategy (Sioux Falls network)

Parameter	re_{ppe}	re_{pe}	re_{prob}	Re_{tTh}	Re_{prob}
Value	1	60	0.5	0	0.5

Table 5.9: The simulation results of applying reference rerouting strategy

Scenario	TTT(hr)	TTD(km)	TWT(hr)
1	31158.30	271493.82	363.25
2	29583.93	271608.09	330.91
3	27971.12	272193.82	315.99
4	25859.48	274206.57	291.16

5.5.2. The optimal rerouting strategy

As with the steps for applying Bayesian optimization on the grid network, the range of parameter optimization and other initial settings are first defined separately for each scenario, and the exact values can be found in Table 5.10 and Table 5.11. Considering the size of the Sioux Falls network and the length of time the simulation needs to be performed, the Bayesian optimization here is performed for only 15 iterations, with an initial set of 5 random solutions, after which the previous left and right results are evaluated in the next 10 cycles to select the next solution. The determination of the range of the parameters (see Table 5.10) combines the conclusions of the grid network and the discussion of SA in the previous section. For all temporal parameters (re_{ppe}, re_{pe}, Re_{tTh}), all discrete values in the solution space for the whole tenth of a second are chosen, this is to narrow the solution space and allow the Bayesian optimization to explore as large a range as possible, avoiding getting stuck in a local optimum. The convergence patterns of each scenario are shown in Figure 5.8.

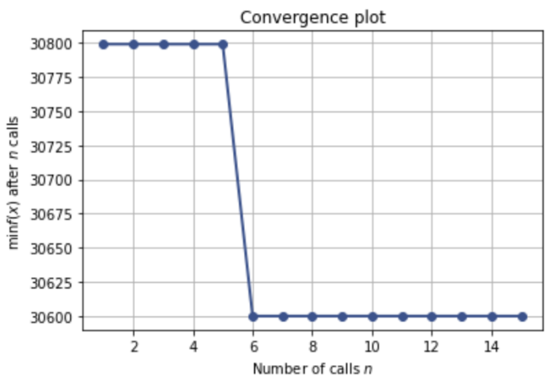
Table 5.10: The parameters search space of BO for the Sioux Falls network

Scenario	S1 (re_{ppe})	S2 (re_{pe})	S3(re_{prob})	S4(Re_{TTh})	S5(Re_{prob})
1	[1,60,120,180]	[1,30,60,...,300]	Real(0.5, 1)	[0,30,60,...,150]	Real(0, 0.5)
2	[1,30,60,...,150]	[1,30,60,...,300]	Real(0, 1)	[0,30,60,...,150]	Real(0.5, 1)
3	[1,60,120,180]	[1,30,60,...,300]	Real(0, 1)	[0,30,60,...,150]	Real(0, 1)
4	[1,30,60,...,150]	[1,30,60,...,300]	Real(0, 0.5)	[0,30,60,...,150]	Real(0, 0.5)

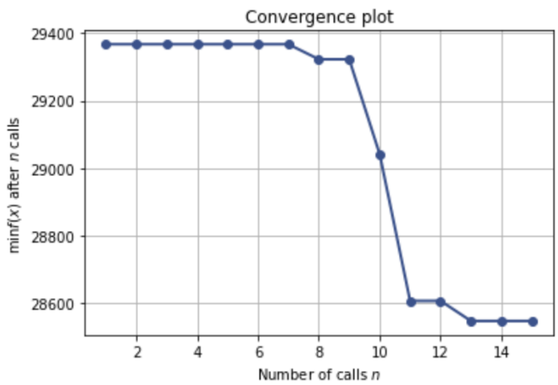
*n_{calls}: the total number of iterations performed by the Bayesian optimization algorithm
*R1: Search space of parameter re_{ppe}
*R2: Search space of parameter re_{pe}
*R3: Search space of parameter re_{prob}
*R4: Search space of parameter Re_{TTh}
*R5: Search space of parameter Re_{prob}

Table 5.11: Other initial settings of BO for the Sioux Falls network

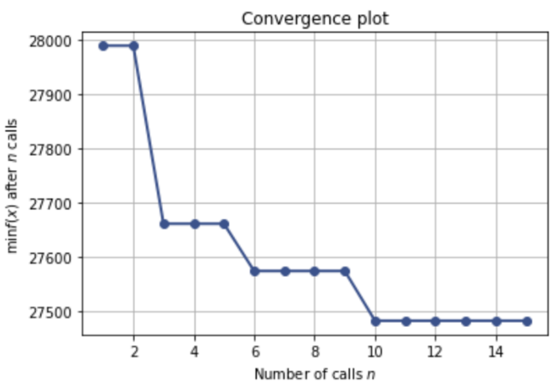
Attribute	n_{calls}	acq_{func}	$n_{randomstarts}$
value	15	gp_{hedge}	5



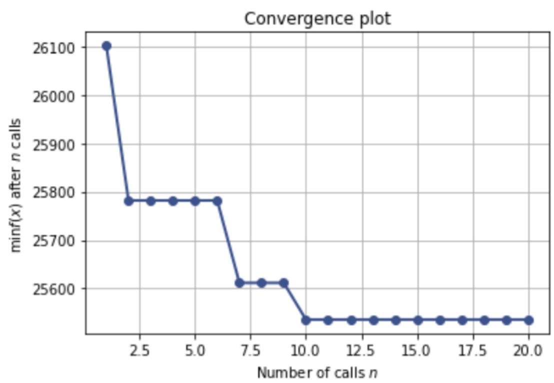
(a) BO convergence pattern - Scenario 1



(b) BO convergence pattern - Scenario 2



(c) BO convergence pattern - Scenario 3



(d) BO convergence pattern - Scenario 4

Figure 5.8: The travel time distribution under reference rerouting strategy (grid network)

The simulation results of applying optimal rerouting strategy are displayed in table 5.12. It can be found that from scenarios 1-4, for every 20% increase in CAV penetration, the TTT decreases by 2052, 1065, and 1947 hours; followed by a decrease in TWT from 351.14 to 294.37 hours, with the largest difference between scenarios 1 and 2. Meanwhile, the increase in TTD is relatively even, with each 20% increase in CAV penetration resulting in an increase in total vehicle detour distance of about 100km.This indicates that the transition from CAV penetration from 20% to 40% and 60% to 80% are both very important to the network, with the process of 20% to 40% significantly reducing traffic congestion, and the process of 60% to 80% further improving the overall mobile efficiency.

Observing the parameters in the optimal solution, it can be found that when the CAV PR is 20 and 40, the optimal rerouting strategy is more aggressive than it of the higher CAV PR situations. When there are only 20% CAVtrips in the network, the rerouter is activated after 2 minutes and it is optimal to control only 25% of the vehicles rerouted. when the CAV penetration is 40, the optimal strategy is to take more aggressive rerouting actions for both CAVs and rerouters, with the most frequent automatic rerouting (re_{pe}=1), immediate effect (Re_{tTh}=0), and force all vehicles to reroute(Re_{prob}=1). However, as the CAV penetration increases, the rerouting probability of both CAV and rerouter tends to decrease. This is due to the fact that more CAVs join to strengthen the automatic traffic regulation function, which enables the traffic on the network to find the optimal path in a shorter time and no need for more chances to reroute.

Table 5.12: The optimal rerouting strategy for different scenarios on the Sioux Falls network

Scenario	Optimal rerouting strategy					TTT(hr)	TTD(km)	TWT(hr)
	re_ppe	re_pe	re_prob	Re_tTh	Re_prob			
1	60	1	1.0	120	0.256	30600.10	269982.10	351.14
2	60	1	1.0	0	1.0	28547.04	270466.45	312.89
3	1	150	0.532	120	0.051	27482.01	271489.86	306.38
4	1	120	0.421	90	0.004	25535.38	272770.53	294.37

5.5.3. Results comparison

Compared to the simulation results of the reference strategy, applying the optimal rerouting strategy obtained using Bayesian optimization leads to a great improvement in traffic conditions. The specific improvements in KPIs are shown in Table 5.13.

Table 5.13: Comparison in KPIs between reference and optimal rerouting strategy (Sioux Falls network)

Scenario	TTT(hr)	TTD(km)	TWT(hr)
1	558.20	1511.72	12.11
2	1036.93	1141.59	17.23
3	489.12	703.92	9.69
4	324.18	1436.07	3.24

As can be seen from Table 4.13, the optimal rerouting strategy significantly improves traffic conditions in terms of TTT, TTD, and TWT across all scenarios. For TTT, there is a reduction ranging from 324 hours to 1036 hours. For TTD, the reduction spans from 703.92 km to 1511.72 km. For TWT, the reduction ranges from 3.24 hours to 17.23 hours. Overall, the improvement is most notable in Scenario 2, which shows a significant reduction in travel time and the shortest path. In Scenario 1 (20% CAV PR), there is a substantial reduction in the number of detours (TTD), though the total running time improves by only 558.2 hours. Scenario 4 (80% CAV PR) shows similar results, with substantial improvements in travel time and distance.

A comparison of the improvements in the individual metrics shows that only a very small portion of the improvement in TTT on the Sioux Falls network comes from a reduction in TWT, due to the fact that the network itself is not congested, and does not result in a significant amount of prolonged traffic congestion, even under the reference strategy.

6

Conclusion & Discussion

In the context of the development of CAV and ITS, this thesis focuses on the traffic management of a common traffic situation in life - the road closure events, and aims to find the optimal rerouting management strategy to cope with the closure event on a network where there is a mixture of CAV and HDV traffic flows. Four levels of CAV penetration (20%, 40%, 60%, and 80%) are considered in the thesis. The goal is to find the optimal rerouting strategy for each scenario that results in the shortest total travel time on the network. In this study, HDVs and CAVs follow different path selection principles, with the former following the UE principle and the latter following the SO principle. Moreover, the information exchange capability of CAVs allows them to continuously receive the latest status of the network and find the optimal path while traveling, however, HDVs can only consider rerouting when they receive information about roadblocks when they are close to a closed road.

In this thesis, a simulation-based approach is used to model the traffic flow applying both micro and meso scale models. The rerouting strategy's are designed based on the rerouting behaviour of vehicles when road closure occurs in life, the control parameters include the control of the CAV's automatic rerouting period, rerouting probability, HDV Knowledge of the time of lane closure, as well as their rerouting probability. Then, a sensitivity analysis of each relevant parameter is performed using a one-factor-at-a-time approach to understand the impact of each parameter on the network traffic condition. Finally, Bayesian Optimization is used to find the optimal rerouting strategy within a certain search range and number of times. In this study, the grid network and the Sioux Falls network are simulated respectively and the relatively optimal rerouting strategies are found for them. The grid network can be regarded as a local area on the network, while the results of Sioux Falls, as a larger network, can provide some basis for city-level traffic management.

This section will discuss the answers to the research questions, reflect on the research methodology and the results obtained, summarise the thesis's contribution to scientific research, and make recommendations for future research.

6.1. Answer to the research questions

The main question of this thesis is **What is the optimal rerouting strategy for CAV and HDV mixed traffic when road closure happens?**, to answer this question, four sub-questions are proposed, the following is the answer to the sub-questions.

1. To what extent does the penetration rate of CAVs affect traffic conditions under road closure? and how can this impact be quantified and assessed?

The presence of CAVs acts as an automatic regulator, they can react in a timely manner to the network at hand to avoid overcrowding on the network, but at the same time they can bring about detours, therefore, to quantify this effect, in this paper, we use the total travel time to assess the network condition, the total travel distance to determine the length of detours, and the total parking waiting time to quantify the level of congestion.

In grid networks, there is a significant increase in network traffic conditions when CAV penetration increases from 20% to 40%, with a significant decrease in TTT, which slows as CAV penetration continues to grow. This suggests that for small networks or localized traffic, it is very important at the early stage of CAV development, and its suitable traffic management strategies need to be further investigated. However, on a larger network, the Sioux Falls network, a CAV penetration of 60% results in a more fragile traffic flow, as evidenced by the large difference between different rerouting strategies, making it critical to find better traffic management for a large network at the middle point of the transferring of vehicle market from HDV to CAV, especially when the CAV flow starts to domain the network.

Additionally, on the Sioux Falls network part, it is found that an increase in CAV prevalence from 20% to 80% leads to an increase in TTD due to the SO principle that CAVs follow, where individuals do not always choose the shortest path optimal for the network, and sometimes engage in detouring behaviours but with a significant decrease in TTD, which explains the large increase in speed of movement of traffic; however, on the grid network The increase in CAV penetration on the Grid network reduces detours during driving. This is due to the difference in the network structure. The grid network is smaller and simpler, and it is easier to equalise the distribution of traffic, so even if a vehicle detours, the increase in distance travelled is limited, and with the limited number of alternative routes to choose from, the vehicle will not diversions too much. In conclusion, increasing CAVs can lead to smoother traffic flow and reduce the occurrence of severe traffic congestion.

2. To what extent does each rerouting parameter affect traffic flow separately? Which parameter is most important?

In this thesis, sensitivity analyses were performed on the parameters of the grid network and the Sioux Falls network, and it was found that the effects of re_{ppe} and Re_{tTh} are similar for the different networks, while re_{pe}, re_{prob}, and re_{prob} have slightly different impacts. The specific answers are given below:

This thesis finds that the effect of the parameter re_{ppe} is slight when a lane closure event occurs in both the grid network and the Sioux Falls network. re_{ppe} decides the information exchange period before CAV departing, consequently, it influences the initial route of vehicles. However, the ability to anticipate road information ahead of time has more potential to benefit trips on the network only when the majority of trips are made by CAVs. In the case of a low penetration rate of CAVs, this functionality will be of little use and may not benefit traffic conditions. At the same time, this thesis found that re_{ppe} will not work after a certain amount of time, 7s for the Grid network and 150s for the Sioux Falls network. Rerouter response times (Re_{tTh}) also have a limit of 100s on the grid network and 150s on the Sioux Falls network.

For the grid network, re_{pe} is more important when the CAV penetration rate is low, while re_{prob} and Re_{prob} are more effective when the CAV penetration rate is high. traffic conditions are more sensitive to changes in re_{prob} under low CAV PR conditions. Furthermore, it can be found that with this default setting of other parameters, if the number of CAVs is less than the number of HDVs, Re_{prob} has a random effect on traffic conditions, but when the percentage of CAVs on the road is higher than 60%, the higher rerouting probability of CAV may instead negatively affect the TTT in the network, especially when closures occur on location B. Nevertheless, when a longer period or lower probability of CAVs' automatic rerouting is applied, the rerouting function of rerouters might be more significant.

For the Sioux Falls network, test results of re_{pe} show that CAV rerouting strategies are more sensitive at CAV penetrations of 40% and 60%, and that longer routing cycles lead to better network conditions in all scenarios. This suggests that a better rerouting strategy is to reduce the number of rerouted vehicles when CAV's market share reaches 80%. For Re_{prob}, which is the maximum sensitivity interval of the rerouter is from 0 to 120 seconds.

In addition, for the gird network, comparing CAV's automatic rerouting with rerouter's rerouting, the latter is more crucial in coping with lane closures in the grid networks, because lower TTTs are detected when adjusting the parameters of the rerouting parameters of routers. However, for the grid network, the results regarding rerouters' parameters suggest that a lower number of vehicles changing routes is usually the best strategy, or in other words, without reroutes, the TTT would instead be lower.

Moreover, for both grid and Sioux Falls network, in the scenario of 80% CAV penetration, the rerouter no longer plays a significant role, this is due to the fact that when most of the trips on the network are by CAVs, they can be informed of lane closures in time, and thanks to their automatic rerouting capability, which already balances the traffic flow well, the passing of the remaining HDVs does not result in congestion near the closed road, therefore, the rerouter's regulation as well is no longer important.

3. How do road closures affect traffic conditions when they occur at different locations? Which road closure locations are more critical?

The question was answered primarily based on the results of testing on grid.

For the more congested smaller networks, intersection approaches are relatively more critical compared to other locations because the reduction in network capacity from road closures on smaller networks is more significant, congestion is more likely to spread, and the location connects surrounding paths with high traffic demand, and a large number of switching routes before the closed road adds additional congestion to the surrounding paths and is difficult to release. For L-type intersections, although there are fewer alternative routes to choose from, the closure of a lane does not result in a large number of vehicles queuing due to low traffic demand, and with the rerouter's effect, sometimes better traffic conditions can be obtained.

In addition, the importance of whether there is congestion upstream or downstream of the closed road is also affected, with more severe congestion being generated if the upstream part of the closed lane is busy, and if the downstream part of the closed lane is more congested, then the closure of that lane may have a positive impact on the network traffic by dispersing the traffic flow.

4. How can the optimal rerouting strategy be determined for a network? What is the optimal rerouting strategy for the selected network and what is its performance in responding to road closures?

It has been shown that relatively optimal rerouting strategies can be found in a short iteration time using Bayesian optimisation. In this, the results of the sensitivity analysis were used to determine the scope of the BO search using the results of the sensitivity analysis, and the number of initial solutions and the number of iterations were determined considering the computation time.

In the grid netowrk, the optimal rerouting strategy shows the parameters re_{ppe} converged to the upper limit of the search space in most scenarios, which indicates that longer rerouting pre-period may be more beneficial in reducing the total traveling time; the parameters re_{pe} and Re_{Th} have a wide range of values from 7 to 144 and from 10 to 104, respectively, suggesting that these two behaviors need to be adapted to specific scenarios; and in most scenarios, the value of CAVs' rerouting probability (re_{prob}) and rerouter's rerouting probability (Re_{prob}) are close to the upper limit of its search space, which imply that higher rerouting probabilities are favourable for improving traffic flow, the search space may narrow down in further research.

Furthermore, the optimal rerouting strategy vary greatly from scenario to scenario, suggesting that for different traffic situations, the rerouting strategy needs to be adapted to obtain the best results. TTT values varied considerably between scenarios, ranging from a minimum of 24.811 hours to a maximum of 86.028 hours. Whilst TTD varied considerably, there was no significant difference in the total distance traveled, the TTD was relatively stable, varying between 733 and 753 km. The best case is Scenario 10, with 80% CAV uptake and Lane A closed, with the shortest TTT of 23.908 hours and the lowest TTD of 733.058km; the worst case is Scenario 3, with 20% CAV penetration on the network and lane C closed, with a TTT of 86. 028 hours, and traffic is completely blocked for 57.1 hours, which is more than half of the TTT.

On the Sioux Falls network, when the CAV PR is 20 and 40, the optimal rerouting strategy is more aggressive than it of the higher CAV PR situations. When there are only 20% CAVtrips in the network, the rerouter is activated after 2 minutes and it is optimal to control only 25% of the vehicles rerouted. when the CAV penetration is 40, the optimal strategy is to take more aggressive rerouting actions for both CAVs and rerouters, with the most frequent automatic rerouting (re_{pe}=1), immediate effect (Re_{tTh}=0), and force all vehicles to reroute(Re_{prob}=1). However, as the CAV penetration increases, the rerouting probability of both CAV and rerouter tends to decrease. This is due to the fact that more CAVs join to strengthen the automatic traffic regulation function, which enables the traffic on the network to find the optimal path in a shorter time and no need for more chances to reroute.

After applying the optimal policy, the TTT, TTD and TWT of the network range from 25535 to 30600 hours, 269982.10 to 272770.53 kilometres and 294 to 351 hours respectively. Comparing the results of applying the reference parameters, the TTT reduction ranges from 324 to 1036 h. The TTD reduction spans from 703.92 to 1511.72 km. the TWT reduction ranges from 3.24 to 17.23 h. The TTD reduction ranges from 2.5 to 3.5 hours.

6.2. Discussion on methodology

6.2.1. Reflection on simulation

In this thesis, both micro and meso models are used in the simulation of mixed traffic flow, and the driving behaviour of CAVs and HDVs are differentiated, which makes the simulation results closer to the real situation; however, on the other hand, the distribution of the number of trips and O-D may not reflect the real situation on the network because the generation of traffic demand is not based on empirical data, which will result in the results of this thesis missing a certain reference value.

Secondly, the traditional Dijkstra's algorithm is used in the paper for the selection of the shortest path, and despite its demonstrated effectiveness, it results in a relatively long computation time due to its limited search efficiency. In this thesis, CAVs store up to five alternative routes, and a new route is randomly added each time the route is updated. This approach leads to an increase in computation time. Additionally, the literature indicates that the number of alternative routes affects the results, a factor not deeply investigated in this thesis. Future research could explore this aspect further, focusing on balancing computation time with optimal routing results.

In addition, due to the default settings of sumo, if a vehicle stays in place for too long or encounters a collision or other event, it will be teleported to any other path. It is worth noting that the occurrence of such a situation will have a significant impact on the TTT calculations, leading to an inaccurate analysis of the results when too many vehicles are teleported. In this thesis, this duration 'time-to-teleport' is set to 300 s. On grid's network, the number of teleports is much higher due to its overcrowdedness, therefore, the real TTT in some scenarios will be higher than in the presented results.

6.2.2. Rerouting strategy and corresponding assumption

Many papers have designed re-routing strategies with the aim of traffic balancing (in other words, to avoid additional congestion caused by all vehicles being assigned to the same shortest path) by introducing new routing algorithms. However, in this study, instead of adding any new constraints on the communication range and rerouting vehicle selection, the CAV is introduced to the network and assumed to seek the SO principle in its path selection, thus achieving automatic traffic balancing during the simulation.

Furthermore, this thesis designs rerouting strategies based on the characteristics of CAVs and HDVs, combining CAVs with more timely information updates and automatic rerouting, and HDVs with later notification. The control of the rerouting period and probability is easier for CAVs; however, it should be more tricky for HDVs, and the default assumption of 100% compliance in this thesis is too POSITIVE, and the behaviour of human drivers is much more difficult to predict in real situations. Additionally, the communication range of the rerouter can have a significant impact on the results; this thesis defaults to its notification range of 2 two streets, however, given the current infrastructure and developments in traffic broadcasting, a larger communication range could be covered.

6.2.3. Reflection on optimization

This thesis applies Bayesian optimization to determine the optimal rerouting strategy, which involves a combination of five parameters. When tested on the grid network, 100 iterations were performed. However, due to computational constraints, only 15 iterations were conducted to find the optimal solution for the Sioux Falls network. Although a relatively optimal solution was identified, there are some limitations to these results.

Firstly, no hyperparameter tuning was conducted. Despite this, the Bayesian optimization with the default hyperparameters was able to find a relatively better solution compared to the reference parameters. Consequently, this study did not pursue further hyperparameter adjustments. On one hand, this indicates that determining the search space based on sensitivity analysis results is an efficient method. On the other hand, there may still be room for improvement. With further hyperparameter tuning, it might be possible to achieve more efficient convergence or find an even better solution.

In addition, due to the small number of runs performed on the Sioux Falls network, it may not be possible to explore enough of the solution space to fall into a local optimum.

6.3. Contribution

Experiment design:
This thesis conducts an effective simulation optimization experiment, not only on a simple grid network, but also for the Sioux Falls network, an urban road network, to find optimal traffic management strategies for the road network in case of road closure. Traffic management strategies under road closure have been rarely studied, some researchers have studied the impact of road closure but have not given the corresponding solutions, this paper adopts a simulation-based approach, and through the process of sensitivity analysis and so on, it succeeds in finding the optimal traffic management strategies for road closure under different circumstances in a limited period of time, which is of some practical significance.

Comprehensive Assumptions:
A number of different hypotheses are integrated in the thesis for the rerouting behavior of CAVs and HDVs during road closures. These assumptions include a variety of driving behaviors, routing behaviors, and rerouting behaviors based on real-time information that have not been explored in depth in previous studies. By incorporating these assumptions, the simulation greatly improves the accuracy of capturing the driving behaviors of vehicles in real life.

Innovation in traffic management strategy:
To the best of the authors' knowledge, no one has investigated traffic management strategies where traditional roadside rerouting cues are paired with the automatic rerouting function of CAVs. The research in this paper makes a series of assumptions to capture as closely as possible the real rerouting behavior of CAVs and HDVs after a road closure has occurred, and tests a range of relevant control parameters and discusses the specific impacts of these parameters. This provides a new way of thinking about traffic management and can provide some theoretical support for the development of traffic management strategies in the near future.

Comprehensive analysis:
This paper comprehensively analyzes the effects of five rerouting parameters on CAVs and rerouters. Within the scope of the authors' knowledge, there is no study that summarizes the specific impact of the two parameters, namely, message reception period and probability of taking action, in the related studies on the impact of CAV's on the network, and this paper fills this gap. Moreover, all the included parameters have

clear physical meaning in real life, which can further help scholars to understand the specific behavior of CAV and its impact.

Methodological integration (micro-&meso-scale TA under road closure)
The simulation process in this thesis includes dynamic traffic assignment in micro- and meso-scale, considers the differences between CAV and HDV in car-following model and lane-change model, and simulates the vehicle rerouting behavior in the road closure scenario and successfully applies SUMO's meso-scale simulation to test the usability of its model.

Methodological integration (BO for simulation)
To the best of the authors' knowledge, there is no relevant literature on its application to the optimization of input variables for traffic simulation; this study makes that attempt by applying the Bayesian optimization method to simulation and obtaining effective results, filling the gap in the application of simulation optimization and opens up a new direction for future research.

6.4. Furture work

Firstly, in the future research, the O-D distribution of different traffic demands and different levels need to be further investigated; at the same time, the performance of different routing algorithms is further discussed to find the most suitable algorithms; for the application of Bayesian optimization algorithms, the parameterization is further tuned to find better solutions more efficiently.

Secondly, there is a need to further develop rerouting strategies, such as introducing machine learning to classify vehicles, and adopting different rerouting strategies for different classes of vehicles for more dynamic traffic management; on this basis, the placement of different rerouters can be analyzed, which will provide meaningful theoretical basis for the construction of urban traffic management infrastructure.

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The BO process visualization

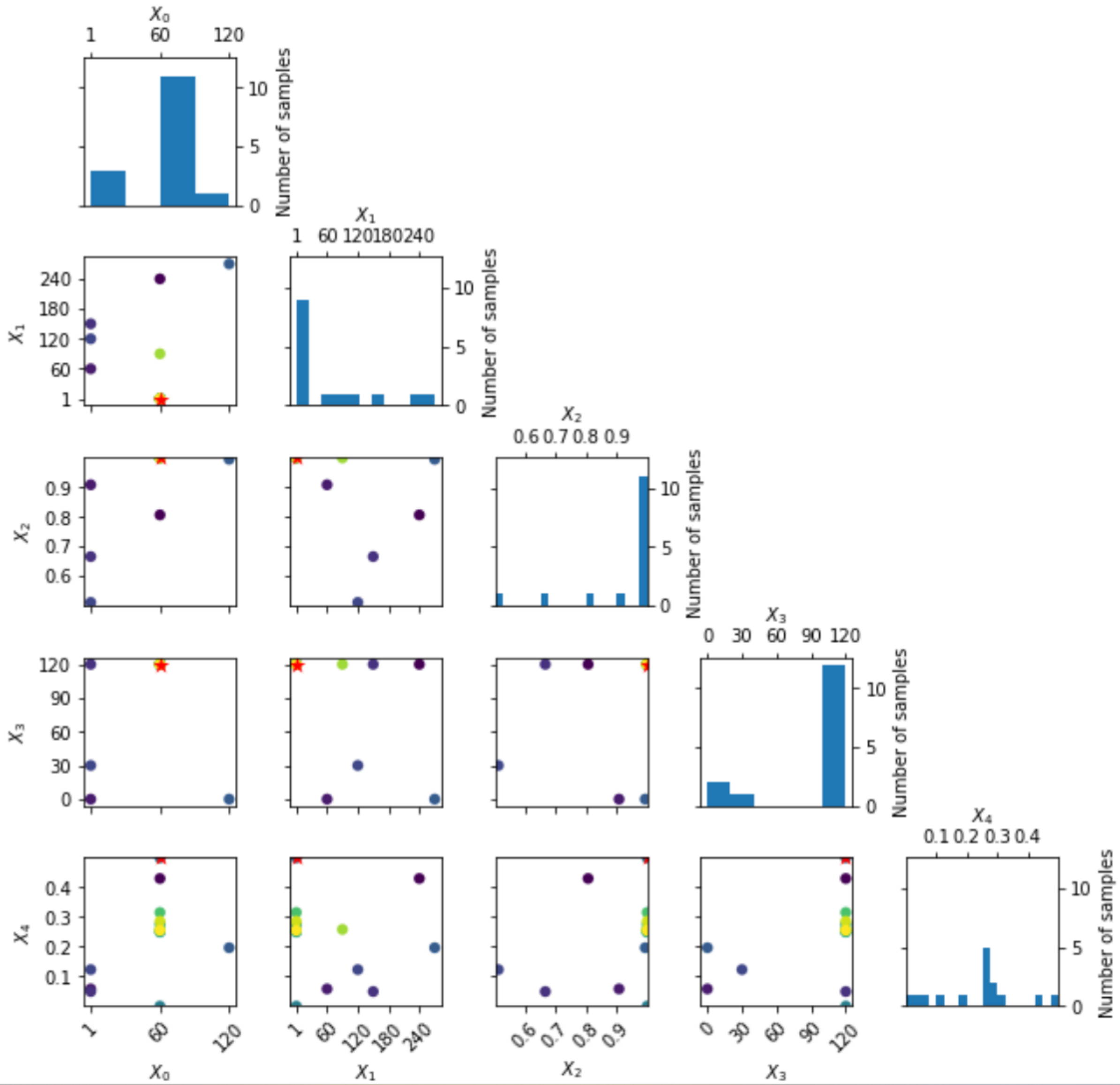

Figure A.1: The order of sampling points in the optimisation process-Sioux Falls network - 20%CAV

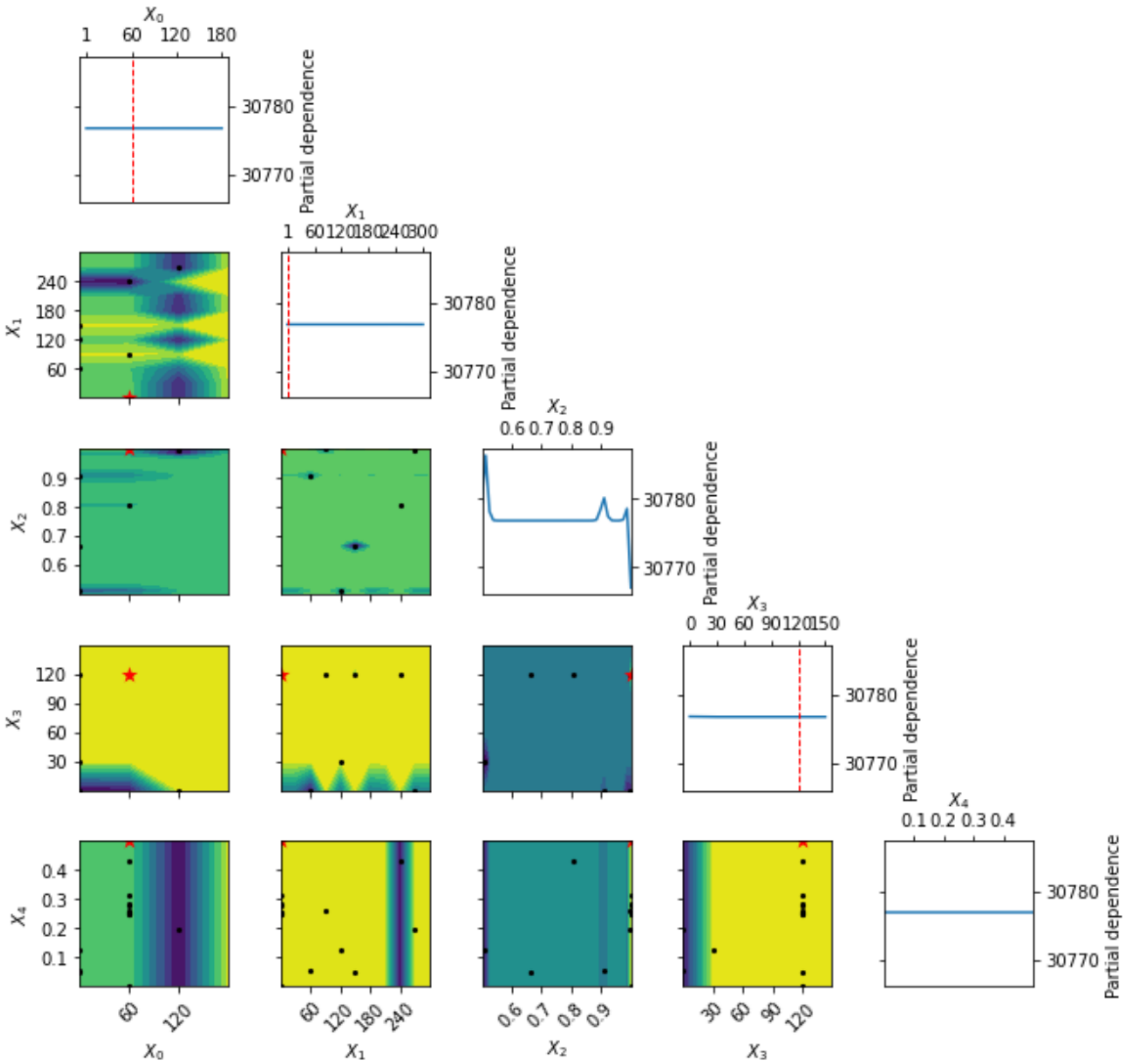

Figure A.2: Partial Dependence plot of the objective function - Sioux Falls network - 20% CAV

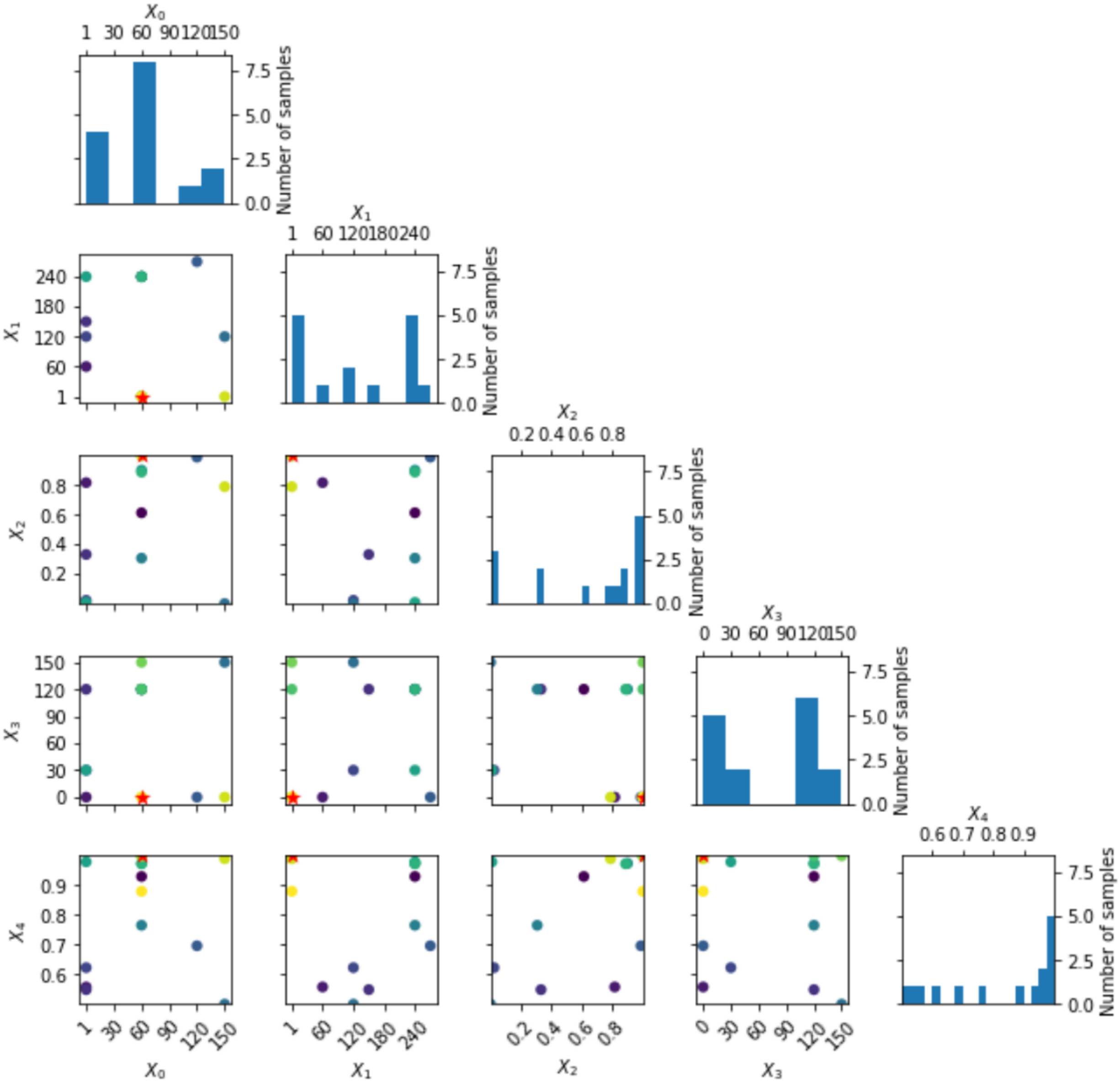

Figure A.3: The order of sampling points in the optimisation process-Sioux Falls network - 40%CAV

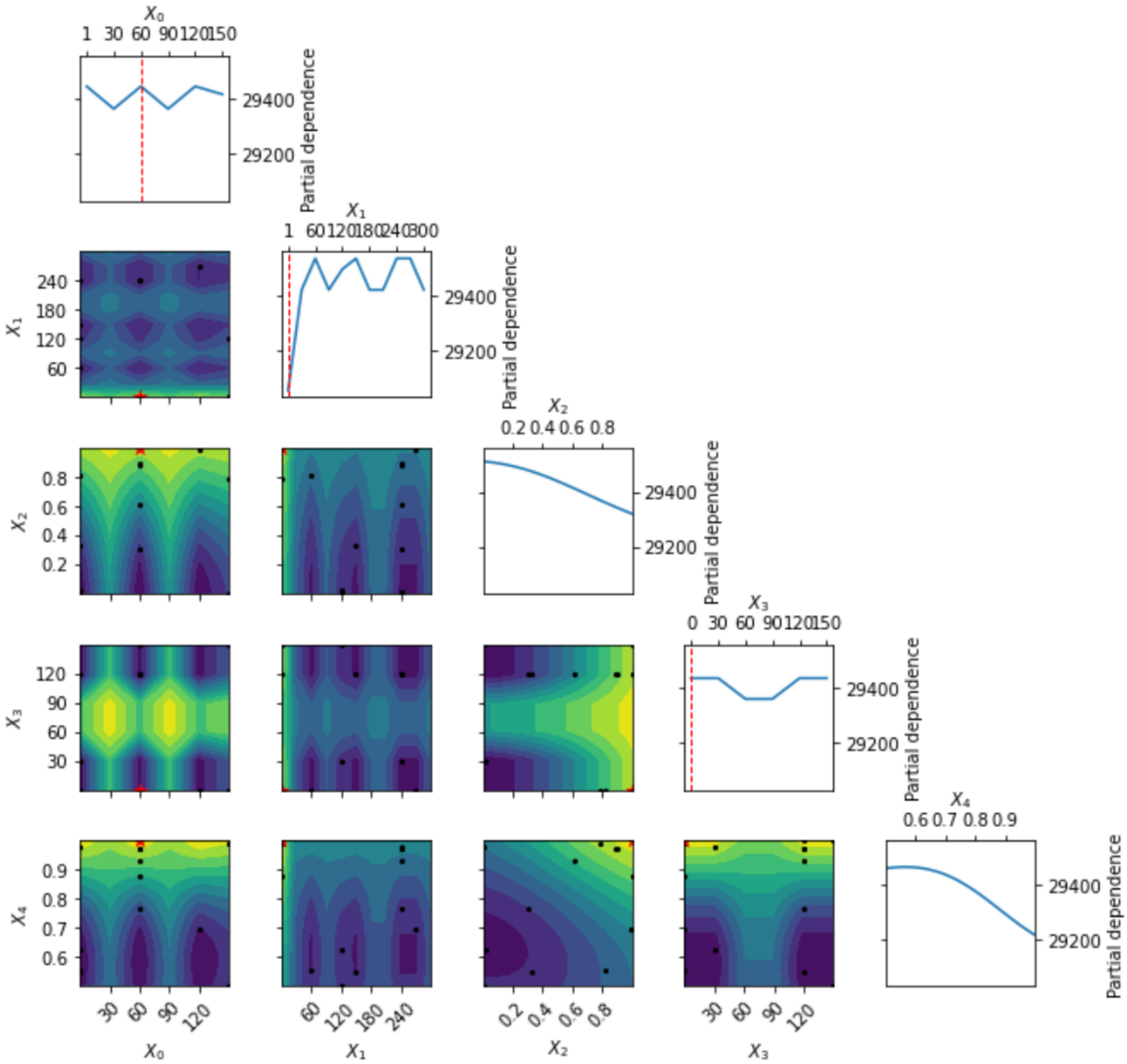

Figure A.4: Partial Dependence plot of the objective function - Sioux Falls network - 40% CAV

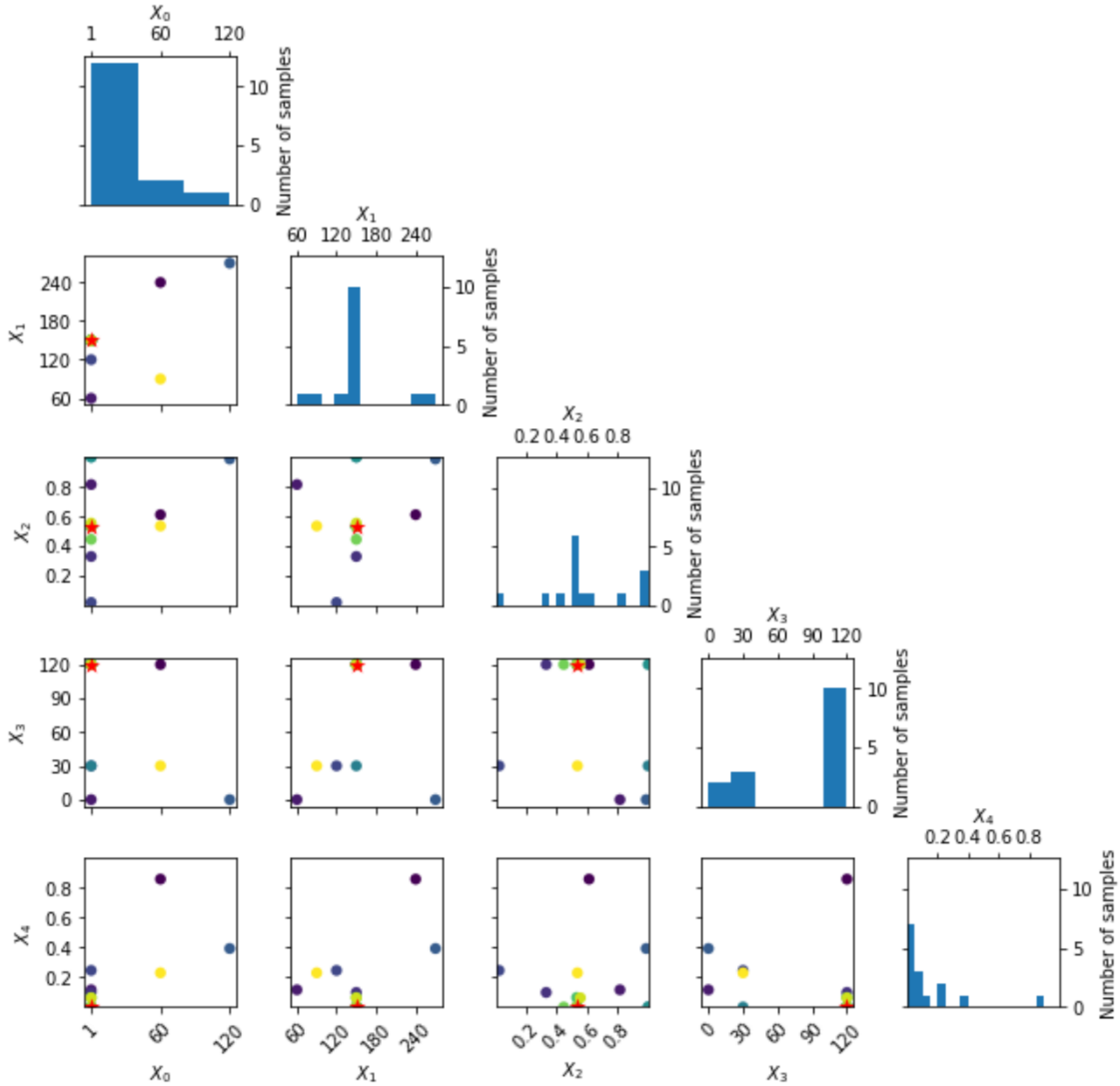

Figure A.5: The order of sampling points in the optimisation process-Sioux Falls network - 60%CAV

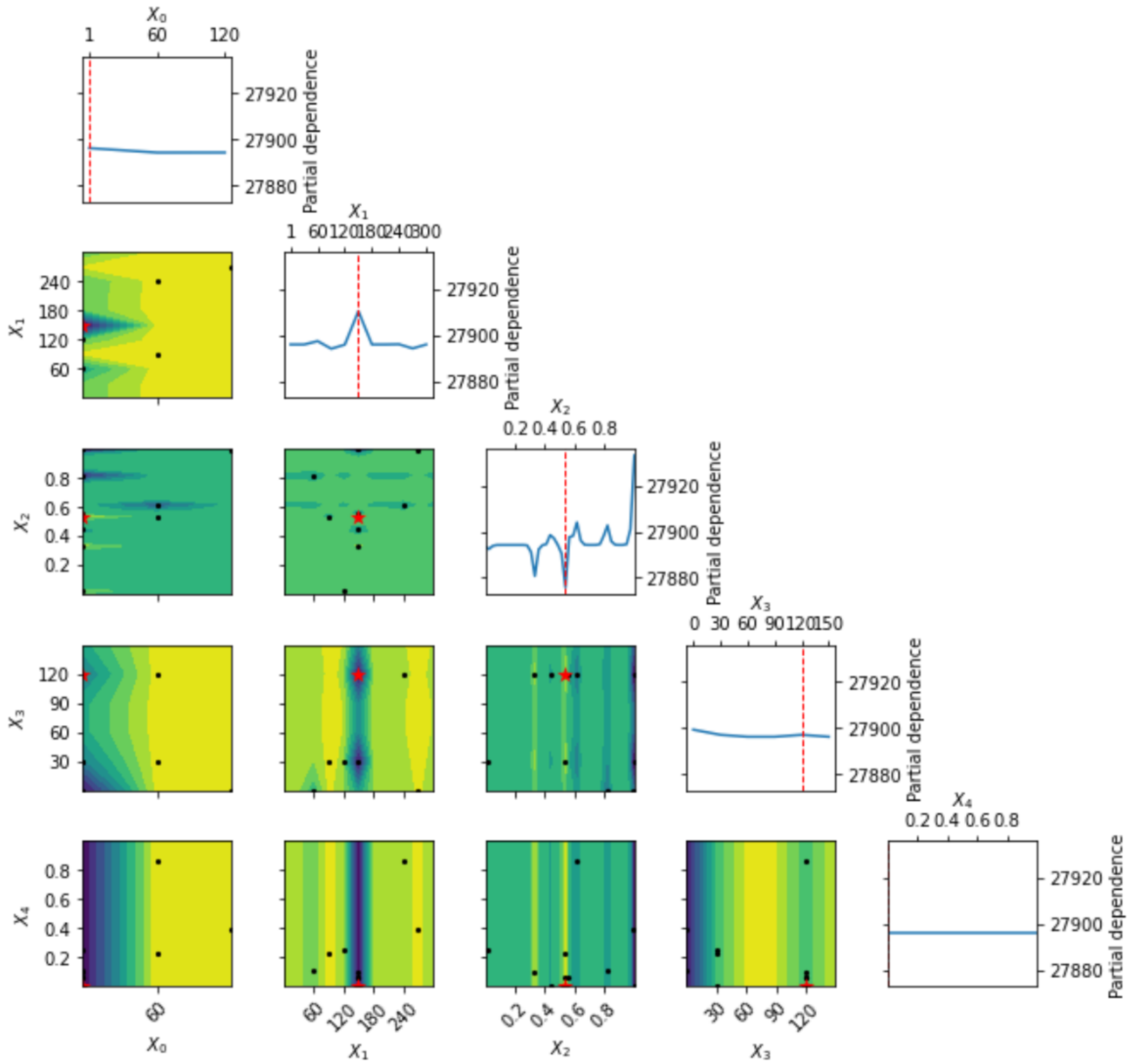

Figure A.6: Partial Dependence plot of the objective function - Sioux Falls network - 60% CAV

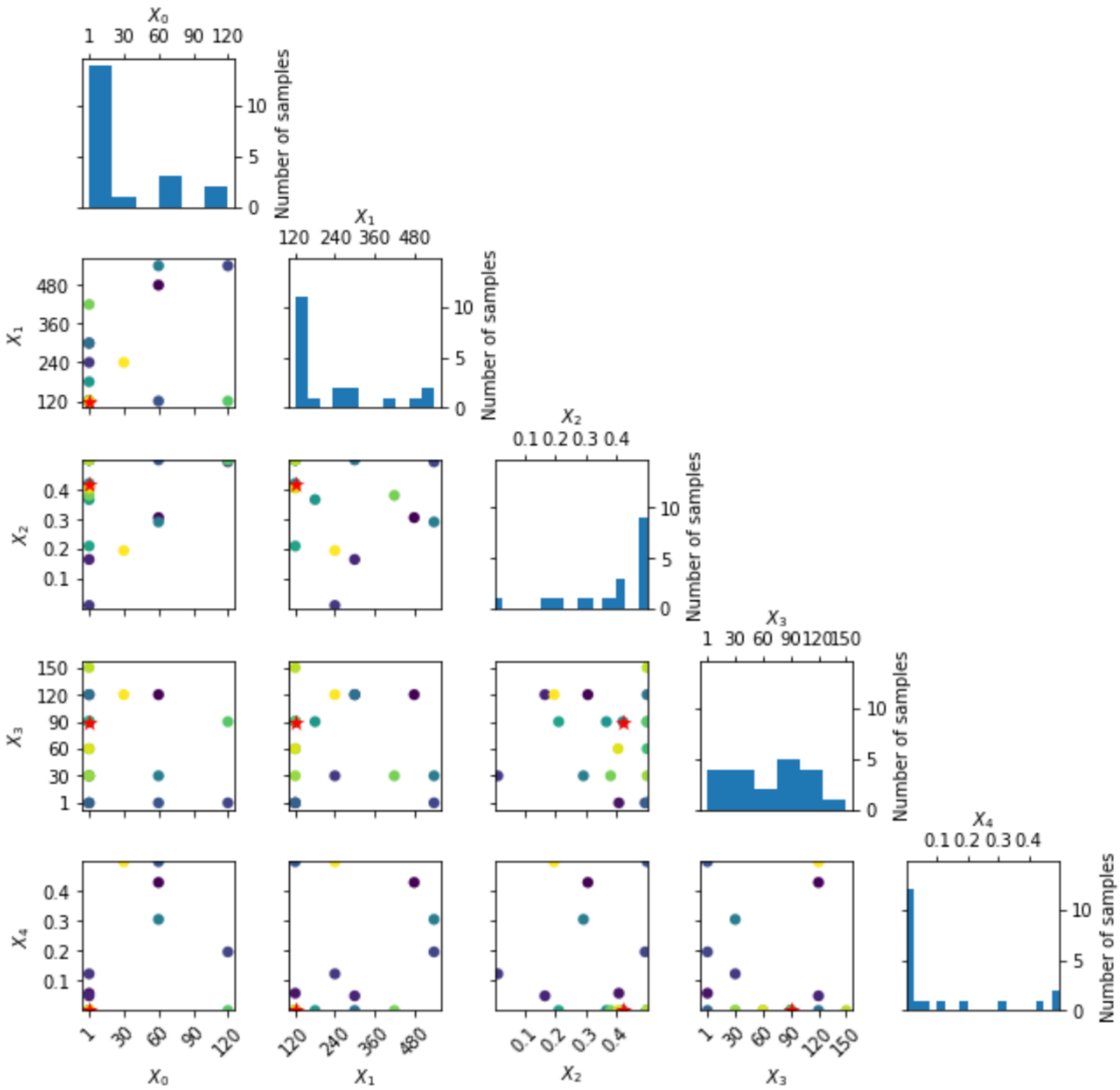

Figure A.7: The order of sampling points in the optimisation process-Sioux Falls network - 80%CAV

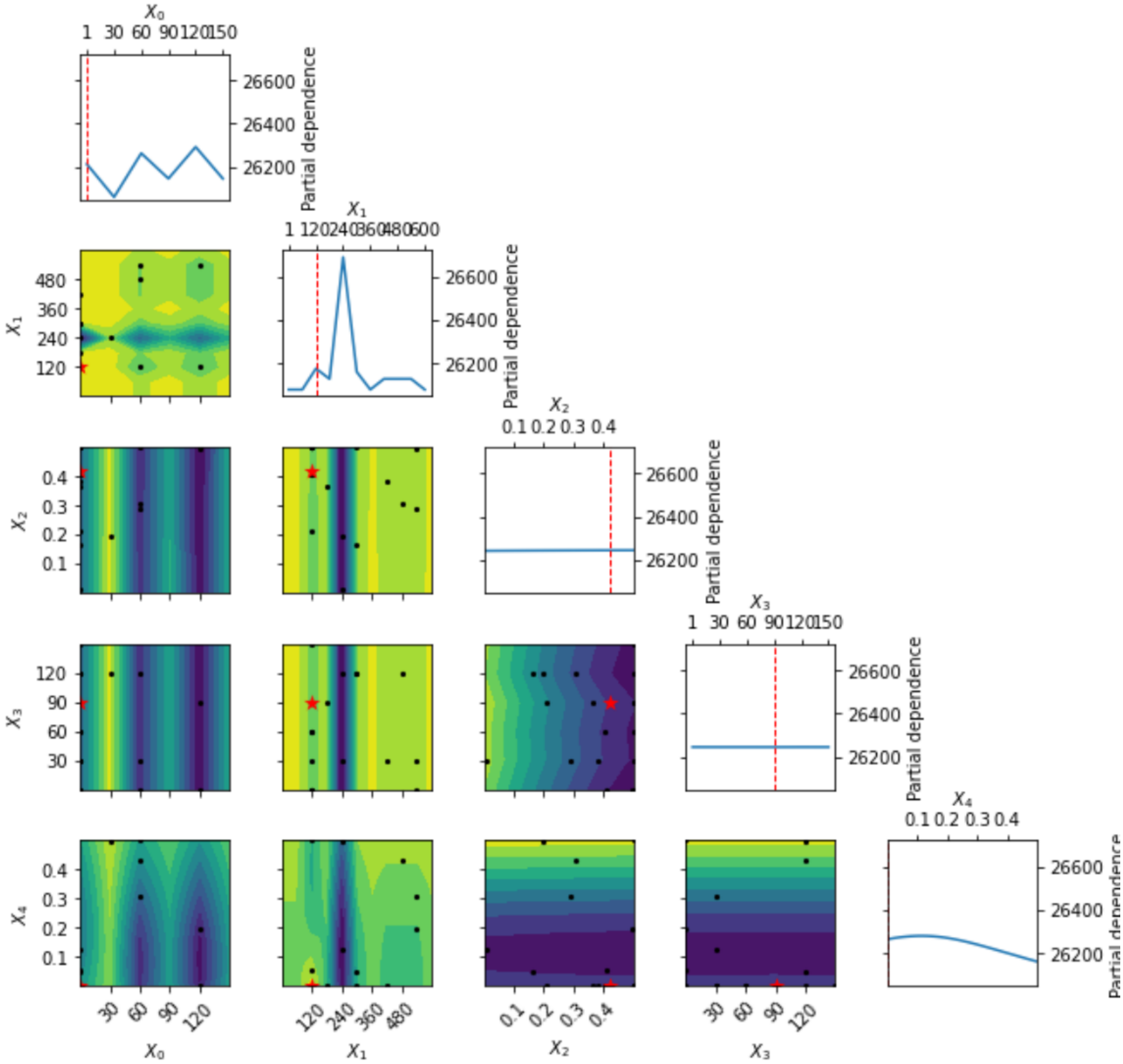

Figure A.8: Partial Dependence plot of the objective function - Sioux Falls network - 80% CAV