DISSERTATION

MULTI-SCALE URBAN TRANSPORTATION RESILIENCE MODELING AND ADAPTIVE INTERSECTION INTERVENTION WITH DISRUPTIONS

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ABSTRACT

MULTI-SCALE URBAN TRANSPORTATION RESILIENCE MODELING AND ADAPTIVE INTERSECTION INTERVENTION WITH DISRUPTIONS

Global urbanization has triggered increasing demands on modern transportation infrastructure systems by the growing density of population and intensity of human activities in the cities. A great challenge has emerged in recent decades in terms of making urban communities more resilient against physical, social, and economic disruptions. As the backbones of urban communities, road networks are expected to provide essential functionality under various disruptions caused by different extreme events and incidents, such as natural hazards, pandemics, and crashes. In response to the existing challenges, this dissertation research aims to develop multi-scale urban transportation resilience modeling techniques and adaptive intersection intervention strategy against disruptions under hazards. Specifically, this dissertation will (1) identify the appropriate simulation platform for microscopic traffic analysis and intervention under hazardous and disrupted scenarios; (2) develop microscopic flow-based and graph-based urban traffic network modeling techniques under typical disruptions; (3) propose resilience-based performance indexes in both global network and local scales of disrupted traffic systems; (4) develop new traffic speed forecasting techniques considering data disruptions using deep learning technology to offer robust traffic performance forecasting

during hazards; and (5) finally establish time-progressive traffic resilience forecasting strategy during hazardous weather to support proactive intervention.

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DEDICATION

To my family and myself

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CHAPTER 1 INTRODUCTION

1.1 Background

Global urbanization has triggered increasing demands on modern transportation infrastructure systems by the growing density of population and intensity of human activities in the cities (Lem, 2016). A great challenge has emerged in recent decades in terms of making urban communities more resilient against physical, social, and economic disruptions (Ganin et al. 2017; Zou and Chen 2020; Ouyang and Wang 2015). As the backbones of urban communities, road networks are expected to provide essential functionality under various disruptions caused by different extreme events and incidents, such as natural hazards, pandemics, and crashes. Despite the diversity of causes, disruptions usually produce multiple bottlenecks and local congestions on vulnerable roads and intersections, and even paralyze the whole traffic network in the region (Miller-Hooks et al. 2012; Hou and Chen 2020). To cope with both local and global impacts of disruptions on a traffic network throughout a hazard or incident requires realistic characterizations of the traffic network's performance in appropriate temporal and spatial scales. Such characterizations often need to go beyond traditional local traffic performance measures, such as travel time, speed and delay of individual roads and intersections, and rather extend to the network resilience performance (Gao et al. 2016; Miller-Hooks et al. 2012).

Resilience is a relatively new concept to engineering which has gained substantial attention and progress in the past decade by focusing on the system behavior under disturbances or attacks, specifically the ability to provide its basic functionality as measured by robustness, redundancy, resourcefulness, and rapidity (Reggiani 2013). Recently, more advanced resilience-based modeling techniques of disrupted traffic systems have been developed to consider more realistic disruptive scenarios under hazards (e.g., Hou et al. 2019), increased crash risks (e.g., Hou and Chen 2020), and interactions with other interdependent infrastructures (e.g., Zou and Chen 2020). With the improved understanding of the complex traffic systems under hazards, it has been found that both local traffic performance and network resilience are essential to fully capturing the performance of any disrupted traffic system under hazards.

Traffic system resilience studies depend on timely and accurate traffic data from either real-world data monitoring or simulation. However, as compared to the abundant data under normal conditions, the site-specific and hazard-specific nature of traffic performance under disruptions often make the available data under specific disruptions very limited and hard to be transferred from another event or location. Such data scarcity is often exacerbated by the data disruption during natural hazards: damages or failures often occur to other critical infrastructure systems such as power and communication systems, which will lead to the malfunctioning of traffic monitoring sensors, data interruptions or transmission bottlenecks (e.g., Zou and Chen 2019). It is therefore critical to provide prompt and reliable traffic data forecast in refined scales during natural hazards by accommodating fast time-variant nature and possible disruptions on both infrastructures and essential data.

With the improved knowledge of traffic performance, critical needs arise in terms of how to effectively improve the resilience performance of disrupted traffic systems through effective mitigation or intervention efforts. Various emerging technologies, such as autonomous driving, smart intersection traffic management, and other Intelligent Transportation Systems (ITS) approaches, have been adopted during the last decades to construct more robust traffic systems against hazards or incidents (Ganin et al. 2019; Andronov and Leverents 2018; Yao and Chen 2022). Vehicle crashes, for example, are the most common type of traffic disruptions responsible for majority of non-recurring congestion and delay during daily operations (Wang et al., 2020). Especially at intersections of urban traffic systems, vehicle crashes often result in long queue lengths so that considerable time resource has been wasted due to induced congestions (Fei et al., 2017). Traffic signal designs, therefore, are critical to traffic safety and efficiency at intersections during day-to-day service including normal or heavy traffic scenarios (Gartner et al., 1995). However, how to develop appropriate traffic intervention strategies for disrupted traffic systems under various hazards or incidents remains a huge challenge. In the following section, a literature review of related topics will be made.

1.2 Literature review

This section reviews past research pertaining to the microscopic traffic simulation platform comparison, smart traffic signal design, traffic network resilience modeling, and traffic data forecasting under hazardous scenarios.

1.2.1 Traffic network modeling in microscopic scale

Numerous traffic simulation and analysis tools have been developed by public agencies, research organizations, and private vendors & consultants. Traffic simulation tools can generally be grouped into three categories by scales: i.e., macroscopic, mesoscopic, and microscopic scales.

<u>Macroscopic simulation</u>

A macroscopic model simulates traffic on a section-by-section basis rather than by tracking individual vehicles. Macroscopic simulation models were first designed to represent traffic in specific transportation subnetworks such as freeways, corridors (containing freeways and parallel arterials), surface-street grid networks, and rural roads (Zhang and Zheng 2016). The flow, speed, and density of the traffic stream are usually in deterministic relationships for macroscopic simulation models. Various assumptions are applied on local details, and the results from macroscopic-scale simulations are usually used for regional traffic analyses when road-level traffic details are not the primary concern.

Microscopic simulation

Based on car-following and lane-changing theories, microscopic simulation models recreate the movement of individual vehicles at the refined road level. Microscopic models are useful for examining extremely crowded circumstances, complicated geometric configurations, and system-level consequences of proposed transportation upgrades requiring sufficient local details. These models can capture local traffic details on each individual road, and in the meantime simulations with microscopic models are time consuming and can require significant amount of data to calibrate (Yin and Rakha 2019).

Mesoscopic Simulation Models

Mesoscopic-scale simulation models are between the macroscopic and microscopic scales in terms of modeling details. Such models incorporate parts of the characteristics of both microscopic and macroscopic simulation models. As a result, mesoscopic models have lower fidelity than micro-simulation tools yet outperform traditional planning analysis approaches (Zheng et al. 2014).

1.2.2 Intelligent Traffic Control

Intelligent technology has been widely applied in traffic control in urban cities to mitigate congestion and reduce vehicle delay in recent years (Andronov and Leverents, 2018). Traffic signal designs are critical to traffic safety and efficiency at intersections during day-to-day service including normal or heavy traffic scenarios (Gartner et al. 1995). Intelligent traffic signal control typically depends on various devices such as traffic monitoring cameras, road sensors, and existence detectors, along with advanced algorithms to satisfy various traffic safety and efficiency needs (Pandit et al., 2013). During the past decades, significant research efforts have been put forth to study signal timing optimization techniques to mitigate recurring traffic congestion during rush hours. For example, an improved automatic traffic volume detection technique using V2I communication was proposed to get the traffic information in time for the following optimization (Sheikh et al. 2000). Discrete dynamic optimization models for optimal cycle length and green time allocation were evaluated to identify the most appropriate design for dealing with congested traffic scenarios (Chang and Lin 2000). In recent years, there have been some emerging research efforts on investigating intersection signal designs for non-recurrent congestion. A cell transmission model for a signalized intersection was developed for different congestion evacuation schemes (He et al. 2017). GPS data was utilized for a global network modeling to evaluate the traffic condition with matrix factorization and clustering methods during emergency recovery (Han et al. 2019). A signal timing optimization model using queue length as the penalty value has also been developed under traffic incident scenarios, in which a heuristic algorithm (simulated annealing algorithm) was adopted (Wang et al. 2020).

1.2.3 Traffic network resilience modeling based on graph theory

Networks are common in our world which have been extensively studied by mathematicians, physicists, and others with broad applications on biology, social science, statistics, computer science and other areas (Newman 2018). For traffic networks, topological robustness provides an important gauge of resilience against various disruptions (Li et al. 2021). Topological robustness study of traffic networks requires minimum site-specific data and can seamlessly leverage existing advances in networks primarily accumulated in other fields (Newman 2018; Abdulla et al. 2021; Li et al. 2015). The adoption of mathematical modeling of networks, graph percolation theory, and community structures has opened doors to many analytical studies of generic networks. Although some site-specific details of a traffic network may be inevitably sacrificed, network science offers convenient and science-based analytical tools which can help understanding the formation and dynamics of traffic networks (Callaway et al. 2000; Huang et al. 2011; Gao et al. 2011; Li et al. 2015; Ganin et al. 2017, 2019; Hamedmoghadam et al. 2021; Li et al. 2021). In addition to the analytical studies with minimum data requirement, another type of network resilience studies depend on intensive empirical data of the traffic network, i.e., traffic flow data through either simulations or data-driven analyses. In recent years, two emerging techniques developed based on graph theory have shown promising potentials, including adopting contagious process to study congestion propagation (e.g., Saberi et al. 2020) and percolation theory to study topological robustness (e.g., Li et al. 2021; Dong et al. 2020). These two techniques will be briefly introduced in the following section.

1.2.3.1 Percolation theory

Percolation is often used to understand the formation and transition process of network dynamics under two general types of attacks: random attacks and target attacks (Newman 2018). In the context of traffic networks, a road segment (or "edge") will be deemed practically "failed" (i.e., heavily congested) according to a set criterion (e.g., speed) or following a probability of failure which is often assumed to be uniform for all the edges of the network. With the increasing criteria or probability of failure, the "failed" road segments will be gradually "removed" from the traffic network, generating different snapshots of "remaining" traffic networks. These snapshots will provide a vivid transition process of the traffic network under different intensities of attacks with some popular measures of robustness such as giant component size and critical percolation threshold (Newman 2018). The uniform probability of failure on each edge provides great convenience on mathematical derivation with classical network science techniques, facilitating some analytical approaches with closed-form results (e.g., Callaway et al. 2000; Newman 2008). Although the analytical approach offers a powerful and neat tool to characterize the general robustness of many networks, recent studies have found it will cause some unrealistic results for traffic networks due to degree assortativity of the specific traffic network (e.g., Dong et al. 2020) and heterogeneous nature of traffic flow (e.g., Hamedmoghadam et al. 2021). In addition to assuming a probability failure rate for each road segment, another approach to study the percolation process uses the real-world traffic data which can inherently capture specific traffic network topology and flow characteristics (e.g., Zeng et al. 2019; Li et al. 2014).

1.2.3.2 SIR model

Among many models forecasting contagious process of epidemic disease, the model called SIR (S: susceptible; I: infected; R recovered) introduced by Kermack and McKendrick (1921) has been widely adopted. The main idea behind the SIR model is a mathematical hypothesis developed to explain the fast rise and drop in the number of infected people with a contagious disease in a contained community over time (Marinov and Marinova 2020). Recently, the SIR model has been successfully applied to simulate traffic congestion with promising capabilities in understanding the transition of disrupted areas from the start to the end (Saberi et al. 2020). In this study, an empirical multi-city analysis of rush-hour traffic data is conducted using the SIR model to forecast the congested link over time (Saberi et al. 2020). If a traffic network is considered as a contained community under a specific disruption, the links adjacent to the congested links were found to be more easily congested at that moment (Saberi et al. 2020). After the disruption is cleared, the recovered links are those links with queues already dissipated. Therefore, the initial congested links of the network were considered just like the first group of infected people. In addition, a hybrid analysis combining percolation process and SIR model to foresee the spread and recession of floodwaters in urban traffic networks was conducted to assist emergency managers, public authorities, residents, first responders, and other decision-makers with flood forecasting on the traffic network (Fan et al. 2020).

1.2.4 Traffic forecasting using machine learning techniques

Urbanization across the globe poses significant challenges on mobility and traffic safety in not only day-to-day normal conditions, but also adverse scenarios associated with inclement weather, natural hazards, and man-made incidents (Ganin et al. 2017; Miller-Hooks et al. 2012; Ouyang and Wang 2015). During the past decades, various technological advances such as autonomous driving, smart intersection traffic management and other Intelligent Transportation Systems (ITS) techniques have been embraced to build a more resilient traffic systems against hazards or incidents (Ganin et al. 2019; Andronov and Leverents 2018; Yao and Chen 2022). One key task to support all these efforts is to offer fast and accurate traffic forecasting such as flow and speeds at road segments, intersections, and the whole traffic network. Traffic performance of disrupted transportation systems during hazards often vary more quickly over time and in a more complex manner than that under normal conditions (Hou et al. 2019).

Deep neural work models have become the prevailing efforts on traffic prediction because of the advantage of capturing complex and nonlinear traffic patterns. In terms of neural network structures, numerous existing works use convolutional neural networks (CNN), recurrent neural networks (e.g., LSTM), feedforward neural networks and the hybrid models to capture temporal and spatial aspects of traffic data (Tedjopurnomo et al. 2022; Kumar and Raubal 2021; Yu et al. 2018). One recent breakthrough in traffic prediction using deep neural network is the graph-based methods (e.g., Xu et al. 2019; Cui et al. 2019; Pan et al. 2019; Yu et al. 2017). For example, Li et al. (2018) proposed diffusion convolutional recurrent neural network (DCRNN) based on a bidirectional graph walk which is then incorporated into a Gated Recurrent Unit RNN to conduct traffic forecasting. Bai et al. (2020) developed adaptive graph convolutional recurrent network (AGCRN) for traffic forecasting to capture fine-grained spatial and temporal correlations in traffic series automatically, which enabled elevated robustness of data analysis. Significant progress has been made in terms of more accurate and efficient deep learning techniques on traffic forecasting, especially by taking advantage of emerging graph techniques and hybrid deep learning modeling. More details about traffic prediction using deep neural networks can be found in Ref (Tedjopurnomo et al. 2022). Most of existing studies focused on advancing the deep learning accuracy and efficiency in the context of time series in general or the forecast of traffic speed or flow in response to recurrent congestions in normal conditions. Only limited studies on adverse traffic conditions were made to consider adverse conditions, such as weather impact as external inputs using secondary datasets (Jia et al. 2017; Soua et al. 2016; Zhang and Kabuka 2017) or accident data (Yu et al. 2017).

1.3 Research gaps and motivations

1.3.1 Urban intersection intervention through optimized traffic control under disruptions

Recurring traffic congestion in urban cities has been considered a huge waste of both time and energy in our daily life, which has attracted significant research efforts. Traffic networks often experience various disruptions because of natural hazards or incidents, such as hurricanes, earthquakes, floodings, car crashes or power outages (Koks et al. 2019; Paprotny el al. 2018). Such disruptions typically result in multiple bottlenecks, lane narrowing or local work zones, causing severe non-recurring congestions on affected roads and intersections (Miller-Hooks et al. 2012; Hou and Chen 2020). Such local non-recurring congestions often start only in small areas being affected and can propagate quickly both spatially and temporally throughout the whole traffic network, which can even paralyze the whole traffic system in a city when reliable and smooth transportation is crucial during hazard/incident response and recovery. As compared to the recurring counterpart, non-recurring congestions caused by hazards or incidents are usually harder to be predicted and mitigated.

Typical modes of operation for traffic signals include pre-timed (fixed time) and actuated operations. Despite being straightforward and easy to coordinate between intersections, pretimed operation is more suitable for close intersections with constant traffic volumes but lacks flexibility to adjust with varying traffic demands and environments. Actuated operation, on the other hand, can adjust phase durations and sequences by detecting real-time traffic conditions, such as prolonging or shortening phase durations and skipping a phase based on traffic demand. As a result, actuated operation does not have a fixed cycle length because of not always displaying a complete sequence and duration of a cycle and therefore is hard to coordinate among intersections.

1.3.2 Traffic resilience modeling with disruptions under hazards

Traffic networks are typically modeled in microscopic, mesoscopic, and macroscopic scales based on traffic flow and graph theory with different granularities. Graph theory, on the one hand, has the advantage of convenience with much less dependence on traffic data, but it cannot capture sufficient details in traffic network which can be used in intersection interventions. Microscopic traffic modeling, on the other hand, can provide all the traffic information in detail on individual roads of the traffic network. However, it requires large amount of time for calibration to match the real traffic pattern in different scenarios, especially when time-progressive disruption nature is to be modeled, for which the optimal moment and intervention approach to apply any intervention using ITS technology become tricky to find out.

To cope with both local and global impacts of disruptions on a traffic network throughout a hazard or incident, it requires comprehensive characterizations of the traffic network's performance in appropriate temporal and spatial scales. It has been found such characterizations often need to include not only traditional local traffic performance measures, such as travel time, speed and delay of individual roads and intersections, but also the network resilience performance (Gao et al. 2016; Miller-Hooks et al. 2012). A road traffic system bears two unique challenges in terms of resilience modeling, though it shares some common characteristics and challenges with other infrastructure systems. These unique challenges of the road traffic system resilience primarily include: (1) sophisticated coupling among individual vehicles, drivers, infrastructures, and environments under disruptions (Hou et al. 2019), and (2) the lack of reliable data under disruptions due to the high site-specific and environment-specific nature under hazards and incidents (Miller-Hooks et al. 2012; Dong et al. 2020).

Another challenge for data-driven studies on traffic network resilience under disruptions is about the data granularity and availability when refined data such as floating car data from reliable sources are not always available because of proprietary nature and cost. Not all stakeholders (e.g., local transportation departments) have access to detailed traffic data on each road segment with refined temporal and spatial scales during a hazard. Rather, it is more common that some stakeholders only have access to the basic and coarse traffic data at some major intersections due to the limitations on the available monitoring infrastructures and operational budget. For natural hazards, it is even more common that only sparse sensors can function properly to provide reliable post-hazard data due to harsh environments or possible power outrage during hazards. The lack of reliable data with sufficient granularity for disrupted traffic systems has been the main cause of the fact that majority of existing traffic resilience studies during hazards are limited to the connectivity and accessibility analyses which require no or little data at local road segment levels (e.g., Taylor 2008; Zhou et al. 2019; Dong et al. 2020).

1.3.3 Data-driven traffic forecasting of disrupted traffic network and proactive intervention under hazards or incidents

During hazards and other adverse scenarios, traffic systems experience various disruptions on infrastructures, such as temporary lane narrowing or closure by debris or accidents, and power outage on traffic signals, etc. (Hou et al. 2019; Hou and Chen 2020). Effective emergency response, intervention and recovery efforts following hazards all rely on timely and accurate traffic information of the disrupted traffic system, which however is considerably different from that during normal conditions (Ganin et al. 2019; Hou and Chen 2019). Data scarcity during traffic disruptions is a significant challenge due to the site-specific and hazard-specific nature of these events. Compared to the abundant data available under normal conditions, the data collected during disruptions is often limited and difficult to transfer from one event or location to another. Natural hazards further compound this issue as they can damage critical infrastructure systems like power and communication, causing malfunctions in traffic monitoring sensors and interruptions in data transmission. This scarcity of data hampers effective analysis and planning during disruptions. (e.g., Zou and Chen 2019).

Therefore, traffic forecasts with sufficient details and granularity in both spatial and temporal scales is often required to support prompt and proactive emergency response and intervention. As discussed above, traffic data disruptions may occur during natural hazards, which are hard to foresee and prepare for. It is therefore critical to provide prompt and reliable traffic data forecast in refined scales during natural hazards by accommodating fast time-variant nature and possible disruptions on both infrastructures and essential data.

With the wide adoption of traffic sensors, large amount of traffic data has become available, which foster extensive research efforts on data-driven traffic prediction, such as traffic flow (e.g., Xu et al. 2019; Pan et al. 2019) and speed (e.g., Cui et al. 2019; Xie et al. 2020; Dai et al. 2017). Following initial work using classical statistical methods and machine learning techniques using shallow networks, deep neural work models have become the prevailing efforts on traffic prediction because of the advantage of capturing complex and nonlinear traffic patterns. In reality, traffic systems experience some unique challenges during natural hazards or other adverse conditions such as disruptions on both infrastructures and possible data availability. Despite all the progress and promising perspectives on traffic forecasting with deep learning techniques, some questions remain in terms of how to take advantage of the state-of-the-art progress to improve the traffic system resilience against natural hazards by accommodating possible disruptions. These questions include: (1) with possible data disruptions during hazards, how to maintain robust and seamless traffic predictions? (2) if emergency recovery of disrupted data is needed, what would be the best prioritization strategy with limited resources? (3) how to use very limited data of the disrupted traffic system during hazards to forecast the traffic performance accurately and promptly? A robust proactive traffic performance prediction strategy for urban traffic networks is necessary to be developed with an attempt to offer some answers to these questions based on the state-of-the-art deep learning techniques.

1.4 Research objectives

This dissertation research aims to develop multi-scale urban transportation resilience modeling techniques and adaptive intersection intervention strategy against various disruptions under hazards. Specifically, this research will have the following five objectives:

1.4.1 Select appropriate microscopic urban traffic network modeling platform to meet research needs

The traffic performance assessment of disrupted traffic networks under hazards depends on accurate flow-based and graph-based modeling. Before conducting any advanced traffic signal studies of traffic networks with various disruptions, appropriate modeling techniques and software need to be evaluated and identified for urban traffic network and signal optimization. Specifically, two different urban traffic networks will be modeled with two popular modeling software: "CORridor SIMulation" (CORSIM) and Simulation of Urban Mobility (SUMO) as candidates for our following study. The modeling process with two candidate software will consist of two parts: (1) modeling a microscopic-scale traffic network for traffic performance assessment, and (2) modeling traffic signal planning and optimization.

1.4.2 Propose resilience-based adaptive single-intersection traffic signal strategy to improve local performance inresponse to disruptions.

Following major hazards and incidents, it is crucial to mitigate the congestion at intersections of urban traffic systems with disruptions, maximize the evacuation, rescue and recovery efficiency and prevent a hazard from turning into a disaster. An optimized traffic signal design strategy can effectively contribute to maintaining an efficient traffic system operation despite various disruptions. Dynamic Phase Selection (DPS) technology is applied to adjust the traffic signal control plan adaptively during the incident stage, while the queue length dissipation (QLD) algorithm is adopted to carry out optimal green time calculation during the recovery stage. The proposed methodology is demonstrated by considering disruptions caused by several typical vehicle crashes at a single intersection.

1.4.3 Propose percolation-based resilience modeling and active intervention of disrupted urban traffic network during hazardous scenarios

Road networks are the backbones of urban communities, which are vulnerable to many disruptions caused by natural hazards, crashes, and rush hours, etc. Numerous efforts have been made in recent years toward building more resilient urban road traffic systems against various disruptions through improved understanding of resilience performance and more effective traffic intervention. A new resilience modeling methodology will be developed in this part for disrupted traffic systems under natural hazards in terms of both local traffic performance and percolation-based robustness at the network scale. Hybrid data enhancement will be conducted by integrating limited real-world data and microscopic traffic simulation to address the common challenge of data scarcity under hazards.

1.4.4 Develop transfer learning-based traffic speed forecast for urban traffic network during snowstorms

During hazards and other adverse scenarios, traffic systems experience various infrastructure disruptions. These disruptions change over time with the progression of hazards and the recovery efforts following hazards, which make the related traffic data become nonstationary and nonlinear over time. More importantly, the traffic data involving various disruptions during hazards is very rare and highly hazard-specific and site-specific. To address the unique challenges of the data scarcity and the “dynamic” nature of the data, a robust traffic performance prediction strategy for urban traffic networks under hazards will be developed to provide satisfactory predictions even with various disruptions during snowstorms.

1.4.5 Propose deep learning-based time-progressive traffic resilience forecasting during hazardous weather

During hazardous weather events, transportation systems face numerous disruptions, making it challenging to predict traffic efficiency, resilience performance, and implement effective mitigation strategies. Therefore, this part of the work will develop a comprehensive time-progressive methodology that can provide a holistic forecast of resilience performance over time, enabling informed decision-making for proactive mitigation efforts in transportation systems during hazardous weather events.

1.5 Dissertation outline

The outline of the dissertation is as follows:

Chapter 1 provides the research background for this dissertation and presents the literature review on the related research topics. Based on the literature review, the research gaps for these research topics are identified and the research objectives are described.

In Chapter 2, to support our subsequent study, two candidate traffic simulation platforms will be studied in terms of traffic network modeling and traffic signal control with different urban traffic networks, namely the public transit network (MAX bus route) and a typical urban corridor in the City of Fort Collins, Colorado. Both networks will be modeled using CORSIM and SUMO as potential simulation platform candidates. The modeling process with the two candidate software will be divided into two parts: Firstly, a microscopic-scale traffic network will be modeled to assess traffic performance. Secondly, traffic signal planning and optimization will be modeled. Following the modeling results, a comprehensive discussion will be conducted to analyze and interpret the findings.

In Chapter 3, an adaptive traffic signal control strategy in response to traffic disruptions at a single intersection is proposed by covering both the incident and recovery stages. Dynamic Phase Selection (DPS) technology is applied to adjust the traffic signal control plan adaptively during the incident stage, while the queue length dissipation (QLD) algorithm is adopted to carry out optimal green time calculation during the recovery stage. The proposed methodology is demonstrated by considering disruptions caused by several typical vehicle crashes at the intersection.

In Chapter 4, a new resilience modeling methodology is developed for the disrupted traffic systems under natural hazards in terms of both local traffic performance and percolation-based robustness at the network scale. Hybrid data enhancement is conducted by integrating limited real-world data and microscopic traffic simulation to address the common challenge of data scarcity under hazards. The study further investigates the feasibility of applying early active traffic intervention through optimizing traffic signal designs only at some strategic intersections to improve both the traffic performance and resilience at local and network scales. A case study of City of Fort Collins during snowstorms is made to demonstrate the methodology.

In Chapter 5, a robust traffic performance prediction strategy for urban traffic networks under hazards integrating a modified DCRNN model and transfer learning method is proposed. It starts with traffic speed short-term forecast modeling with the DCRNN techniques of the whole network with hybrid data from normal conditions, followed by refined traffic speed forecasting under snowy conditions through transfer learning. Comparisons with other counterpart models are made. A case study of the City of Fort Collins during a major snowstorm in Colorado is conducted to demonstrate the proposed methodology and it was found the transfer-learning-based traffic speed forecasting strategy can provide satisfactory predictions even with various disruptions during snowstorms.

In Chapter 6, a holistic time-progressive resilience performance forecasting methodology is proposed based on graph theory and deep learning techniques to address the significant challenges on predicting the traffic efficiency, resilience performance, and applying any informed mitigation efforts. Such a methodology consists of two components: (1) modified DCRNN-based short-term traffic forecasting module; and (2) time-progressive resilience forecasting module integrating percolation-based robustness assessment and SIR-based congestion propagation modeling.

Chapter 7 summarizes the main findings of the dissertation, followed by some suggestions for future research.

CHAPTER 2 MICROSCOPIC URBAN TRAFFIC NETWORK MODELING AND TRAFFIC SIGNAL OPTIMIZATION

2.1 Introduction

To conduct research on traffic network modeling and possible intervention through traffic control under natural hazards and disruptions, appropriate simulation and modeling techniques for urban traffic network and associated traffic control are critical. First, the state-of-the-art in terms of traffic network modeling and intelligent traffic control techniques would be briefly reviewed. Then, two popular microscopic traffic simulation platforms will be investigated as candidates for the related research in terms of urban traffic network simulation. Next, the potential to support intervention research through adaptive intersection control algorithms in normal conditions is studied for both platforms through two examples including a bus route and an urban road network. Finally, the main findings are summarized, followed by some discussions in terms of the strength and weakness of each candidate platform to meet the specific research needs in this dissertation research. The appropriate simulation platform for the following research on traffic network modeling and intervention will be identified for the following research under natural hazards and various disruptions.

Popular traffic signal modes of operation include pre-timed (fixed time) operation and actuated operation. The pretimed operation has some advantages such as easiness to design, operate and maintain, and is ideal for coordination of close intersections with constant traffic volumes, such as downtown grid areas to release fixed traffic flow to next intersection without any detections. On the other hand, the disadvantage of pre-timed traffic control is the lack of ability to adjust due to traffic demands, which could cause excessive vehicle delays in some circumstances. Such delays will become more critical when the traffic flow is interrupted and delayed by construction work or accidents on the street. Actuated operation can adjust phase duration and sequences by using detection to prolong or shorten phase duration and skip a phase based on the actual traffic demand. However, actuated operation doesn't have a fixed cycle length because of not always display a complete sequence and duration of a cycle. Therefore, actuated operation is typically not coordinated. Apparently, typical traffic light controls, as summarized above, have their own pros and cons. A more intelligent and adaptive traffic control system is needed to accommodate the steady growth in number of vehicles, which has put environmental stress on urban centers in various forms, particularly causing traffic congestion (Pandian et al., 2009).

Before conducting any advanced traffic signal studies of traffic networks with various disruptions, appropriate modeling techniques and software need to be evaluated and compared for urban traffic network and signal optimization. In this chapter, two different urban traffic networks will be modeled with two popular modeling techniques as candidates for our following study. The first network is about the public transit network (MAX bus route) modeling and the second network is a typical urban corridor in the City of Fort Collins, Colorado. Both networks will be modeled with real-life data and traffic signal plans as baseline scenarios. The modeling process with two candidate software consists of two parts: (1) modeling a microscopic-scale traffic network for traffic performance assessment, and (2) modeling traffic signal planning and optimization. Following the modeling results, some discussions are made in the end.

2.2 Microscopic Traffic Network Simulation with CORSIM and SUMO

2.2.1 Basics of CORSIM and SUMO Software

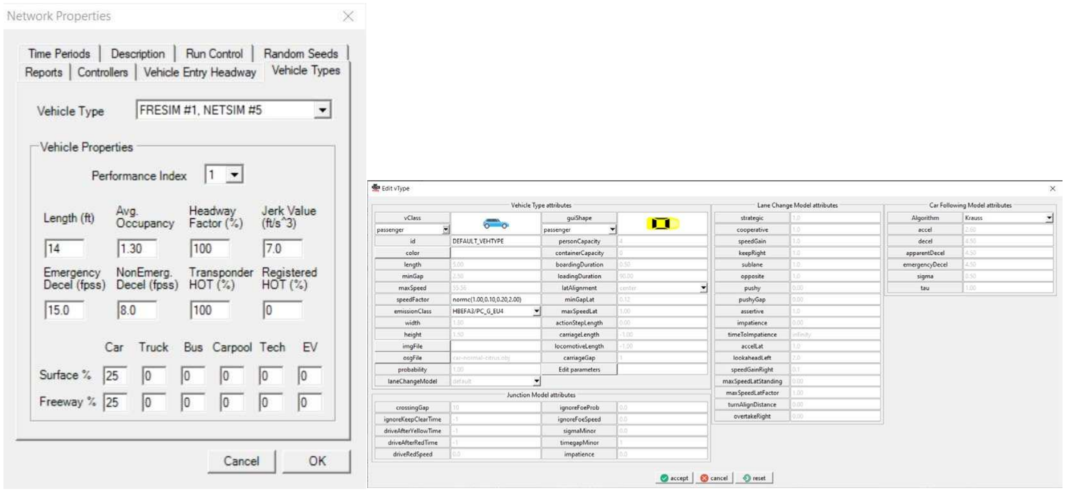
The Traffic Software Integrated System (TSIS) is a set of software tools that traffic engineers and researchers often use. TSIS began as a simple shell for "CORridor SIMulation" (CORSIM) and has since evolved into a sophisticated toolkit. CORSIM is a popular comprehensive microscopic traffic simulation software that can be applied to surface streets, freeways, and integrated networks. CORSIM models the movements of individual vehicles realistically by capturing the influence of geometric conditions, control conditions, and driver behavior. It uses widely accepted vehicle and driver behavior models to simulate the traffic flow and traffic control systems. CORSIM combines two popular traffic simulation models: NETSIM for urban streets and FRESIM for freeways. CORSIM has been used by thousands of practitioners and researchers all over the world, which allows the user to customize the parameter setting, define and manage traffic analysis projects, model traffic networks, create inputs for traffic simulation analysis, execute traffic simulation models, and interpret the results of those models (Mahmud and Town 2016).

Simulation of Urban Mobility (SUMO) is an open source, highly portable, microscopic, and continuous road traffic simulation package designed to handle large road networks. SUMO traffic simulation employs software tools to simulate and analyze road traffic and traffic management systems. New traffic strategies can be tested in a simulation before being implemented in real-world scenarios (Tonguz and Ozan 2018). SUMO has also been proposed as a toolchain component for developing and validating automated driving functions using different X-in-the-Loop and digital twin approaches. SUMO is often used in research applications such as traffic forecasting, traffic light evaluation, route selection, and vehicular communication systems. SUMO users can experiment with new approaches by making changes to the program source code via the open-source license (Weber 2020).

2.2.2 Comparison of simulation setups between CORSIM and SUMO

CORSIM and SUMO are all good candidates for microscopic traffic network simulations. However, in terms of simulation model building steps, there is some major difference between these two software in terms of vehicle types, traffic route generation for vehicles, and traffic signal controls. Some brief comparisons are made in the following section.

Vehicle types represent the characteristics of running vehicles in the traffic network simulations and a comprehensive collection of customized vehicle types has huge potential for research and development. CORSIM has 16 presets of vehicle types and combinations which ease the building process of simulation but limits the customization capability for research purposes (Fig. 2.1a). When it comes to reality simulations, CORSIM can shorten the model building time and improve the efficiency by applying presets and standard vehicle models into simulations. SUMO also has some presets for different vehicle types and properties (Fig. 2.1b), but with more flexibility and customization capabilities. One example is that SUMO can create customized vehicles by manipulating different vehicle properties and car following model to carry out various traffic scenarios.



a. CORSIM vehicle type input b. SUMO vehicle type input

Fig. 2.1 Vehicle type input difference

Route generation approaches of SUMO (Fig. 2.2a) and CORSIM (Fig 2.2b) are different: CORSIM distributes traffic volume on site for different vehicle movements by setting relative turning ratios of each direction at the intersection, which is more focused on revealing the real traffic movements from the simulations. And SUMO has more freedom to set route for the simulation for research purposes by creating customized routes for individual vehicles or traffic flow. There are various applications that can be used to define vehicular demand for SUMO, with a vehicle model in SUMO consisting of three parts:

1. a vehicle type which describes the vehicle's physical properties,
2. a route the vehicle shall take,
3. the vehicle ID, departure position and time.

Both routes and vehicle types can be shared by several vehicles. It is not mandatory to define a vehicle type – a default type is available. JTRROUTER is used for route generation in SUMO. JTRROUTER computes routes that may be used by SUMO based on traffic volumes and junction turning ratios to build vehicle routes from demand definitions using junction turning percentages.

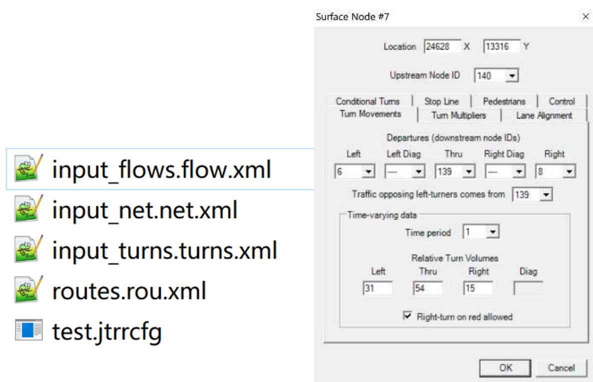
The input information (mandatory) includes (Fig 2.2a.):

1. a road network as generated via NETCONVERT or NETGENERATE

2. a demand definition,

3. Junction turning definitions.

Output: Definition of Vehicles, Vehicle Types, and Routes usable by SUMO.

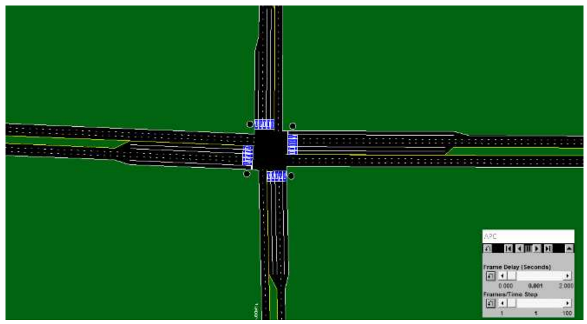


a. SUMO input b. CORSIM input

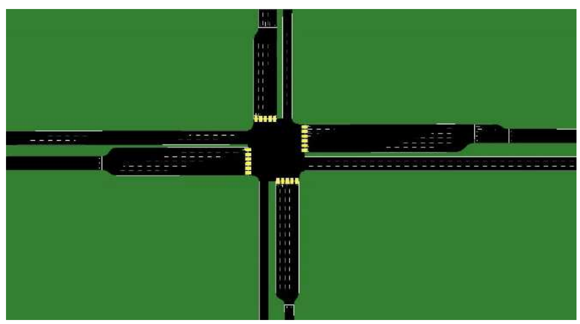
Fig. 2.2 Route generation input for SUMO and CORSIM

2.2.3 Traffic Signal Planning based on Microscopic Traffic Network Modeling

Both SUMO and CORSIM support actuated traffic light using detectors at the intersections. CORSIM offers two approaches to limiting the amount of time a phase can remain green under continuous flow conditions based on vehicle detections, Maximum Green, and Maximum Extension (Fig. 2.3a). Maximum green is the maximum amount of time a phase will be allowed to be active. Maximum extension is the amount of extra time a phase will be allowed after the minimum green and variable initial time has elapsed. SUMO supports gap-based actuated traffic control; the control scheme works by prolonging traffic phases whenever a continuous stream of traffic is detected and switching to the next phase after detecting a sufficient time gap between successive vehicles. This allows for better distribution of green time among phases and affects cycle duration in response to the dynamic traffic conditions. The time gaps which determine the phase extensions are collected by induction loop detectors, which are placed at the stop lines by default but can be customized for a desired distance (Fig. 2.3b).



a. CORSIM intersection view



b. SUMO intersection view

Fig. 2.3 Traffic lights and sensors for SUMO and CORSIM

In summary, CORSIM has full presets of traffic signal control close to the realistic traffic signal controls, which save tons of time for traffic signal programing in traffic network simulation. In contrast, SUMO gives the full customization ability in traffic signal control using TraCI which has more potential for research purposes. In this section, traffic signal planning is conducted for MAX – a bus rapid transit using CORSIM.

2.2.3.1 <u>Traffic signal optimization of MAX BRT</u>

MAX Bus Rapid Transit (BRT) serves major activity and business throughout the Fort Collins community including Midtown, Colorado State University and Downtown. MAX links other TRANSFORT bus routes, Park-n-Rides, the City's bicycle/pedestrian trail system, and other local and regional transit routes to provide seamless service for passengers. MAX follows a dedicated transit-only guideway and mixed-traffic streets that run parallel to the BNSF Railway between the South Transit Center (south of Harmony Road) and downtown. It is served by 12 stations and stops as shown in Fig. 2.4.

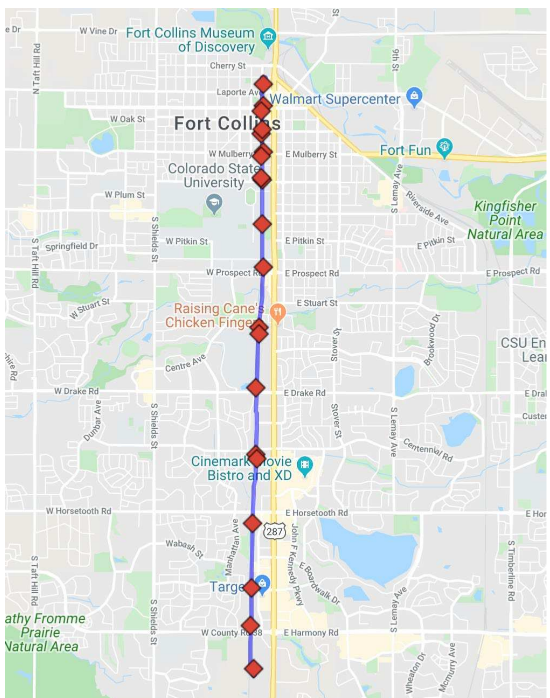
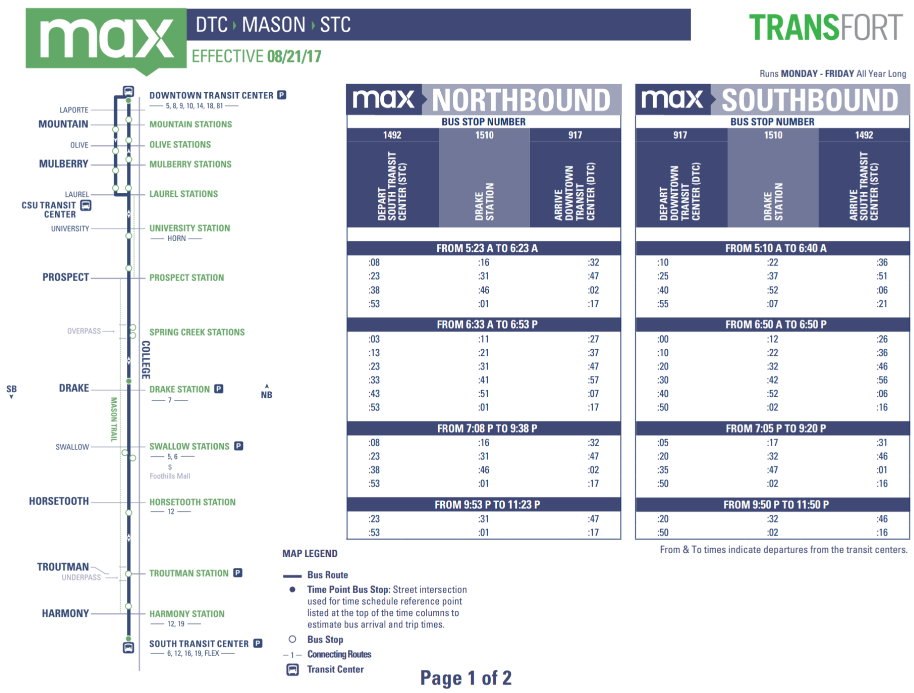


Fig. 2.4 MAX route and station map

MAX operates 365 days a year, including Sundays and holidays. MAX service runs on Monday through Saturday, from 5 a.m. – midnight and on Sundays and holidays from 8 a.m. - 7 p.m. The holidays are New Year’s Day (January 1), Memorial Day (last Monday in May), July 4 (Independence Day), Labor Day (first Monday in September), Thanksgiving Day (fourth Thursday in November), December 25. When

Colorado State University and Poudre School District are in session, MAX operates additional routes and expanded service time if necessary. Fig. 2.5 shows MAX route information and estimated arrival time for each station in the southbound and northbound directions in weekday, Saturday, and Sunday and holidays.



max NORTHBOUND

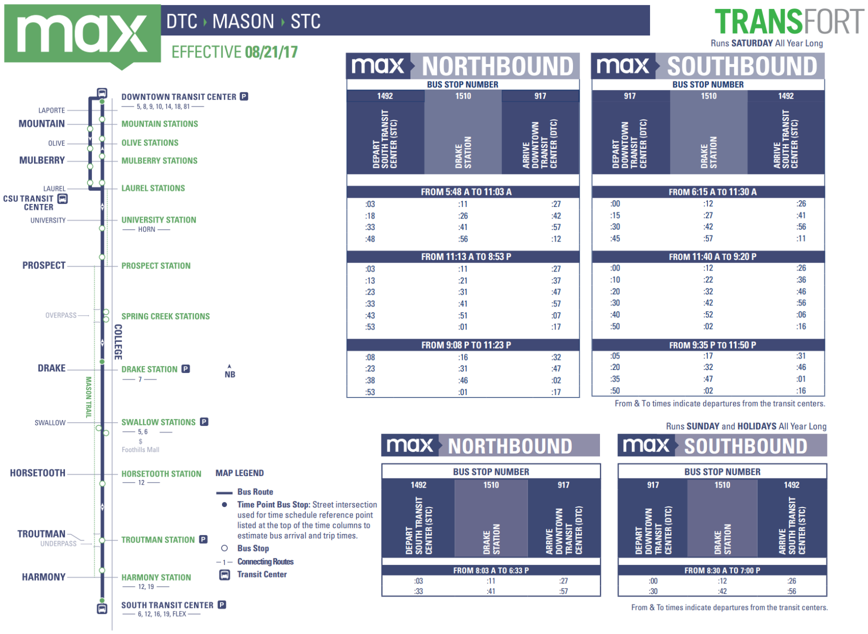
1492 DEPART SOUTH TRANSIT CENTER (STC)	1510 DRAKE STATION	917 ARRIVE DOWNTOWN TRANSIT CENTER (DTC)
FROM 5:23 A TO 6:23 A		
:08	:16	:32
:23	:31	:47
:38	:46	:02
:53	:01	:17
FROM 6:33 A TO 6:53 P		
:03	:11	:27
:13	:21	:37
:23	:31	:47
:33	:41	:57
:43	:51	:07
:53	:01	:17
FROM 7:08 P TO 9:38 P		
:08	:16	:32
:23	:31	:47
:38	:46	:02
:53	:01	:17
FROM 9:53 P TO 11:23 P		
:23	:31	:47
:53	:01	:17

max SOUTHBOUND

917 DEPART DOWNTOWN TRANSIT CENTER (DTC)	1510 DRAKE STATION	1492 ARRIVE SOUTH TRANSIT CENTER (STC)
FROM 5:10 A TO 6:40 A		
:10	:22	:36
:25	:37	:51
:40	:52	:06
:55	:07	:21
FROM 6:50 A TO 6:50 P		
:00	:12	:26
:10	:22	:36
:20	:32	:46
:30	:42	:56
:40	:52	:06
:50	:02	:16
FROM 7:05 P TO 9:20 P		
:05	:17	:31
:20	:32	:46
:35	:47	:01
:50	:02	:16
FROM 9:50 P TO 11:50 P		
:20	:32	:46
:50	:02	:16

From & To times indicate departures from the transit centers.

a. Weekday schedule



max DTC ‣ MASON ‣ STC

EFFECTIVE 08/21/17

TRANSFORT

Runs SATURDAY All Year Long

max NORTHBOUND

BUS STOP NUMBER		
1492	1510	917
DEPART SOUTH TRANSIT CENTER (STC)	DRAKE STATION	ARRIVE DOWNTOWN TRANSIT CENTER (DTC)
FROM 5:48 A TO 11:03 A		
:03	:11	:27
:18	:26	:42
:33	:41	:57
:48	:56	:12
FROM 11:13 A TO 8:53 P		
:03	:11	:27
:13	:21	:37
:23	:31	:47
:33	:41	:57
:43	:51	:07
:53	:01	:17
FROM 9:08 P TO 11:23 P		
:08	:16	:32
:23	:31	:47
:38	:46	:02
:53	:01	:17

max SOUTHBOUND

BUS STOP NUMBER		
917	1510	1492
DEPART DOWNTOWN TRANSIT CENTER (DTC)	DRAKE STATION	ARRIVE SOUTH TRANSIT CENTER (STC)
FROM 6:15 A TO 11:30 A		
:00	:12	:26
:15	:27	:41
:30	:42	:56
:45	:57	:11
FROM 11:40 A TO 9:20 P		
:00	:12	:26
:10	:22	:36
:20	:32	:46
:30	:42	:56
:40	:52	:06
:50	:02	:16
FROM 9:35 P TO 11:50 P		
:05	:17	:31
:20	:32	:46
:35	:47	:01
:50	:02	:16

From & To times indicate departures from the transit centers.

Runs SUNDAY and HOLIDAYS All Year Long

max NORTHBOUND

BUS STOP NUMBER		
1492	1510	917
DEPART SOUTH TRANSIT CENTER (STC)	DRAKE STATION	ARRIVE DOWNTOWN TRANSIT CENTER (DTC)
FROM 8:03 A TO 6:33 P		
:03	:11	:27
:33	:41	:57

max SOUTHBOUND

BUS STOP NUMBER		
917	1510	1492
DEPART DOWNTOWN TRANSIT CENTER (DTC)	DRAKE STATION	ARRIVE SOUTH TRANSIT CENTER (STC)
FROM 8:30 A TO 7:00 P		
:00	:12	:26
:30	:42	:56

From & To times indicate departures from the transit centers.

Page 2 of 2

b. Weekend schedule

Fig. 2.5 MAX route schedule

2.2.3.2 CORSIM model and traffic signal plan

The CORSIM model is built for MAX route analysis under different signal control plans. The model is made based on real data from Google Maps and all stations are located by referencing the MAX Parking Map from TRANSFORT, a transit information website administered by City of Fort Collins. The simulation time duration is 900 seconds, covering PM peak hour. The headway of each MAX run is 15 minutes according to the MAX route schedule shown in Fig. 2.5. The average dwell time at the station is 10 seconds. Figure 2.6 is the overview of the MAX route in the CORSIM model.

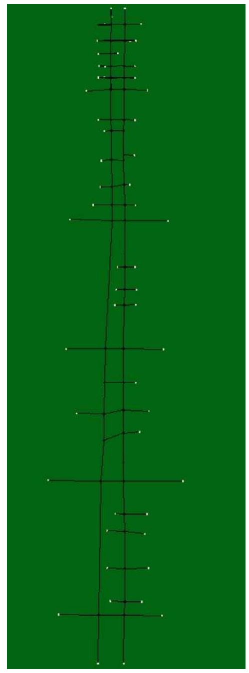


Fig. 2.6 CORSIM MAX route model

Signal control plan adopts different methods to operate MAX route in an intersection connecting other avenues and roads. Currently, there are 4 signal control plans: MAX with No Priority, MAX with Preemption, MAX Priority with Advanced Detection, MAX Priority with Stop Line Detection. Table 2.1 illustrates the main difference of each signal control plan in terms of coordination, sensor type, sensor location, cycle length, and permissive period.

Table 2.1 Signal control plan

Signal Control Plan	No Priority	Preemption	Priority with Advanced Detection	Priority with Stop Line Detection
Coordination	Coordinated	Free	Coordinated	Coordinated
Sensor Type	Presence Detector	Presence Detector	Presence Detector	Presence Detector
Sensor Location	Stop Line	Road	Stop Line & Road	Stop Line
Cycle Length (sec)	120	N.A.	120	120
Permissive Period (sec)	3	N.A.	75	75

"No priority" signal control plan means MAX is treated as a regular vehicle at this intersection, and the controller is fully actuated and coordinated with the 120 seconds cycle length. Sensors are presence detectors located at stop lines and roads. Each MAX must wait till its permitted phase starts, then MAX can have the right to go through the intersection. "Preemption" signal control plan means whenever MAX is approaching the intersection, green light for MAX will automatically turn on to let MAX go through regardless of the traffic condition on the other directions of the intersection. Therefore, there is no cycle length and permissive period for this method. The signal coordination is open, only changing based on the arrival of MAX. "Priority with Advanced Detection" and "Stop Line Detection" control plans are similar except for the sensor locations. The cycle length for both control plans is 120 sec, and the permissive period is 75 sec, which means if MAX arrives in 75 sec, the green light will automatically turn on to let it go through the intersection. Otherwise, MAX must wait till the next cycle. MAX only has single chance during one cycle to use the permissive period to pass the intersection. Advanced Detection and Stop Line Detection have different location arrangement of presence sensors as shown in Fig. 2.7. Advanced Detection placed the sensors at the bus stop and Stop Line Detection placed the sensors at the intersection stop line.

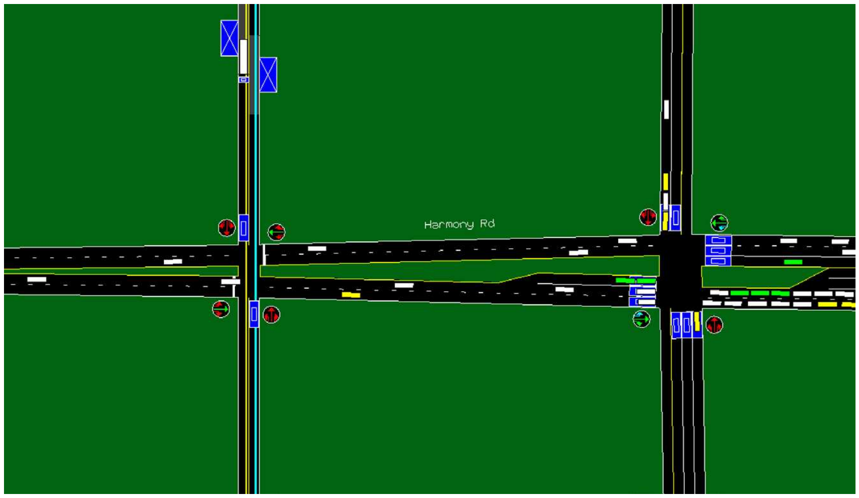


Fig. 2.7 Sensor locations and bus stations

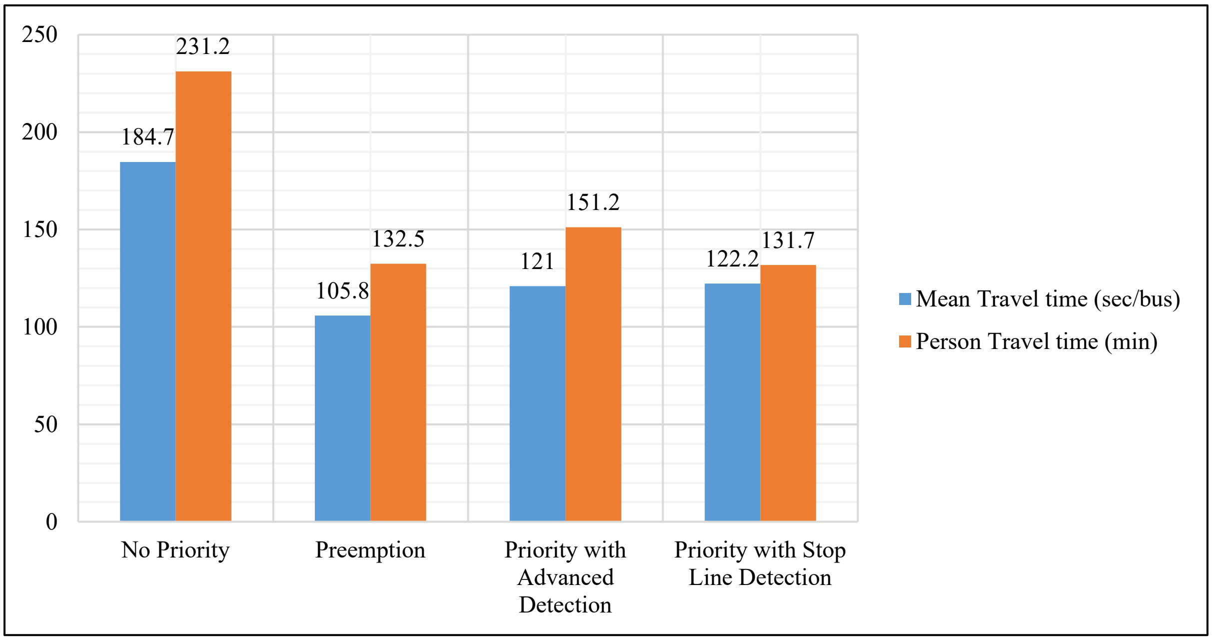
Four different signal control plans have been applied on the MAX route in CORSIM respectively, and the modeling results have shown a considerable difference on mean travel time (sec/bus) and person travel time (min) of southbound and northbound directions. The number of bus trips is 3 for all the plans, which means there are 3 buses passing the intersection in each direction during the simulation. The occupancy is 25 for all plans, which means these estimates assume an average bus occupancy of 25 passengers per bus throughout the network (Table 2.2).

Table 2.2 CORSIM person trips

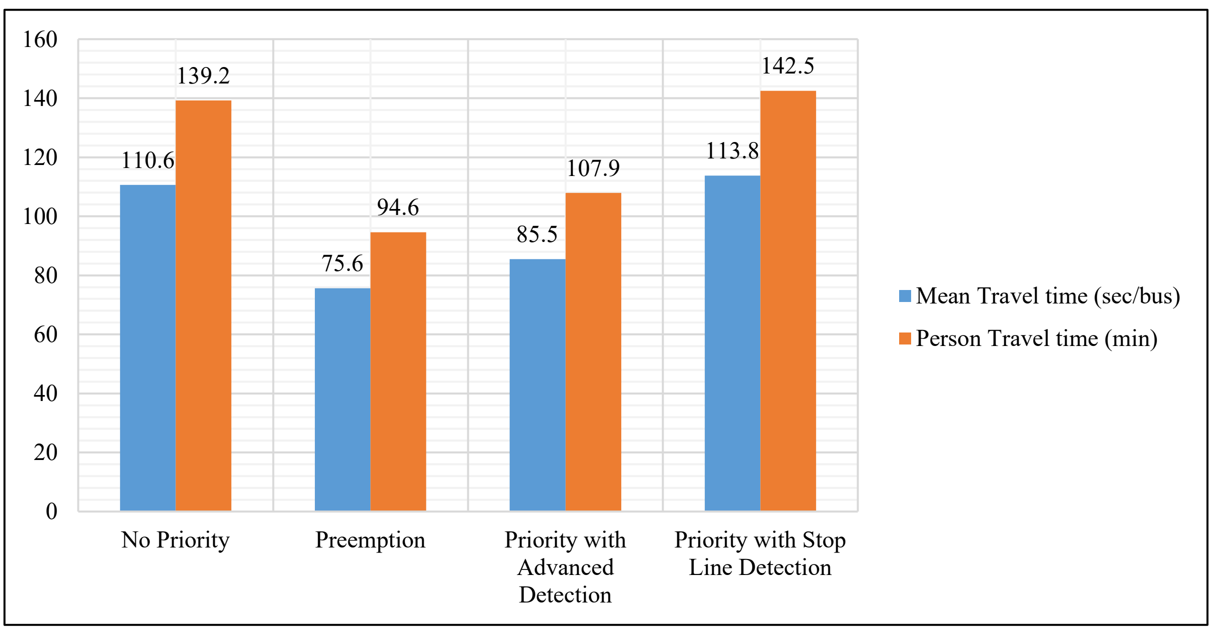
Bus Trip	Occupancy	Person Trips
3	25	75

Fig. 2.8 shows the results of mean travel time and person travel time for the 4 plans in both directions. From Fig. 8a, no priority signal control plan has the highest mean travel time of 231.2 sec/bus and person travel time of 184.7 min on the southbound route. Those with no priority and priority with stop line detection have higher mean travel time and person travel time than the other 2 plans on northbound in Fig. 8b. The

results show that comparatively “no priority” and “priority with stop line detection” are not the ideal plans for MAX route operation.



a. Southbound results



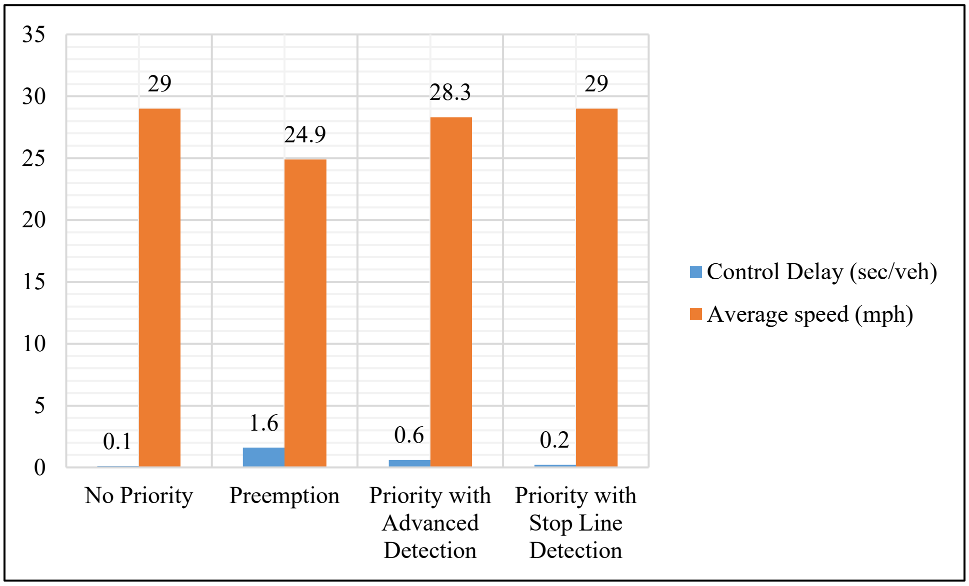
b. Northbound results

Fig. 2.8 Mean travel time and person travel time

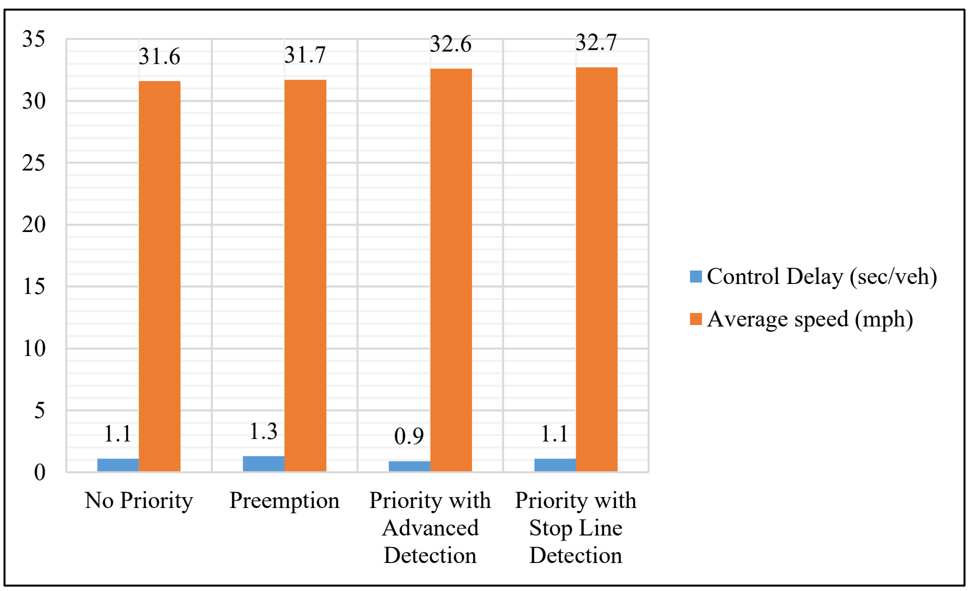
By comparing the simulation results for four traffic control plans with the CORSIM model of MAX, it is found that “preemption” and “priority with advanced detection” plans seem to be more promising for MAX operation. However, the traffic conditions on roads crossing the MAX route should also be evaluated since it is not reasonable to only improve the traffic performance on the MAX route at the cost of significantly increasing congestion on other crossing roads. Therefore, MAX-crossing road is also analyzed as the next step. Particularly, Harmony Road is selected for evaluation purposes because of its significance to the whole traffic network, large traffic volume, and higher risk of possible congestion during a day. The parameters for analyzing traffic performance including possible congestion are control delay and average speed. Control delay is the portion of the total delay attributed to traffic signal operation for signalized intersections, which is often measured by the comparison with the uncontrolled condition. Control delay is quantified as the difference between the travel time that would have occurred with and without the intersection control. Average speed represents the space-mean speed that is the distance traveled divided by average travel time. Like MAX CORSIM results, eastbound and westbound directions are both studied.

Fig. 2.9 shows the results of control delay time and average speed of Harmony Road westbound (Fig. 2.9a) and eastbound (Fig. 2.9b) traffic, respectively. For the westbound traffic, “no priority” plan has the lowest control delay 0.1 sec/veh and highest average speed of 29 mph. For eastbound traffic, all signal control plans have close values of control delays and “priority with stop line detection” has the highest average speed of 32.7 mph. Each signal control plan has different tradeoffs depending on the traffic control priorities. By considering the overall impact on both MAX bus route and the crossing roads (i.e., Harmony

Road), it is found "priority with advanced detection" plan is the optimal one by more efficiently improving MAX bus running speed and causing less impact on eastbound and westbound traffic on Harmony Road.



a. Westbound results



b. Eastbound results

Fig. 2.9 Control delay and average speed

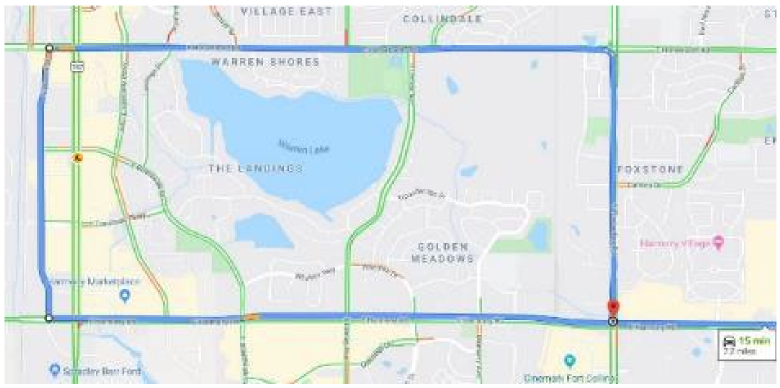
After conducting traffic signal optimization on MAX BRT with CORSIM, it is found CORSIM has some limitations. CORSIM cannot present the temporal transient data of each time point during the simulation. Instead, CORSIM is only able to provide the result after the simulation process is completed. Moreover, as a close-to-reality simulation software, CORSIM has limited customized capability such as vehicle type, drive behavior, car following model, and emission model etc. to accommodate various research needs. Whereas SUMO allows the existence of different types of vehicles, roads with several lanes, traffic lights, graphical interface to view the network and simulated entities, and interoperability with other applications at runtime through an API called TraCI. TraCI is Traffic Control Interface giving access to a running road traffic simulation, and it allows to retrieve values of simulated objects and to manipulate their behavior during the simulations. Also, it allows importing real-world road networks from Open Street Map, and the vehicles can enter the system from any positions in the network. Additionally, the most attractive feature of SUMO is that it can collect the transient data of each vehicle at each second, which offers huge potential to track the dynamic change of the simulation network to enable more accurate and adaptive traffic light control during disrupted traffic scenarios.

2.2.4 Urban corridors optimal traffic management using SUMO

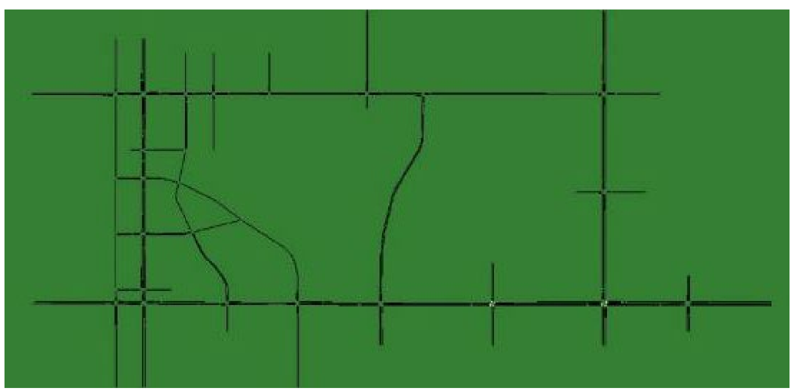
In this part, a customized adaptive traffic light control plan is studied using SUMO-based traffic corridors signal optimization method. The traffic light system will use the information from the whole network to calculate the optimal signal timings in real time or detour traffic, if necessary, to avoid congestion and mitigate delays. Such an adaptive system allows dynamic signal timings and phase sequences based on real-time traffic situations. The major advantage of this method is to use limited information on site such as traffic cameras or road sensors at the intersection to determine the traffic situation of congestion, accident, or no traffic to make the right timing scheduling for traffic signals.

2.2.4.1 Case study simulation network building

The simulation model is built for the Harmony Corridor network by including all major intersections with the corridor and adjacent major roads at 11/6/2019 for AM, NN (noon), and PM peak hour scenarios. This model covers the large area from Harmony Road to Horsetooth Road along with Mason Street to Lady Moon (Fig. 2.10 a-b).



a. Simulation network



b. SUMO simulation

Fig. 2.10 Simulation network overview

All traffic parameters including traffic volume, actuated traffic signal timing planning, turning ratios at intersections are from the City of Fort Collins. This model aims to provide comprehensive insights into the traffic performance of the whole network. With the SUMO model, the traffic performance under different time periods and traffic volumes of a typical day and various traffic situations have been systematically studied. The duration of whole simulations is 2000 seconds with 1000s initialization period which allows vehicles entering the simulated network gradually to replicate the real traffic scenarios.

2.2.4.2 Methodology of adaptive control algorithm

The main idea behind the algorithm is to use active traffic intersections lane occupation as input for traffic signal operation management, which is called Dynamic Phase Selection algorithm. When traffic congestion has occurred, typically very few or no vehicles from the approach with minor roads utilize the green light periods. Therefore, such a period can be allocated to other phases to improve the mobility of the remaining approaches to avoid long queues. DPS can adaptively choose the best phase sequence of a cycle to make the traffic more efficient with the help from monitoring detectors. Starting at the major road movement, the next phase is chosen dynamically based on all candidate phase options with the following algorithm (Zubillaga et al. 2014):

1. Compute the priority for each phase given in the list of indices (the sequence of potential phases that will be used for the next phase when the current one is over.) for the next possible movements as 'next' attribute. Priority is made according to the number of active detectors for that phase. A detector is deemed "active" when either of the following conditions is met:
    a. The time gap between consecutive vehicles is shorter than the threshold.
    b. Vehicle existence is detected after the signal has turned red from the last cycle.
2. The current phase is available to continue implicitly if its maximum duration (MaxDur) is not reached. The current phase detector gets a bonus priority.
3. The phase with the highest priority is used for the next cycle over other possible movements.

4. If no traffic is detected, the phases will follow the default cycle defined by the first value in the 'next' attribute.

5. If a particular phase needs to remain active for a no-traffic scenario, it must have a high maximum duration value and its index number is on the 'next' list.

6. If the time that an active detector was not served exceeds the preset time threshold, such a detector will receive bonus priority of the time that was not served. This could prevent those phases serving more traffic from being consistently served.

Based on the algorithm introduced above, DPS can choose the next phase according to the real-time traffic situation. In such a case, a certain amount of time could be saved for better selection of the intersection for other phases. The fourth step is to set dynamic phase selection traffic light control programs for different traffic scenarios. And the final step is to apply TraCI to decide which traffic light control program is used based on the traffic information from the network of each intersection.

Normal Peak-hour scenarios

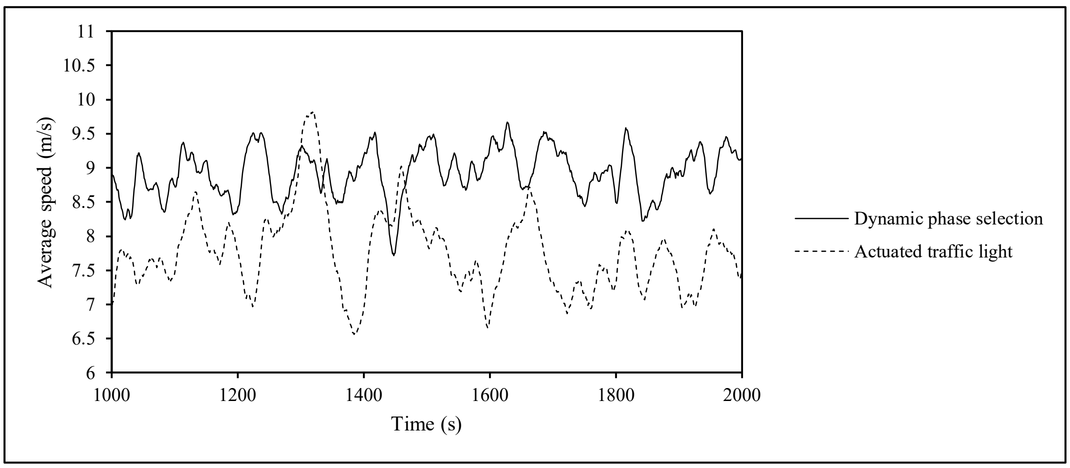
Different peak-hour traffic scenarios experience significant changes in traffic volume in different directions. Table 2.3 shows the traffic count at the Harmony intersection at AM, NN, and PM peak-hour time. Traffic volume from southbound increases from 802 vph to 1836 vph during the same day, which requires a highly adaptive traffic light control to make this intersection to operate efficiently without excessive delay and congestion.

Table 2.3 Harmony intersection traffic count

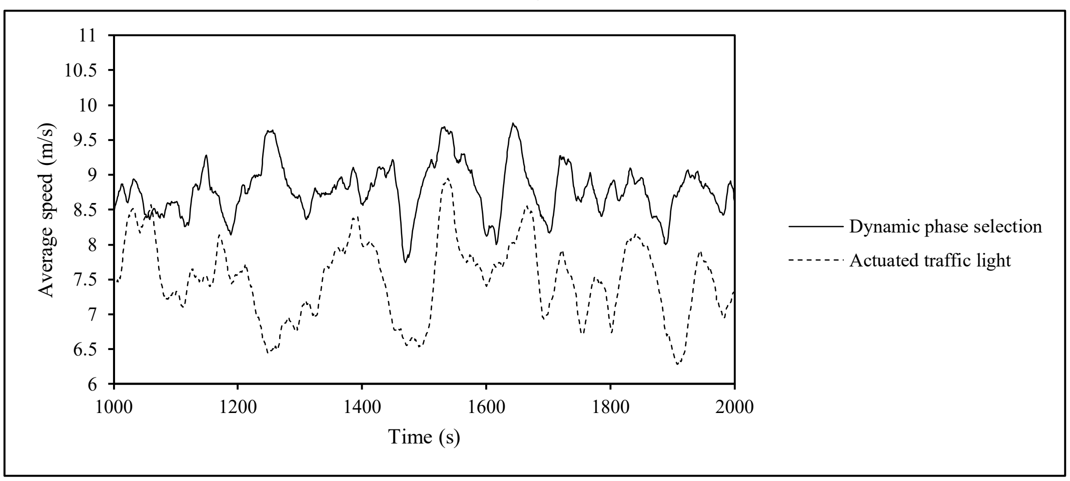
Time	SB	WB	NB	EB	Total
AM	802	1146	1598	1035	4581

Mid	1363	1350	1352	941	5006
PM	1836	1690	1507	1115	6148

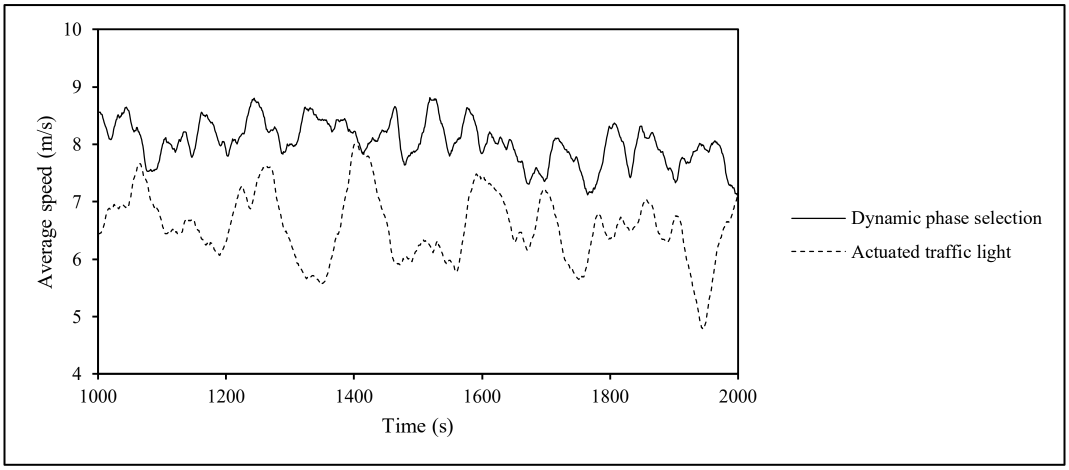
Fig. 2.11 shows the average speed results of AM, NN, and PM peak hour situations of using conventional actuated traffic light control and dynamic phase selection traffic light control. Dynamic phase selection traffic control performed better for higher average speed during all peak hour scenarios under the same traffic situations. Clearly dynamic phase selection traffic signal control is more efficient than conventional actuated traffic signal control.



a. AM peak-hour average speed comparison



b. NN peak-hour average speed comparison



c. PM peak-hour average speed comparison

Fig. 2.11 Peak-hour average speed comparison

Construction block scenario

SUMO also supports traffic disruption scenarios by closing specific roads to simulate disruption impact. The starting time and duration of closed roads are fully customized during the simulations (Fig. 2.12). When considering construction scenario, the traffic flow changes rapidly due to segment failure to serve. Traffic will suffer delays and congestion if the current traffic signal control plan remains the same as usual. In this case, dynamic phase selection traffic signal control can perform a better solution to detouring part of vehicles to other routes to avoid congestion and delays. In this study, PM peak hour traffic volume was selected for demonstration. The simulation duration is 2000s and other parameters remain the same as the simulations conducted above.

Fig. 2.12 Construction location

Fig. 2.13 represents the waiting time and time loss of 2 traffic signal control plans. Waiting time is the time in which the vehicle speed was below 0.1m/s, while time loss is about the time being lost because of driving below the ideal speed. Based on the result as shown in Fig. 13, dynamic phase selection traffic signal control performs much better in terms of both waiting time and time loss.

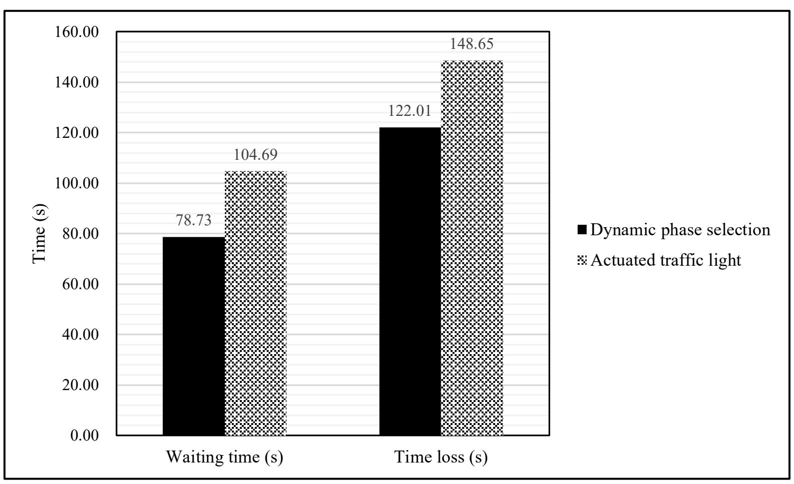


Fig. 2.13 Waiting time and time loss comparison

After the comparative studies between two microscopic traffic simulation software are made, Table 2.4 summarizes the major difference between CORSIM and SUMO in terms of building the models, creating simulation scenarios, conducting traffic signal control planning, and analyzing the results. In general, CORSIM is more suitable for reality problem solving by using default presets and summarized report results, while SUMO is more research-friendly due to its strong capabilities of customization and interference during the simulations. Furthermore, the detailed time-transient results offered by SUMO makes it ideal for advanced traffic control studies under normal and disrupted scenarios in the following sections.

Table 2.4 CORSIM and SUMO differences

	CORSIM	SUMO
Model building	Efficient using presets	Fully customized with detailed traffic information
Simulation scenarios	Normal scenarios only	Normal and disrupted scenarios
Traffic signal control	Pre-timed, Actuated, Stop sign	Fully customized using TraCI
Results format	Summarized report for the whole simulation	Temporal results for each traffic element in the simulation

2.3 Discussion and summary

In this chapter, CORSIM and SUMO are introduced and compared for microscopic traffic simulation for research purposes. With CORSIM, the MAX bus route simulation was conducted for different traffic signal plan comparison. Both MAX route and Harmony intersection are studied in terms of traffic performance and signal control. By comparing four different traffic control plans, a more appropriate traffic signal plan has been identified for MAX route to achieve the best travel time saving along with least impacts on Harmony Road traffic operation.

Although CORSIM is found to be able to simulate the real-life scenario closely for its presets, it also limits the variation of these parameters for research purposes. The following are the advantages and disadvantages of CORSIM:

a. CORSIM can simulate real-life scenarios for traffic signal control plans, vehicle types, and drivers' behaviors.

b. CORSIM presets improve the efficiency of simulation building time expense.

c. CORSIM limits parameter variation for research purposes.

d. CORSIM provides only final simulation results, not temporal changes.

SUMO is adopted to study a typical urban traffic network successfully, including both traffic performance and traffic signal control plans. The following are the advantages that SUMO has over CORSIM for research purposes:

a. SUMO offers more ability to adjust traffic network configuration, traffic signal control plan, vehicle types, and drivers' behaviors

b. SUMO provides more potential for research activities

c. Temporal results are crucial for research studies on urban traffic signal operation management and optimization.

With the SUMO model, a new traffic signal control algorithm using DPS and TraCI control was proposed to make traffic signal control system more adaptive both on different traffic demand and accidental cases. By using SUMO modeling a real-life network of Fort Collins, the results of average speed, time loss, waiting time, and the number of arrived vehicles have demonstrated that the new method has a clear advantage compared to other traditional counterparts. Such a model was further studied for some disrupted scenarios to demonstrate the feasibility and potential of adopting SUMO to carry out the following studies on disrupted traffic systems under hazards.

CHAPTER 3 RESILIENCE-BASED ADAPTIVE TRAFFIC SIGNAL STRATEGY AGAINST DISRUPTION AT SINGLE INTERSECTION[1]

3.1 Introduction

Intelligent technology has become a key solution to traffic control in urban cities to mitigate congestion and reduce delays (Andronov and Leverents, 2018). Intelligent traffic signal control efforts primarily focus on applying different algorithms to meet the needs of traffic safety and efficiency with the data from monitoring cameras, road sensors, and existence detectors, etc. (Pandit et al., 2013). Typical modes of operation for traffic signals include pre-timed (fixed time) and actuated operations.

Most of the existing studies focused on congestion mitigation during the recovery stage from crashes, rather than the whole process following crash occurrence. In addition, existing studies all assumed simplified and generic congestion scenarios, without looking at the realistic time-progressive nature of congestion developments following crashes at intersections. In fact, different types of crashes may occur at intersections, which will cause different nature and severity of congestion to deal with. As a result, the optimal traffic control strategy in response to disruptions is rarely generic and should be adaptively adjusted with specific incident and congestion information. Furthermore, there are usually more traffic crashes when driving environments deteriorate before, during and after some natural or man-made hazards and major incidents. During those critical moments, every second counts to mitigate the congestion, maximize the evacuation and rescue efficiency, save more lives, and prevent a hazard from turning to a disaster. To have a more adaptive and smarter traffic control strategy covering not just the static and genetic congestion

[1] This chapter is adapted from a published paper by the author (Yao and Chen 2022) with permission from ASCE.

scenarios during the recovery stage, rather the dynamic scenarios covering the whole process including both emergency response and long-term recovery following a disruptive event, therefore becomes critical.

Dynamic phase selection (DPS) has been successfully adopted in some fully actuated traffic signal controls to skip unused phases when there is no call for service, so the green time can be allocated to other phases. As a result, the whole process of traffic signal control would be more intelligent and adaptive by reducing unused waiting time and improving the overall efficiency (Eom & Kim, 2020). With DPS, traffic signal control at intersections becomes self-organized in response to different traffic needs during normal traffic conditions (Zubillaga et al., 2014). Despite great potential, little effort has been reported in terms of adopting DPS on traffic signal designs during disrupted traffic scenarios. This chapter proposes an adaptive traffic signal control strategy in response to traffic disruptions at a typical intersection by integrating microscopic traffic simulation, traffic signal design with dynamic phase selection (DPS) technology, the queue length dissipation (QLD) algorithm and resilience modeling concept. After the methodology is introduced, disruptions caused by typical vehicle crashes at intersections are specifically studied including rear-end, angle-impact, and opposite-direction (left-turn vs through) crashes. The proposed resilience-based strategy is applied to adjust the traffic signal control plan adaptively covering the whole period immediately following the incident until the congestion is fully recovered to the normal condition by aiming to achieve the optimal traffic efficiency and resilience outcome. With the adaptive strategy, the sequence of signal phases is adjusted based on the near real-time optimization and calculation of optimal signal timing without fixed cycle length and phase sequence, which may vary from cycle to cycle based on real-time traffic condition.

3.2 Methodology

3.2.1 SUMO-based microscopic traffic simulation platform at a signal intersection

The proposed strategy is developed based on the popular microscopic traffic simulation tool "Simulation of Urban Mobility (SUMO)". SUMO is an open source, highly portable, and continuous road traffic simulation package designed to handle large road networks, etc. For applications at intersections, SUMO not only offers microscopic-scale traffic flow simulation, but also accommodates various types of vehicles, roads and traffic lights with an excellent graphical user interface and interoperability with other applications at runtime (Lopez et al., 2018). The microscopic-scale traffic modeling with SUMO at a typical intersection provides reliable and accurate traffic performance information which will lead to optimized traffic signal designs. Figure 1 shows the typical movement of a four-way intersection, of which phases 1, 3, 5, and 7 are for left-turn movements and phases 2, 4, 6, and 8 are for through and right-turn movements at different directions. Normally, phases 1, 2, 5 and 6 are used for major roads with high and consistent traffic volumes. The rest phases are primarily for minor roads with low traffic volumes. As shown later, dynamic phase selection (DSP) will be applied based on the phase movements depicted in Fig. 3.1:

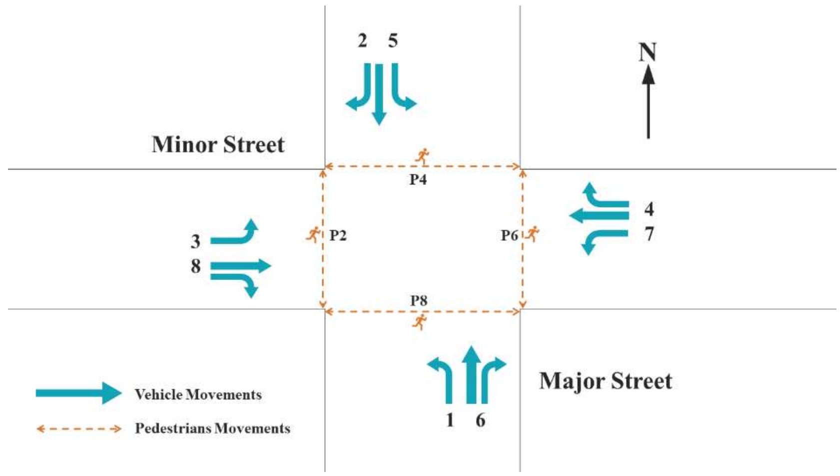


Fig. 3.1 Intersection phase movements

3.2.2 Adaptive traffic signal strategy in response to disruptions at intersection

The adaptive traffic signal strategy is developed for the two stages following an incident: the incident stage covers the time between the incident occurrence and the time when the rescue or emergency response efforts are finished; the recovery stage covers the duration following the incident stage until the traffic has returned to normal. Basically, dynamic phase selection (DPS) is adopted to skip unnecessary phases during the incident stage, and the queue length dissipation (QLD) algorithm is used to dissipate the queue length at crash lanes once the recovery stage starts. The whole process for the traffic signal strategy is called DPS+QLD plan and the overall workflow is shown as follows:

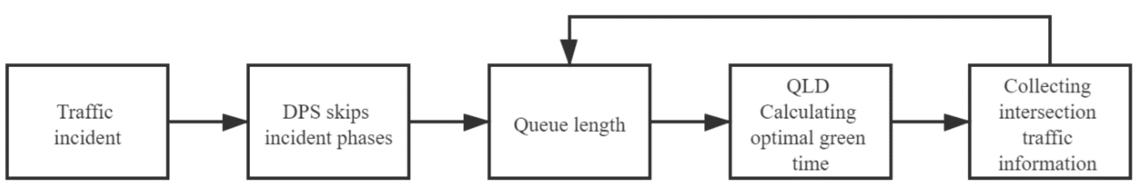


Fig. 3.2 Adaptive traffic flow strategy workflow

As shown in Fig. 3.2, during the first stage immediately following the incident, dynamic phase selection (DPS) is used for skipping unused phase of the blocked approach due to incidents to save the time loss of the intersection operation. The second stage is when the incident is cleared, and the queue length information is collected to calculate the optimal signal timing to dissipate the queue as soon as possible. When the maximum green time g_{max} is reached, the controller will move to the next phase to avoid redundant green time causing long queue lengths on other approaches. After the first cycle, queue length information at the end of the red time is collected again for the following signal timing calculations. In the following sections, both DPS and QLD algorithms focusing on incident and recovery stages are introduced in detail.

3.2.2.1 Dynamic Phase Selection (DPS) algorithm: immediately following disruption

After a traffic incident has occurred, typically very few or no vehicles from the approach with the incident uses the green light. Therefore, such a period can be allocated to other phases to improve the mobility of the rest approaches to avoid long queues. DPS can adaptively choose the best phase sequence of a cycle to make the traffic more efficient with the help from monitoring detectors. Starting at the major road movement, the next phase is chosen dynamically based on all candidate phase options with the following algorithm (Zubillaga et. al., 2014):

1. Compute the priority for each phase given in the list of indices (the sequence of potential phases that will be used for the next phase following the current one) for next possible movements as 'next' attribute. Priority is made according to the number of active detectors for that phase. A detector is deemed “active” when either of the following conditions is met:
    a) the time gap between consecutive vehicles is shorter than the threshold.
    b) vehicle existence is detected after the signal being turned to red from the last cycle.

2. The current phase is available to continue implicitly if its maximum duration (MaxDur) is not reached and the current phase detector gets a bonus priority.
3. The phase with the highest priority is used for next cycle over other possible movements.
4. If no traffic is detected, the phases will follow the default cycle defined by the first value in the 'next' attribute.
5. If a particular phase needs to remain active for no-traffic scenario, it must have a high maximum duration value and its index number is on the 'next' list.
6. If the time that an active detector was not served exceeds the preset time threshold, such a detector will receive bonus priority for the time that was not served. This could prevent those phases serving more traffic being consistently served.

Based on the algorithm introduced above, as shown in Fig. 3.3, DPS can choose the next phase according to the real-time traffic situation, which was originally used to skip unnecessary phases for minor roads if there is no vehicle to use the green light. Similar algorithm will be applied to skip the phases for the movement at the incident location with disruptions and reallocate the green time to other phases to make the rest parts of the intersection work efficiently. Taking rear-end crash as an example, vehicles from the approach with the crash occurred cannot pass the intersection because of traffic disruption. Therefore, the through phase of this approach is skipped by moving onto the next available phase. The skipped phase will not be used again until the crash is cleared, and vehicles resume movement on the affected lanes. In such a case, a certain amount of time could be saved for better movement of the intersection for other phases.

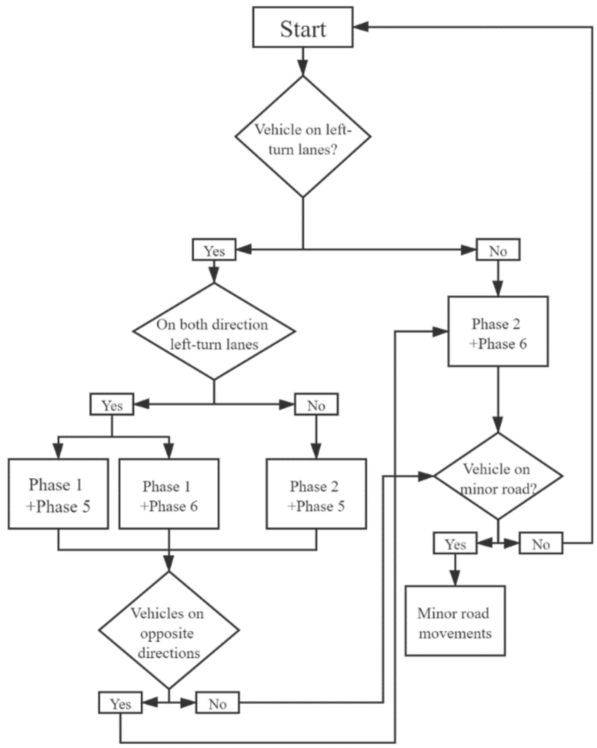


Fig. 3.3 DPS algorithm flowchart

3.2.2.2 Queue length dissipation (QLD) algorithm: recovery process

After the incident (e.g., crash) is cleared, queued-up vehicles on the approach with the incident need longer green time for queue dissipation. However, the required green time should be calculated based on the queue lengths of not only the approach experiencing the incident, but also other approaches of the intersection at the same time to avoid causing additional congestion in other directions. Therefore, the maximum green time g_{max} should be applied to balance the green time allocations among different approaches. Based on the analytical method by Akçelik (1994, 1995a), the average green time and cycle length of an actuated controller adopt a fixed unit extension setting by assuming the arrival headway follows the bunched exponential distribution (Cowan 1978). Existing vehicles remaining in front of the green light are defined as bunched vehicles while new arriving vehicles are defined as free vehicles. Different proportions of bunched and free vehicles define the minimum and maximum green time, g_{min} and g_{max} respectively. The green extension time e_g is set based on the queue length at the red-light ending time point, and the phase change does not happen during the saturated portion of the green period.

The green time g can be estimated by (Akçelik, 1994):

$$g = g_s + e_g \tag{3.1}$$

where g is the green time and g_s is the saturated portion of the green period; e_g is the extension time if the phase change happens after the queue clearance period.

The green time range is set as:

$$g_{min} < g < g_{max} \tag{3.2}$$

The saturation portion of the green period is calculated by:

$$g_s = \frac{f_q y r}{1 - y} \tag{3.3}$$

where:

f_q = queue length calibration factor to allow for variance in queue clearance time.

r = effective red time for the phase.

y = q/S, ratio of arrival flow rate (q) to saturation flow rate (S).

The average extension time except for the saturated portion can be calculated by (Cowan, 1978):

$$e_g = n_g h_g + e_t \tag{3.4}$$

where:

n_g = average number of arrivals before phase change after queue clearance.

h_g = average headway of arrivals before phase change after queue clearance.

e_t = terminating time at phase change (is often equal to the unit extension time U).

For most cases, $e_t = U$ and Equation 4 becomes:

$$e_g = \frac{1}{q} + \left(\frac{\Delta}{\varphi} + \frac{1}{q}\right) e^{q(U-\Delta)} \tag{3.5}$$

where:

q = arrival flow rate.

Δ = minimum headway.

φ = proportion of free vehicle.

U = unit extension time (1s).

The green light distribution for the approach with the incident follows the rules considering the queue lengths of other approaches (Cowan, 1978):

$$g = \begin{cases} g_s + e_g, & for\ g_s < g_{sj} \\ g_s, & for\ g_s > g_{sj} \end{cases} \tag{3.6}$$

where g_{sj}=the saturation portion of the green period of the j^{th} direction and j= 1,2,3.

To facilitate resilience-based traffic signal design, two indexes are introduced. One is travel time index (TTI), which is to characterize the mobility of the intersection immediately following the disruption with the ratio between the travel time of any candidate signal plan with disruption and the intersection travel time without disruption. The other is queue length index (QLI), which is to define the efficiency of the traffic signal performance during post-disruption recovery process. The definitions of TTI and QLI are outlined below:

$$TTI(t) = \frac{Travel\ time\ with\ disruption}{Travel\ time\ without\ disruption} \tag{3.7}$$

$$QLI(t) = \frac{Queue\ length\ with\ disruption}{Queue\ length\ without\ disruption} \tag{3.8}$$

3.3 Traffic signal study following crashes at intersection

The proposed methodology can be applied to study disruptive traffic scenarios from different incidents. In the following section, several typical traffic crashes are studied at the prototype intersection as a demonstration. Details are discussed in the following.

3.3.1 Study area

City of Fort Collins in Colorado is a typical urban community with a moderate size in the western part of the country, which is chosen as the prototype study region due to its representative nature and data availability. The Harmony and Timberline Road four-way intersection is selected as the study area because it is one of the most representative major intersections in the city which links two busy corridors. A microscopic traffic model of the Harmony and Timberline intersection is built with SUMO (Fig. 3.4). All the intersection geometry and lane arrangements follow the actual data except for the approach lengths which are different from the reality so that the simulation can accommodate various queue length scenarios. By replicating the realistic turn bay lengths, spillover and spillback situations during post-crash periods can be appropriately modeled. The actual intersection fixed traffic signal plan is modeled as the baseline scenario and the monitored traffic volume data provided by the City of Fort Collins is adopted. The basic intersection and traffic data are shown in Table 3.1 and Table 3.2, respectively.

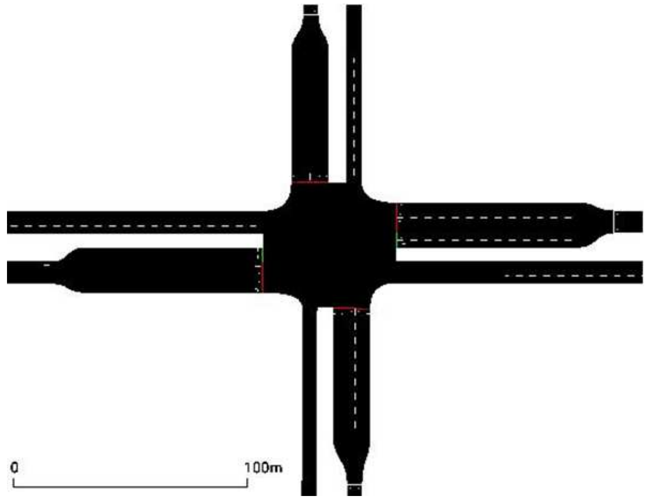


Fig. 3.4 Intersection modeling in SUMO

Table 3.1 and Table 3.2 provide the basic information and parameters to simulate intersection with SUMO based on the real-life data. In Table 3.1, the length is about the through lane length from different directions to the intersection; turn pocket length is the length of left-turn and right-turn lanes; the numbers of the left-turn lanes and right-turn lanes are the same for different directions; the through lane numbers in southbound and northbound directions are 2, and the through lane numbers in eastbound and westbound direction are 3. Table 3.2 lists the actual traffic volumes coming from different directions through the intersection during PM peak hour of a typical weekday and the free flow speed adopts the respective speed limits for all the directions.

Table 3.1 Intersection layout

	Southbound	Northbound	Eastbound	Westbound
Length(m)	500	500	1000	1000
Turn pocket length (m)	55	54	77	78
Through lane	2	2	3	3
Left-turn lane	2	2	2	2
Right-turn lane	1	1	1	1

Table 3.2 Traffic volume information

	Southbound	Northbound	Eastbound	Westbound
Traffic volume (vph)	1490	1315	2280	2064
Left-turn traffic volume (vph)	328	408	410	289
Through traffic volume (vph)	775	710	1528	1507
Right-turn traffic volume (vph)	387	197	342	268
Free flow speed (m/s)	17.88	17.88	20.12	20.12

3.3.2 Crash types investigated in this study

To demonstrate the proposed adaptive strategy under incidents, three different vehicle crash types are studied: rear-end, angle-impact, and opposite-direction (left-turn vs through) crashes. It is noted that occasionally partial closure rather than full closure of the approach may be implemented after the crash occurs. However, partial closure involves many factors with high uncertainties which are hard to quantify and validate with current data. To avoid possibly ambiguous findings and keep reasonable research scope by focusing on the worst scenarios, the whole approach with the crash occurrence is assumed to be closed in this study. For the opposite-direction crash scenario, left-turn lanes at the eastbound approach and all the through lanes at the westbound approach are closed.

The PM peak hour traffic in a weekday is chosen as the simulation scenario and the typical actual traffic volume data is adopted. The total simulation period is 3600s, which can be divided into 3 parts: 1) initialization part (900s)- the vehicles start getting into the network and the simulation results become stable and remain in equilibrium; 2) crash part (900s)- the crash has happened and the affected approach is closed when vehicles start queueing up; and 3) clearance part (1800s)- the crash has been cleared, and the remaining queue starts to be dissipated. No pedestrian is considered in this study and the impact of emergency vehicles on the traffic movement is ignored.

To compare the proposed traffic signal design with traditional traffic signal plans, both fixed and actuated traffic signal control plans are modeled for the same intersection under the same conditions. Fixed traffic signal plan uses constant green time and unchanged phase sequence which follow the actual intersection traffic signal design. In this study, to provide an easy and fair comparison without introducing too many variables, the actuated traffic signal control is limited to adjusting the green time based on traffic volumes, but not the phase sequences. The green durations for fixed traffic signal and the ranges for the actuated traffic signal plan for all the phases are shown in Table 3.3:

Table 3.3 Signal time for fixed and actuated traffic signal control plans

	Eastbound and Westbound Left Turn	Eastbound and Westbound Through	Northbound and Southbound Left Turn	Northbound and Southbound Through
Fixed traffic signal	15s	38s	14s	33s
Actuated traffic signal	5-20s	15-60s	5-20s	15-60s

3.3.3 Rear-end crash

A rear-end crash is assumed to happen at the westbound approach through lanes (Fig. 3.5). The red strip in Fig. 3.5 stands for the closed segment because of the crash at the intersection. Although left-turn vehicles can theoretically pass the intersection (left turn bay is open), vehicles usually quickly jam the left-turn lanes without movement due to spillover effects. Therefore, all the lanes on this approach are practically closed quickly following the crash. The intersection layout for rear end crash and the spillover effect are shown below in Fig. 3.5 & 3.6:

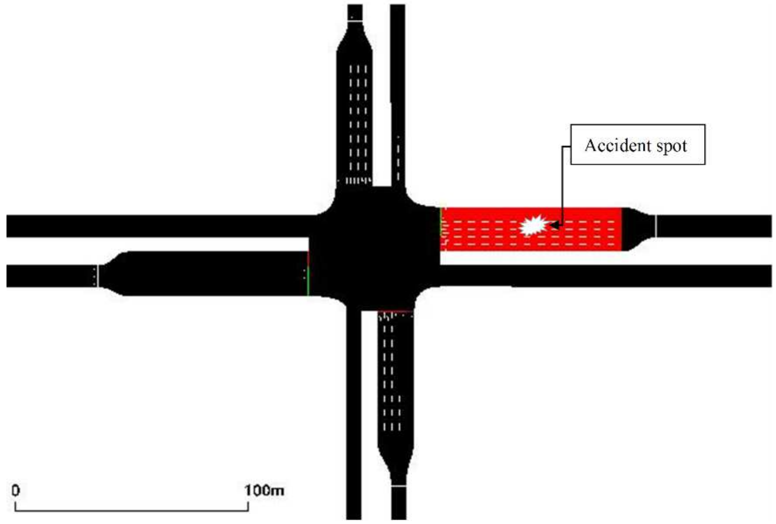


Fig. 3.5 Rear end crash spot and crash segment

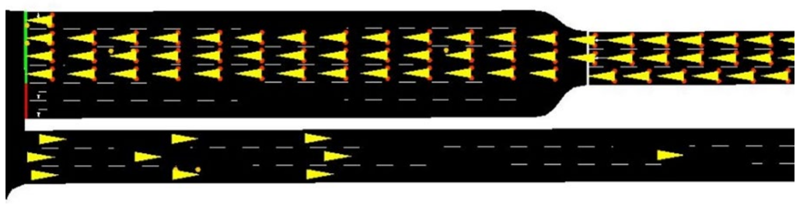


Fig. 3.6 Spillover effect

3.3.4 Angle-impact crash

Angle-impact crash here is about a vehicle crashing with another from different directions at an intersection (e.g., right-angle or "T-bone" collisions). In this study, the crash spot and closed segment are shown in Figure 3.7. Most parameters such as the simulation and crash durations remain the same as the rear-end scenario except both the approaches of westbound and northbound traffic are closed. As compared to the rear-end scenario, angle-impact crash may experience longer and more complex queue which needs to be considered for green time allocation. An optimal balance between green time and queue length of different disrupted approaches should be achieved.

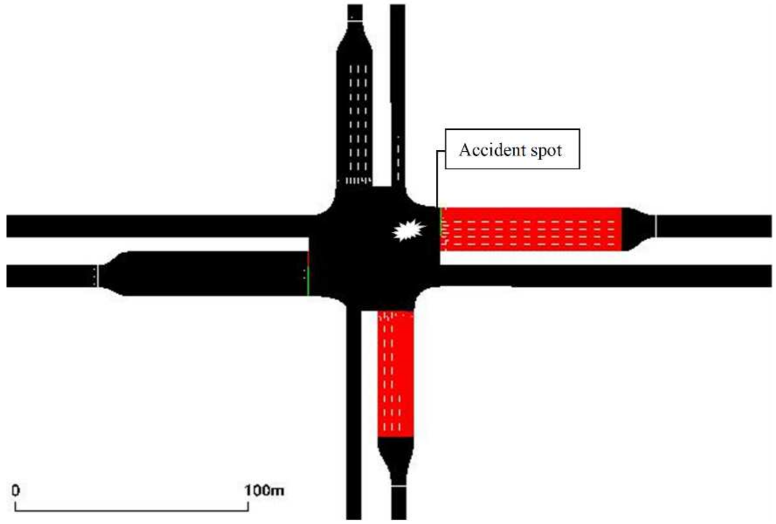


Fig. 3.7 Angle-impact crash spot and closed segment

3.3.5 Opposite-direction crash (left-turn vs through)

Opposite-direction crash is a rare but critical crash type at the intersection with severe consequences. Unlike angle-impact crash at intersections, it is about the conflicts between vehicles in opposite directions (e.g., left-turn vehicles vs. through vehicles from the opposite direction). The crash spot and closed segment are shown in Figure 3.8 & 3.9. In this case, the left-turn lanes of the east-bound direction and all the lanes on the west-bound direction are closed. The left-turn vehicles from the eastbound direction will be queued up resulting in spillback effect to block the through vehicles.

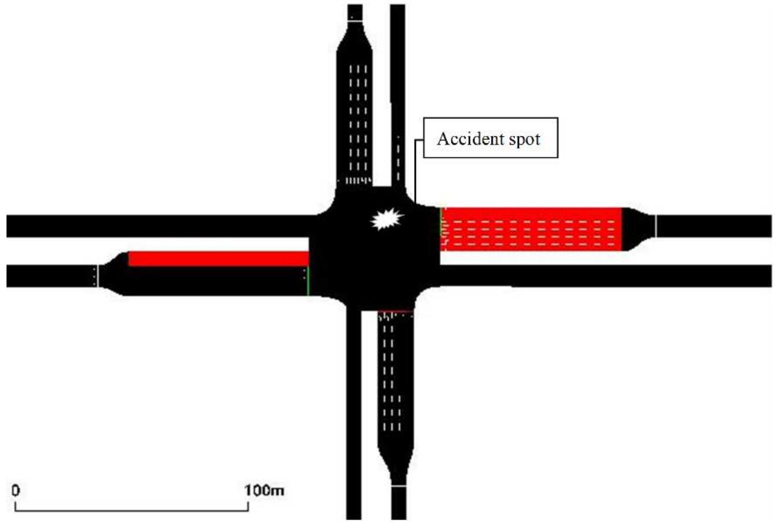


Fig. 3.8 Left turn approach crash spot and closed segment

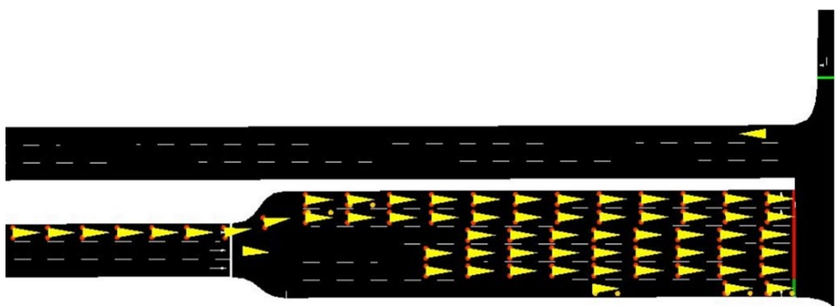


Fig. 3.9 Spillback effect

3.3.6 Impact of traffic disruptions caused by crashes

Before investigating any new traffic control plan, the impact on the traffic performance from crashes is studied first. A comparison is made in terms of the traffic performance between two moments: before and after the rear-end crash. Figures 3.10 and 3.11 give the results of queue lengths at the crash spot and average speed of the whole intersection. In Fig. 3.10, the results of the recovery stage are listed (i.e., after 30 min since the simulation starts). It is found the queue length at the crash spot dramatically increases to over 350 m right before the recovery stage. During the recovery stage, the queue is eventually restored to that for normal situation about 45 mins after the simulation has started.

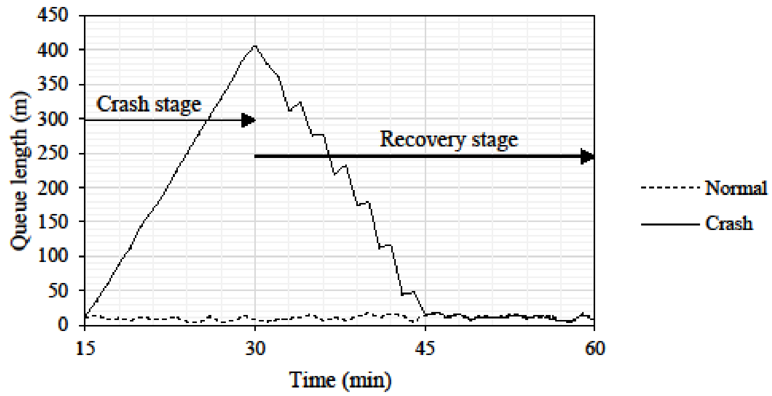


Fig. 3.10 Queue length at crash spot

As shown in Figure 3.11, the average speed of the intersection quickly dropped to around 2 m/s within about 15 mins after the crash has occurred. It will take about another 20 mins to return to normal average speed. Apparently significant delay at the intersection would occur as the result of the crash, which can be critical during emergencies. To achieve the best performance, the signal optimization work needs to be conducted for both the incident (crash) stage immediately following the disruption and the recovery stage.

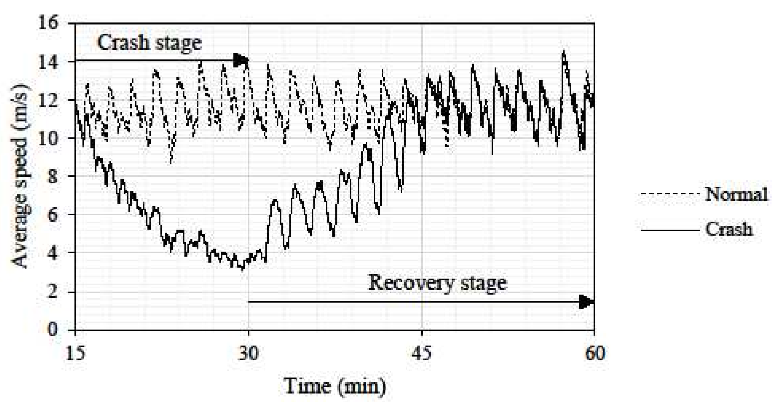


Fig. 3.11 Intersection average speed

3.3.7 Comparison of three traffic signal control plans

In the following sections, a comparison of three traffic signal control plans is made: fixed time, actuated and the proposed DPS+QLD plans.

3.3.8 Rear-end crash

In Figure 3.12, it shows the variation of the queue length of the approach with the crash over simulation time. The *x*-axis starts from 30 minutes after the simulation starts, which corresponds to the beginning of the recovery stage when the crash site has been cleared. The initial queue QLI for this approach is 59 right before the recovery starts. DPS+QLD signal control plan can dissipate the queue length faster than the other approaches and make the performance of the intersection back to normal in only 12 minutes. In contrast, 15 minutes and 14 minutes are respectively required for recovering the mobility of the intersection for fixed and actuated signal controls.

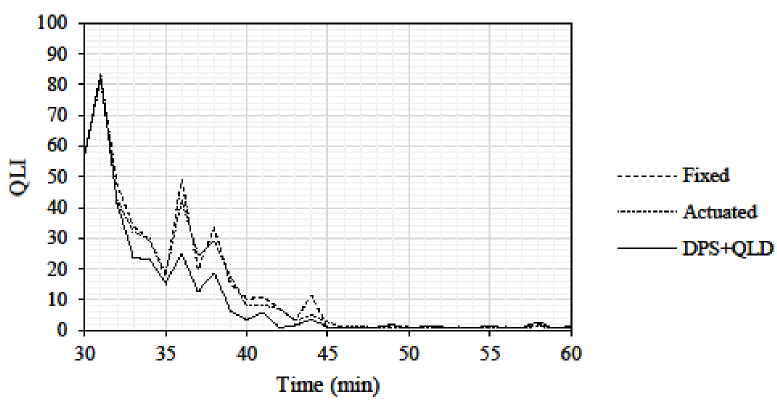


Fig. 3.12 Crash approach queue length index variation for rear-end crash

Figure 3.13 represents the time loss on the westbound approach under different traffic control plans. The time loss is calculated based on the comparison of the travel time passing through the intersection with the speed limit for the entire traffic during the simulation. DPS+QLD plan has the time loss of 36 seconds, which is lower than 44 seconds and 46 seconds for the fixed and actuated traffic signal plans, respectively. Apparently, DPS+QLD plan has the potential to not only dissipate the queue length as quickly as possible, but also optimize the traffic performance on the approach directly affected by the crash.

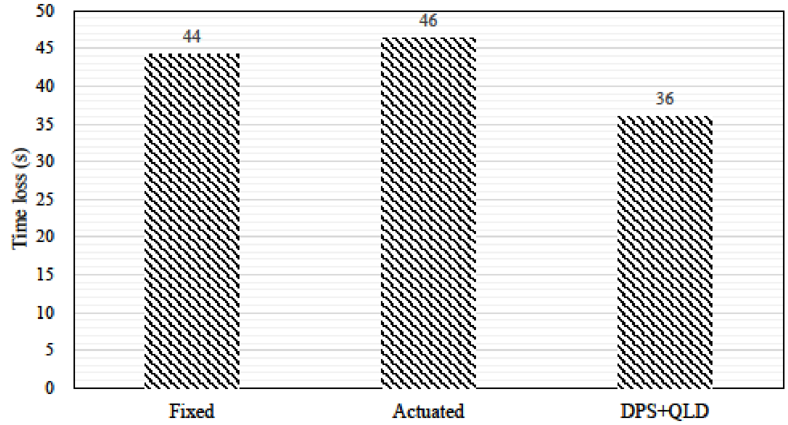


Fig. 3.13 Time loss for westbound approach comparison for rear-end crash

After comparing the queue dissipation ability at the crash approach for these traffic signal control plans, it is important to study the whole intersection performance during and following the crash stage. Figure 3.14 shows TTI of the whole network using different traffic signal control plans. The data is collected from the beginning of crash occurrence (900s) to the moment when the disruption is fully recovered (2700s). During the incident (crash) stage, DPS+QLD plan has lower travel time than those with the other two signal control plans because the phase for the crash approach is skipped and the corresponding green time is then allocated to other phases. During the recovery stage, DPS+QLD plan also exhibits relatively lower travel time as compared to the other two strategies. So, the traffic efficiency using DPS+QLD plan has been consistently improved during both crash and recovery stages for the rear-end crash scenario.

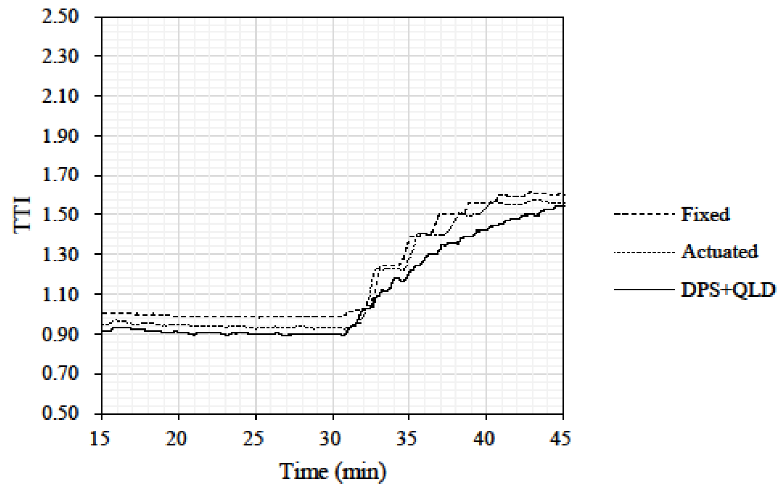


Fig. 3.14 Travel time index comparison at the intersection for rear-end crash

3.3.9 Angle-impact crash

Angle-impact crash scenario is studied in this section. Figures 3.15 & 3.16 show the queue length variations over time on westbound and northbound approaches, respectively. For the westbound approach, the results for DPS+QLD, fixed and actuated traffic signal plans exhibit similar results, while DPS+QLD plan only performs slightly better than the other two plans (13 minutes vs. 15 minutes) (Fig. 3.15). Significant difference is observed on the results for the northbound approach (Fig. 3.16). DPS+QLD plan quickly reduces the queue length in about 11 minutes and remains constant queue lengths for the remaining period of the recovery stage. In contrast, fixed and actuated traffic signal control plans will have larger queue lengths which also vary considerably from cycle to cycle. The large fluctuations of queue lengths between cycles are not ideal from both traffic control and traffic safety perspectives.

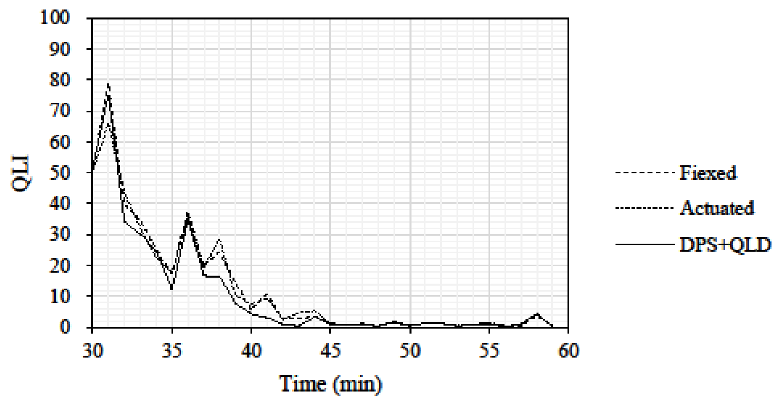


Fig. 3.15 QLI for westbound approach

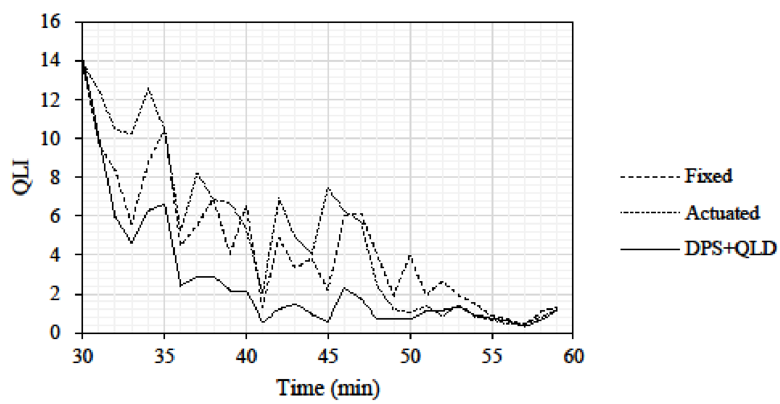


Fig. 3.16 QLI for northbound approach

Figure 3.17 summarizes the time loss data for two approaches with different traffic signal plans. It is found that in addition to queue length clearance efficiency DPS+QLD plan also achieves superior performance in terms of time loss for the angle-impact crash scenario. DPS+QLD plan can lead to the lowest time loss of 43s and 44s for the westbound and eastbound approaches, respectively.

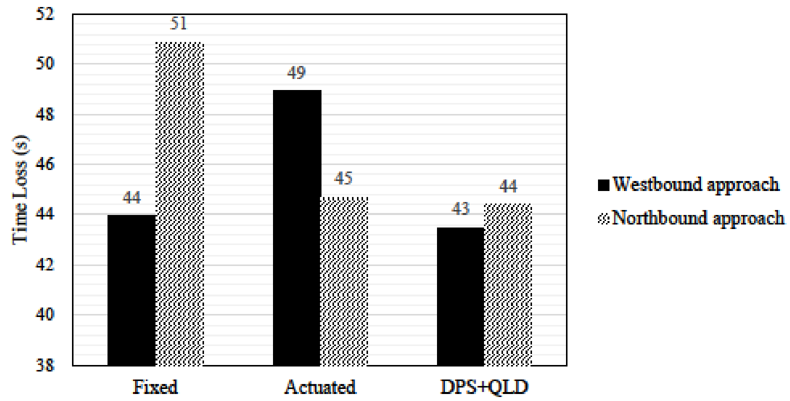


Fig. 3.17 Time loss of three traffic signal strategies on two approaches for angle-impact crash

Speaking of the whole intersection, Figure 3.18 shows the TTI values over time for the three traffic signal control plans. DPS+QLD plan is still found to have the best overall intersection performance among the three traffic signal control plans. By comparing the results in Fig. 3.18 and Fig. 3.14, it can be found that the advantage of DPS+QLD plan over the other two traffic signal control plans in terms of TTI for angle-impact crashes is less significant than that for rear-end crashes. During the time immediately following the incident (crash) stage, DPS+QLD plan for these 2 types of crashes have similar TTI around 0.9. However, during the recovery stage, TTI for rear-end crashes increase much slower than that for angle-impact crashes, which means the recovery speed in terms of travel time is generally lower for rear-end crashes than that for angle-impact crashes.

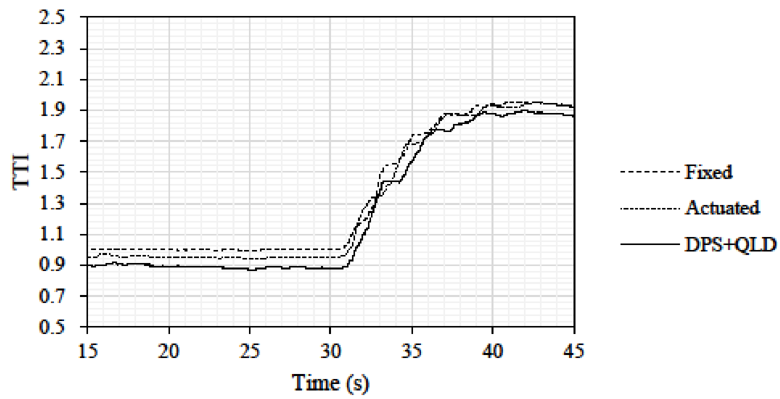


Fig. 3.18 TTI of the intersection for angle-impact crash

3.3.10 Opposite-direction crash (left-turn vs through)

For opposite-direction crashes like left-turn movement vs. through traffic, the QLI values for the left-turn lanes are plotted in Figure 3.19 for three traffic signal design plans. Because of the phase skipping function for DPS+QLD plan, the initial QLI of DPS+QLD plan was only 8.99, which is much smaller than those of the fixed and actuated signal control plans (both around 12.37). Such an initial advantage makes DPS+QLD plan to dissipate the queue length in only 5 minutes, while the other two traffic signal control plans would take 8-10 minutes to bring the intersection performance back to normal. The QLI results for the westbound approach are not shown here because of similarity to that of the rear-end crash scenario.

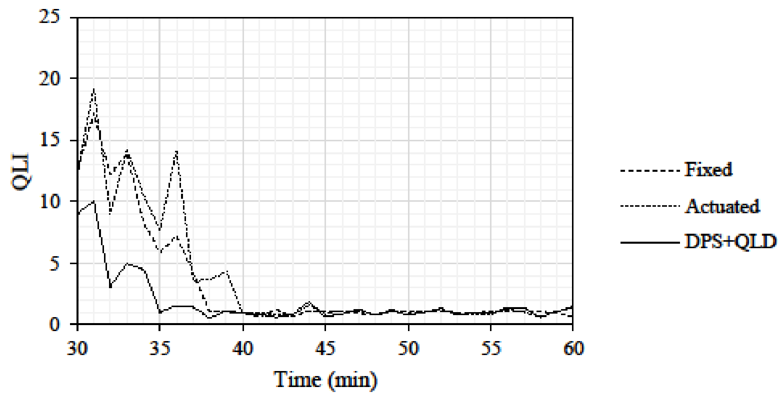


Fig. 3.19 QLI comparison for left-turn lane

Figure 3.20 provides the time loss data of the left-turn lane and through lane for the three traffic signal plans over the whole simulation period. The high time loss at the left-turn lane is mainly attributed to the spillover effect that both left-turn and through vehicles are in queue. Among the three traffic signal plans, DPS+QLD plan is still found to be the most efficient one with the lowest time loss for both left turn and through approaches.

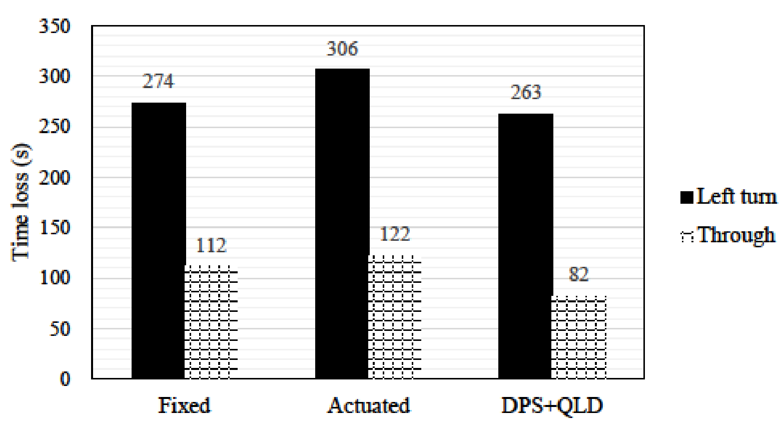


Fig. 3.20 Time loss of left-turn lanes and through lanes

3.4 Conclusion

This chapter has proposed a new adaptive traffic signal strategy integrating dynamic phase selection (DPS) and queue length dissipation (QLD) for disrupted scenarios with incidents at a single intersection.

DPS technique is applied to skip unused phases during the incident period to avoid time waste, which may not only shorten the queue lengths at the impacted approaches, but also improve the intersection overall traffic performance. Optimal green time is further decided by applying QLD signal timing optimization algorithm. The proposed DPS+QLD traffic signal design plan aims to improve the resiliency of a typical intersection against disruptions caused by hazards or incidents by clearing queue faster, reducing overall traffic loss time and recover intersection mobility quickly. Depending on the specific scenario of traffic disruptions, there may be some time periods during which no vehicle remains on some specific lanes or approaches of the intersection due to the disruption. Since no call of service is needed for that phase during certain time periods, DPS can skip the unused phase and reallocate green time to other phases to shorten the whole cycle length. Such an adaptive adjustments on traffic signal control may not only shorten the queue length near the disrupted area, but also help mitigate overall congestion at the intersection. For disruptions caused by various hazards or other emergency events, the relief on traffic delay at major intersections can greatly support emergency response and recovery efforts to potentially save more lives and build a more resilient traffic network.

During the demonstrative study, a typical major intersection at the City of Fort Collins was modeled using the actual PM peak-hour traffic data in weekdays. Three typical crash types were studied as disruption scenarios: rear-end, angle-impact, and opposite direction crashes. The results of queue lengths variation and time loss of the impacted approaches over time were studied by establishing two resilience-based indexes QLI and TTI. The cumulative travel time results over the simulation period and for the whole intersection were studied.

CHAPTER 4 PERCOLATION-BASED RESILIENCE MODELING AND ACTIVE INTERVENTION OF DISRUPTED URBAN TRAFFIC NETWORK DURING SNOWSTORM[2]

4.1 Introduction

Networks are common in our world which have been extensively studied by mathematicians, physicists, and others with broad applications on biology, social science, statistics, computer science and other areas (Newman 2018). For traffic networks, topological robustness provides an important gauge of resilience against various disruptions (Li et al. 2021). The adoption of mathematic modeling of networks, graph percolation theory and community structures has opened doors to many analytical studies of generic networks. Although some site-specific details of a traffic network may be inevitably sacrificed, network science offers convenient and science-based analytical tools which can help understanding the formation and dynamics of traffic networks (Callaway et al. 2000; Huang et al. 2011; Gao et al. 2011; Li et al. 2015; Ganin et al. 2017, 2019; Hamedmoghadam et al. 2021; Li et al. 2021).

4.1.1 Percolation-based robustness modeling of disrupted traffic network

Percolation is often used to understand the formation and transition process of network dynamics under two general types of attacks: random attacks and target attacks (Newman 2018). In the context of traffic networks, a road segment (or "edge") will be deemed practically "failed" (i.e., heavily congested) according to a set criterion (e.g., speed) or following a probability of failure which is often assumed to be uniform for

[2] This chapter is adapted from a published paper by the author (Yao and Chen 2023) with permission from ASCE.

all the edges of the network. With the increasing criteria or probability of failure, the "failed" road segments will be gradually "removed" from the traffic network, generating different snapshots of "remaining" traffic networks. These snapshots will provide a vivid transition process of the traffic network under different intensities of attacks with some popular measures of robustness such as giant component size and critical percolation threshold (Newman 2018). The uniform probability of failure on each edge provides great convenience on mathematical derivation with classical network science techniques, facilitating some analytical approaches with closed-form results (e.g., Callaway et al. 2000; Newman 2008).

4.1.2 Active traffic intervention of disrupted traffic systems through intersection signal designs

As a type of active intervention measures, smart traffic signal designs have been extensively studied to improve urban traffic safety and efficiency at intersections through signal timing optimization and incident detection techniques (e.g., Sheikh et al., 2020, 2021; Chang et. al., 2000; Yao and Chen 2022). Given the lack of knowledge about and the complexness of disrupted traffic networks under hazards, some "smart" traffic system and optimal algorithms of active intervention measures originally designed for intact networks under normal operational conditions may not work well for the disrupted networks under hazards (Ganin et al. 2019). For example, they may help improve local traffic performance at certain time, but not the overall performance of the whole network or over the whole hazard duration. Given the devastating impact of natural hazards on traffic systems, how to take advantage of active intervention measures such as smart intersection signal design to effectively improve the traffic performance, safety and resilience of disrupted traffic systems remains a challenge, yet with limited research progress so far (Yao and Chen 2022).

In this chapter, a new resilience modeling technique of disrupted urban traffic systems is developed in terms of both local traffic performance and percolation-based robustness at the network scale under natural hazards. Based on the new resilience modeling techniques, it further investigates the feasibility of applying early active traffic intervention measures through optimizing traffic signal designs only at several strategic intersections. The novelty of this study is reflected through addressing existing technical challenges as summarized above in terms of real data scarcity for disrupted traffic systems under hazards, percolation-based robustness modeling and active traffic intervention. Specifically, a hybrid approach to provide enhanced data is firstly developed by combining limited historical real-world data from major intersections collected by scarce sensors at an urban community and the popular microscopic traffic simulation tool "Simulation of Urban Mobility (SUMO)". The calibrated SUMO-based simulation model for both normal conditions and snowy events can provide sufficient microscopic traffic data with high granularity on each link and node under different hazardous conditions. Secondly, with the enhanced traffic data under disruptions, the resilience of disrupted traffic network is assessed with not only traditional traffic performance at local scales, but also global robustness based on the data-driven percolation theory at the network scale. Finally, the feasibility of applying active traffic management measures in terms of optimizing traffic signals at only some strategic intersections identified by resilience assessment is investigated.

4.2 Methodology of disrupted traffic network resilience modeling and active intervention

The proposed methodology consists of three interrelated components: 1) hybrid data enhancement of traffic network under disrupted scenarios through integrating limited real-world data and SUMO-based traffic simulation; 2) resilience modeling of the disrupted traffic network focusing on both traffic performance and percolation-based robustness; and 3) active traffic intervention strategy through only optimizing strategic intersection signals identified by percolation-based robustness analyses to improve the network resilience effectively. Details of these three components are provide below.

4.2.1 Hybrid data enhancement for disrupted traffic network under hazards

First, a hybrid approach of integrating real-world traffic data at major intersections and SUMO-based microscopic traffic simulation is proposed to provide enhanced “real” data. Given the fact that the detailed local traffic real-world data under hazards or incidents are usually lacking, the proposed approach only relies on limited real-world data at major intersections provided by scarce sensors during hazards and incidents to maximize the generality and transferability to other communities. The whole approach includes following steps: (1) the traffic network is firstly modeled with SUMO including network topology, individual road segment details, and intersection signal designs; (2) the model will first be calibrated with real traffic data in normal traffic conditions at different typical traffic scenarios to make sure the site-specific topology, traffic flow characteristics and intersection signal designs are appropriately captured; (3) with the calibrated SUMO traffic network model for normal conditions, the model will be further calibrated with limited real data from major intersections under historical hazards or incidents which are closest to the specific disruptive event of interest; (4) finally, extensive simulations are made on the calibrated SUMO model for disruptive scenarios to provide refined data at road segment levels, with which the traffic performance and resilience at both local and global scales are subsequently assessed.

4.2.2 Resilience modeling of disrupted traffic network: performance and percolation-based robustness

For traffic networks in normal conditions, traffic performance such as travel speed and time are mostly critical as it reflects the functionality and performance of any traffic network. Hazards and incidents will cause various disruptions to the traffic network and therefore resilience concept has been introduced to quantify the characteristics of any system subjected to disruptions with four attributes: robustness, rapidity, redundancy, and resourcefulness (Bruneau et al. 2003; Huang et al. 2011). The term "robustness" can be thought of as the inverse of "vulnerability" (Iyer et al. 2013; De Oliveira et al. 2014). The effects of failing a portion of the network, such as a link or node, on the whole network performance are referred to as network vulnerability (Taylor 2008), which is also defined as "a sensitivity to events that might result in significant decreases in road network serviceability" by Berdica (2002). The term "attack" vulnerability comes from the field of computer science and refers to a drop in network performance caused by the removal of a specific group of nodes or connections (Holme et al. 2002; Huang et al. 2011; Dong et al. 2013).

Robustness measure R of a typical network can be defined as:

$$R = \frac{1}{N}\sum_{Q=1}^{N} s(Q) \tag{4.1}$$

where N = the total number of nodes in the network; Q = number of removed nodes from the network; and s(Q) = the fraction of nodes in the largest connected component after removing Q number of nodes. The theoretical value of R varies from 1/N (star graph) to 0.5 (fully connected).

In complex networks, percolation is closely linked to attack vulnerability (Newman and Engelhardt 1998). Percolation theory covers network structure development under various occupancy probabilities, which are strongly associated with network node/link failures (Gao et al. 2011, 2016). When most of the nodes/links are connected, the network can achieve at least partial functioning. Thus, the size of the network's largest connected component, also known as the giant component size or giant connected component (GCC) size in percolation theory, is often used to qualitatively reflect its resilience subjected to failures (Newman and Engelhardt 1998). A network that can withstand the loss of a substantial proportion of its nodes is deemed resistant to random failures.

Callaway et al. (2000) employed the generating function approach to offer an analytical solution for site percolation on random graphs with generic vertex degree distributions (Newman 2010). The percolation process can be considered with the probability ϕ that a vertex is present (or occupied) in the network and ϕ is often called occupation probability. k represents the degrees of freedom, namely the numbers of links of one node. Assume that p_k is the probability that a randomly selected vertex from the network has degree k, and ϕ_k is the probability that the vertex is present (or occupied) if it has degree k. Then, the probability of having the degree of k present in the network is $p_k\phi_k$. The probability generating function for this distribution is defined as (Callaway et al. 2000; Wilf 2013):

$$F_0(x) = \sum_{k=0}^{\infty} p_k \phi_k x^k \tag{4.2}$$

Therefore, the equivalence of Eq. (4.1) for a vertex is defined as:

$$F_1(x) = \frac{\sum_k k p_k \phi_k x^{k-1}}{\sum_k k p_k} = \frac{F_0'(x)}{z} \tag{4.3}$$

where z = average vertex degree, and $F_0(1) = \phi$ where ϕ is the overall fraction of presented (occupied) nodes. In the special case of uniform removal probability, one can simply set $\phi_k = \phi$ for all k. In the case of $\phi=1$, which means the nodes are all present (occupied), then one has $G_0 = \sum_k p_k x^k$ and $G_1 = \frac{G_0'(x)}{z}$ that correspond to the probability generating functions for a random network as introduced by Newman (2010).

Because of the unpredictable nature and uncertainties, natural hazards may have different impacts on various areas in the traffic network. However, to apply the analytical percolation approach on transportation networks under a hazard (e.g., snow event), the hazard needs to be approximately modeled as a random attack (failure). Therefore, $1 - \phi$ is used to represent the disaster scale. The giant component size S is often chosen to quantify the network robustness, which can be calculated by:

$$S = \phi(1 - G_0(u)) \tag{4.4}$$

$$u = 1 - \phi + \phi G_1(u) \tag{4.5}$$

With equations (4.4)-(4.5), the giant component size of a network under uniform attack with any given degree distribution can be derived.

4.2.3 Active intervention strategy through signal optimization to improve resilience

Active traffic intervention is crucial to maximizing the post-hazard mitigation and response of transportation systems following disruptions. Traffic signal optimization at intersections has been a major active management option for urban traffic networks. The queue length dissipation (QLD) algorithm is used herein to dissipate the queue length at congested lanes (Yao and Chen 2022). The required green time should be calculated based on the queue lengths of not only the approach experiencing congestion but also other approaches of the intersection at the same time to avoid causing additional congestion in other directions. Therefore, the maximum green time g_{max} should be applied to balance the green time allocations among different approaches. Based on the analytical method by Akçelik and Rouphail (1994) and Akçelik (1995), the average green time and cycle length of an actuated controller adopt a fixed unit extension setting by assuming the arrival headway follows the bunched exponential distribution (Cowan 1978). Existing vehicles remaining in front of the green light are defined as bunched vehicles while new arriving vehicles are defined as free vehicles. Different proportions of bunched and free vehicles define the minimum and maximum green time, g_{min} and g_{max}, respectively. The green extension time e_g is set based on the queue length at the red-light ending time point, and the phase change does not occur during the saturated portion of the green period. The associated equations are presented from Eqn. 3.1-3.6 in chapter 3.

4.3 Case study of urban traffic network subjected to snowstorm

4.3.1 Prototype urban traffic network and snowstorms

Colorado is a state in the United States well known for frequent snowstorms during winters, which have caused significant traffic disruptions to the communities in the history. City of Fort Collins in Colorado is a typical medium-sized urban community with the area of 58.5 mile^2 and population of 343,000 in year 2021. It is selected as the prototype community for the case study to demonstrate the proposed methodology due to the high number of similar communities across the country and the accessibility to the traffic monitoring data.

All historical data of snowfall events in the City of Fort Collins from 2018/1/1 to 2020/12/31 were collected from the Colorado Climate Center at Colorado State University (CSU) (https://climate.colostate.edu/data_access.html). Traffic speeds of all roads in an average of 15 minutes were collected on snowy days from the traffic operation division of the City of Fort Collins. Figure 4.1 shows the average speed results versus recent historical snowy events identified by the dates.

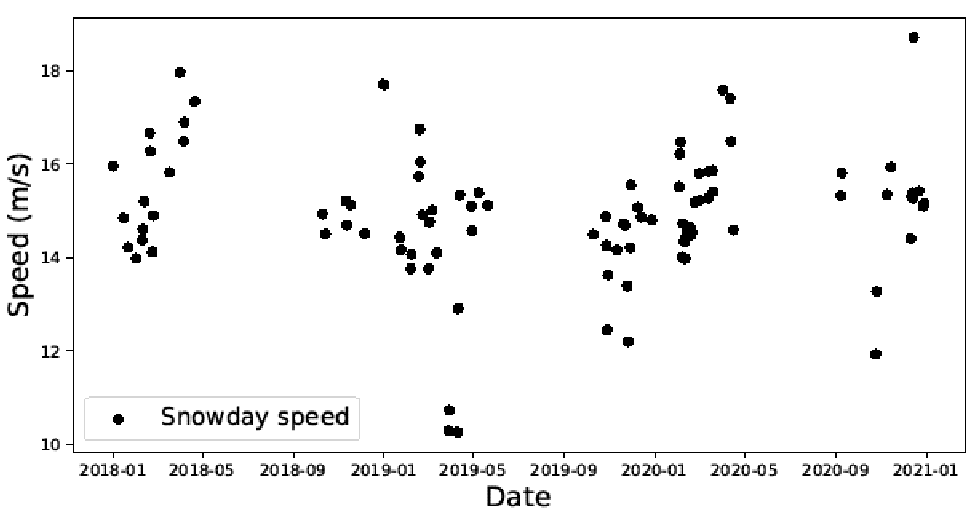


Fig. 4.1 Average speed of Fort Collins traffic network on snow days from 2018-2020

The relationships between snowfall inches and average traffic speeds in Fort Collins are presented in Fig. 4.2 and the dash line represents the linear regression result. Apparently, with heavier snowfall in terms of inches of snow accumulation, the average traffic speed will generally drop due to worsen road conditions. However, the traffic speeds do not vary in a monotonic pattern with the snow depth, indicating the traffic performance over the whole community/network on snowy days is rather profound. Out of recent 3-year historical snow events, the most severe snowstorm event with 16.5-inch snowfall happening between 2019/11/25-2019/11/26 is selected for the following case study. For this snow event, the refined traffic data in an average of 5 minutes is adopted for the following case study.

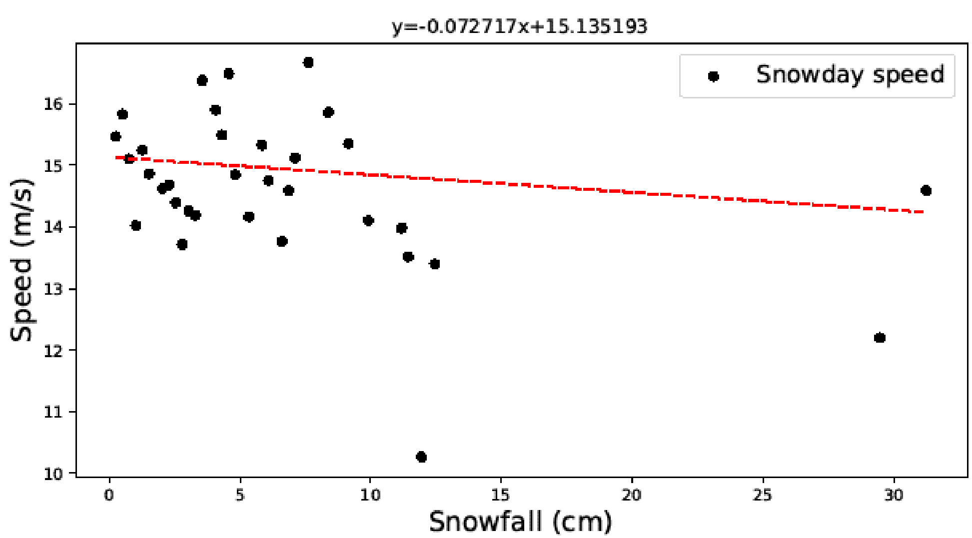
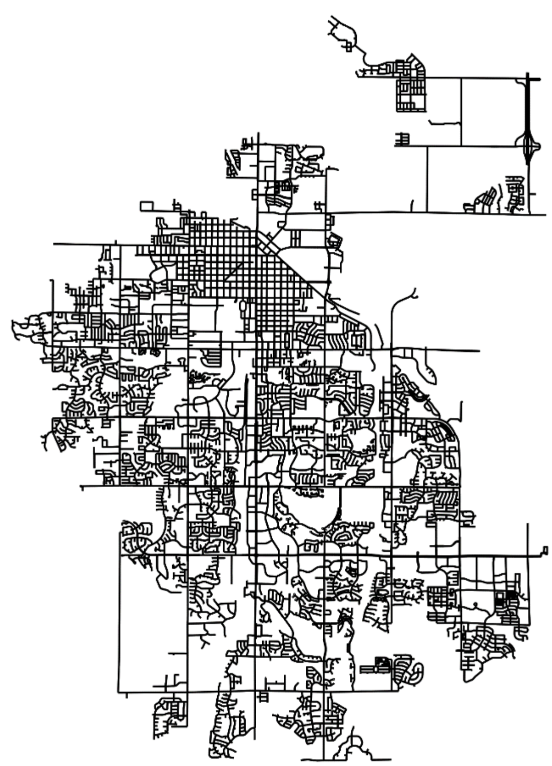
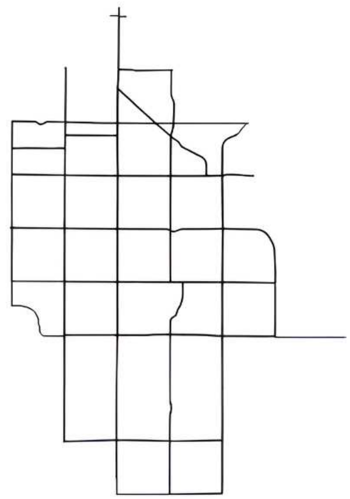


Fig. 4.2 Average speed vs snowfall in Fort Collins

The traffic network data of Fort Collins is acquired from the publicly accessible Python package OSMnx (Beoing 2017) developed based on OpenStreetMap as shown in Fig. 4.3a, including primary and local roads. Since the real-world traffic average speed data was only from major intersections collected by the city traffic operation division, the whole refined traffic network from OSMnx (Fig. 4.3a) is pruned to keep only major roads as shown in Fig. 4.3b to facilitate the following study and calibration with real-world data. In this demonstrative example, the traffic volumes for normal conditions at corresponding time are applied for the snowy events for following reasons: (1) advanced traffic volume monitoring infrastructures may not always be available or work properly during hazardous conditions. It is aimed in this study to introduce a general approach not heavily dependent on the site-specific advanced infrastructure to provide advanced volume data during hazards; (2) although the traffic volume during snowy days will vary from that in normal days, such trends have not been well understood or modeled. In order not to introduce additional uncertainty or site-specific characteristics into our observations, we chose to use the same traffic volume in the demonstrated example. It is noted the proposed approach can easily adopt actual traffic volumes observed in snowy days, if available, to conduct site-specific case study for any community.



a. Whole refined network

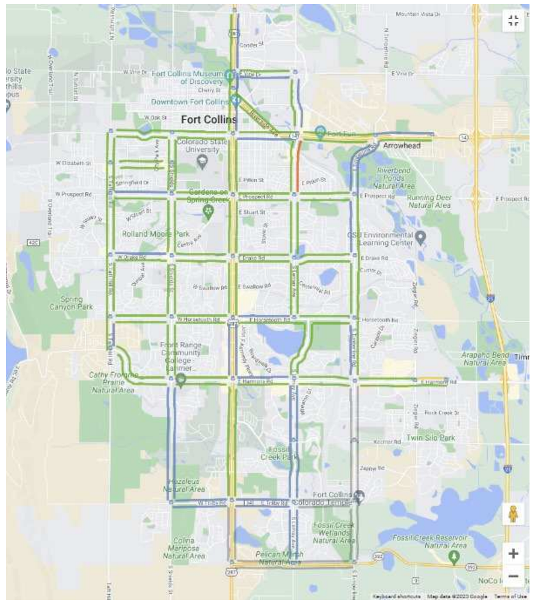


b. Network with major roads

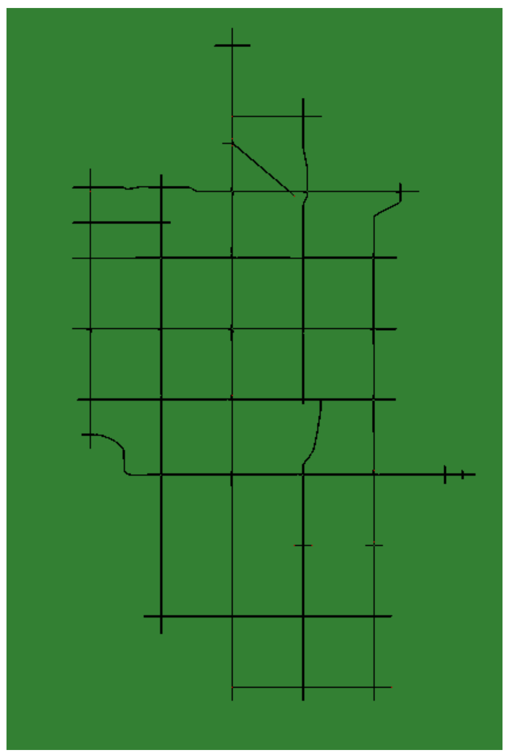
Fig. 4.3 Traffic network of City of Fort Collins from OSMnx

4.3.2 Hybrid simulation-based traffic data enhancement during snow events

SUMO has gained high popularity in both research and engineering applications in recent decades as an open source, highly portable, and continuous microscopic traffic simulation package designed to handle large road networks. The process starts with developing a SUMO traffic network model, which will be calibrated with real traffic data at major intersections. To implement traffic signal optimization, a SUMO traffic network model with all major roads and intersections of Fort Collins is built and Figs. 4.4a-b present the map view and model view of the network. All geometries and details of roads and lane arrangements at intersections are replicated following Fig. 4.4a. Traffic signals in the SUMO model are fixed signal systems using real cycle lengths as well as green-light and red-light allocations from the City of Fort Collins (https://www.fcgov.com/traffic/signals.php). The traffic volumes AADT of each road and direction are also from the City of Fort Collins (https://www.fcgov.com/traffic/traffic-count-disclaimer).



a. Network on map (map data © 2021 Google)



b. SUMO network model

Fig. 4.4 Major roads network and the SUMO model in Fort Collins

After the network is built, the following task is to calibrate all roads with the real-life data. The SUMO model was firstly calibrated with real traffic data in normal driving conditions to make sure all the model parameters including those of intersection traffic control are appropriately defined. In the next phase, the SUMO model will be calibrated with limited historical data in snowy days. Figure 4.5 shows the historical network average traffic speed (5-min interval) for the snowy events between 11/25/2019-11/26/2019. The grey area marked on Fig. 4.5, i.e., between 15:30 to 16:30 on 11/25/2019 was selected for the simulation with SUMO when the network traffic speed was dropping fastest due to heavy snowfall.

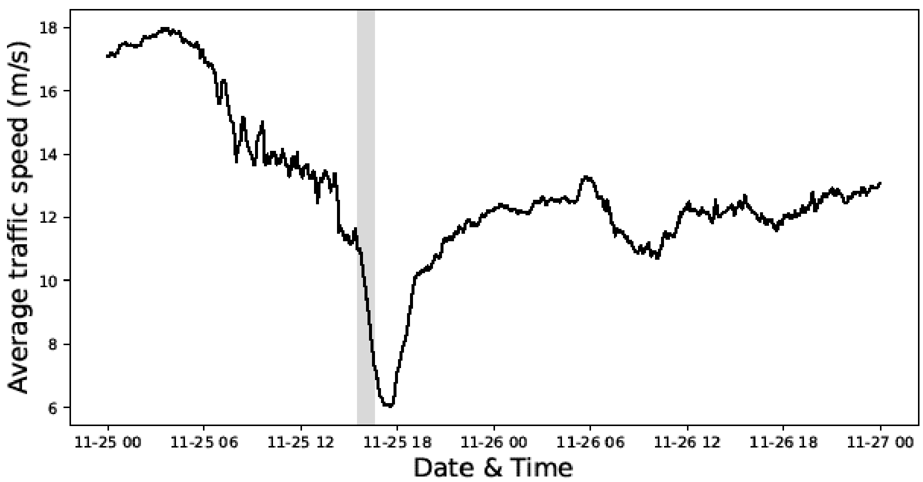


Fig. 4.5 Historical traffic network average traffic speed during snowstorm

By applying the average speed of each road segment from the sensors during historical snowy events to the SUMO model, the model parameters are calibrated leading to the simulation results closest to the reality. Figure 4.6 shows the average speed comparison of the whole network between the simulation and real historical data over the 1-hour simulation period during the snowstorm. The network average speed from the SUMO model shows general agreements over time with the historical records with errors varying between -4.32% and 6.73%.

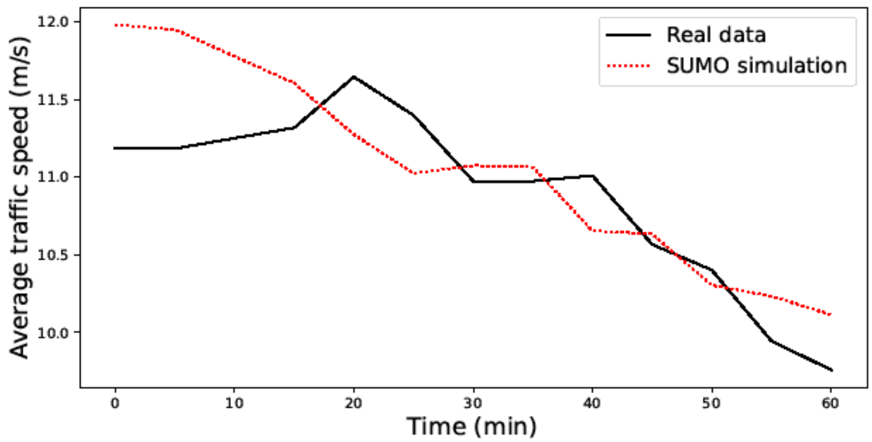


Fig. 4.6 Network traffic average speed comparison between real and simulation data with SUMO

4.3.3 Percolation-based robustness assessment

As discussed above, percolation-based robustness studies have often been conducted with (1) theoretical (analytical) or empirical methods with the assumption of uniform failure probability under random attacks, and (2) data-driven percolation analysis primarily using real data, if available. In the previous section, microscopic-scale traffic data has been generated with the hybrid data enhancement using the calibrated SUMO model. In this section, percolation-based robustness assessment is carried out as two parts: (1) theoretical and empirical percolation analyses of the prototype network under random attacks; and (2) data-driven percolation analysis during the snowstorm based on the results from the enhanced "real" data.

4.3.3.1 *Theoretical and empirical percolation results under random attacks*

As discussed in the introduction section, the uniform failure probability of traffic networks under random attacks may not represent the realistic vulnerability nature of individual road segments of the traffic network subject to natural hazards considering the site-specific disruptions, traffic capacity, demand, and travel behavior. However, as a popular network robustness analysis scenario, percolation study under random attacks can still provide approximate but valuable baseline information about traffic network dynamics and transition during hazards. According to the network theory, node degree refers to the number of links connected to the node in the network. The traffic network of Fort Collins as shown in Fig. 4.3b has 266 total nodes, 506 edges, and the average node degree is 3.19. Table 4.1 shows the node numbers for each node degree and the robustness value of R is calculated to be 0.2339 according to Eq. (4.1).

Table 4.1 Node degree distribution

Degree	1	2	3	4	5
Number of Nodes	8	6	59	83	0

With Eqs. (4.2-4.3), analytical percolation analysis of the traffic network is conducted, and the size of giant connected component (GCC) can be analytically derived. In addition, an empirical study is conducted based on the node and edge data of Fort Collins from OSMnx to manually simulate the percolation process on the same network. For each percentage of nodes being removed reflecting the failure probability, the corresponding number of nodes will be randomly selected to be removed from the network to form the disrupted network, from which the size of the giant connected component (GCC) will be obtained by searching the connected clusters. Such an experiment of randomly removing the nodes will be repeated for 200 times and the average GCC will be calculated for each percentage of nodes being removed to accommodate the randomness and uncertainties.

Figure 4.7 shows the percolation-based robustness results based on the theoretical and empirical methods under random attacks with uniform probability of failure. As shown in Fig. 4.7, the two methods provide somehow different results, and the empirical method is more conservative when the removed nodes are more than 20% of the total nodes. Two approaches give similar critical percolation threshold values, but different critical failing point values in terms of the percentage of removed nodes: 0.6 for the theoretical approach and 0.52 for the empirical approach. The difference between the results from the theoretical and empirical methods was also found by Dong et al. (2020), in which the difference was found attributed to the degree assortativity and spatially embedded features of transportation networks.

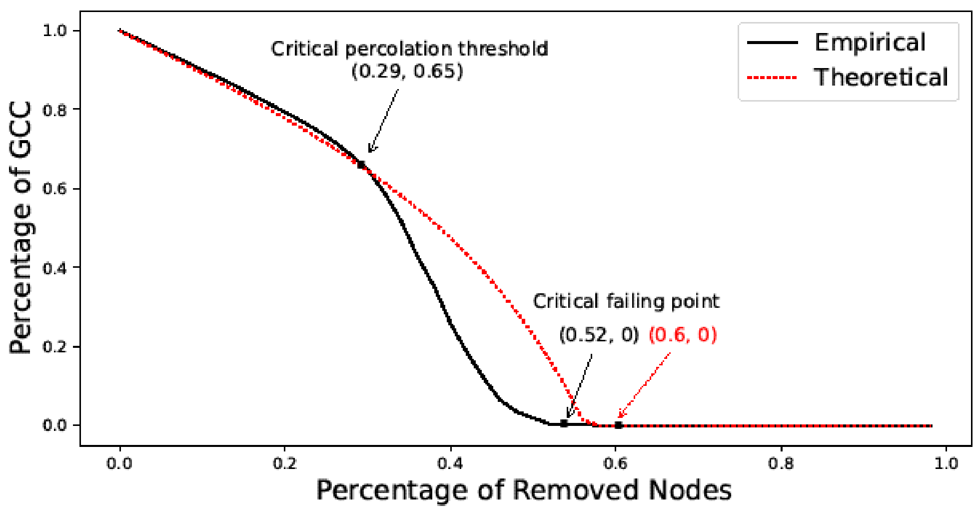


Fig. 4.7 Giant component size of classical percolation analysis under random attacks

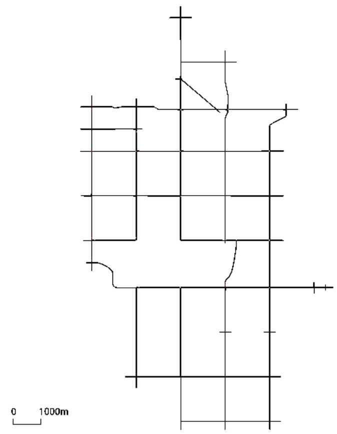
4.3.3.2 Data-driven percolation analysis results on snowy days with enhanced data

Although percolation of networks under random attacks can provide useful information about the general robustness of a typical network, traffic networks have unique features which warrant more specific and insightful investigations (Dong et al. 2020). For natural hazards like snow events, to model the congestion of any road segment with uniform probability of failure under random attacks with traditional analytical or empirical approaches is not ideal. Rather, data-driven percolation analysis of traffic networks with the real monitored data under the specific hazard can provide more realistic insights of the network performance (Li et al. 2015).

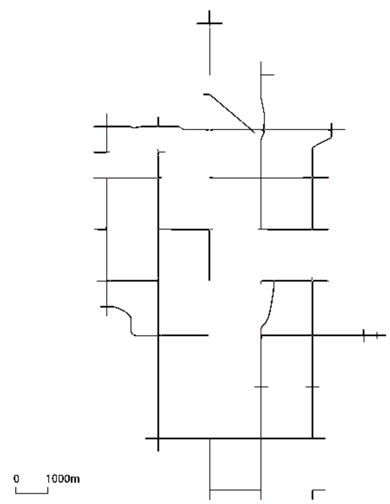
In the previous section, enhanced microscopic traffic data during snowy events has been generated through the hybrid data enhancement with the calibrated SUMO model. These data will be used as “real” data to carry out the data-driven percolation analysis in this section. For the traffic network, nodes and edges represent the intersections and the road segments between two intersections, respectively. The average traffic speed varies during a day according to real-time traffic volume for each edge and is calculated from the microscopic traffic data. For each edge e_{ij}, the corresponding actual speed limit is assigned. $r_{ij}(t)$ is the ratio between its current speed and its speed limit, which serves as a dimensionless performance indicator. For a given threshold q, the road e_{ij} can be classified into two categories: functional when $r_{ij} \geq q$ and dysfunctional for $r_{ij} < q$.

$$e = \begin{cases} 1, & r_{ij} \geq q \\ 0, & r_{ij} < q \end{cases} \tag{4.10}$$

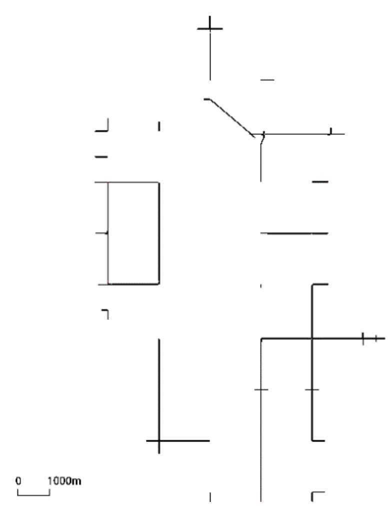
With the “real” data generated from the hybrid data enhancement in snowy days, data-driven percolation analyses can be conducted, and Figure 4.8 shows the percolation results under three different q values. The network starts to fall apart by exhibiting a decreasing size of giant connected components (GCC) when q is more than 0.297. Based on the removed nodes and size of GCC curve, this network is about to break into smaller pieces at q = 0.59. When q =0.7, the network is extensively fragmented, which means there is no significant GCC existing.



a. q =0.297



b. q =0.59



c. q =0.7

Fig. 4.8 Percolation results of remaining traffic network under three different q values

By calculating the GCC sizes for all the varying q values, the results of GCC sizes over q are plotted in Fig. 4.9, in which *x*-axis is about the q value and *y*-axis shows the percentage of GCC over the whole size of the network. With the increase of q, the percentage of GCC gradually reduces from 1, with a sharp reduction occurring at q_c=0.297. q_c is often termed as critical percolation threshold under which the whole network starts to break apart into smaller components while most of the roads remain connected. With the further increase beyond q_c, the percentage of GCC decreases quickly until reaching 0.68, after which the network is barely connected. By comparing Figs. 4.9 and 4.7, it is found that the percolation results from the data-driven approach with the "real" data and those from the analytical and empirical approaches under random attacks are noticeably different. Apparently, for traffic networks under natural hazards, it is preferred to use data-driven approach with the actual data, rather than generic network percolation approach, to provide more realistic results.

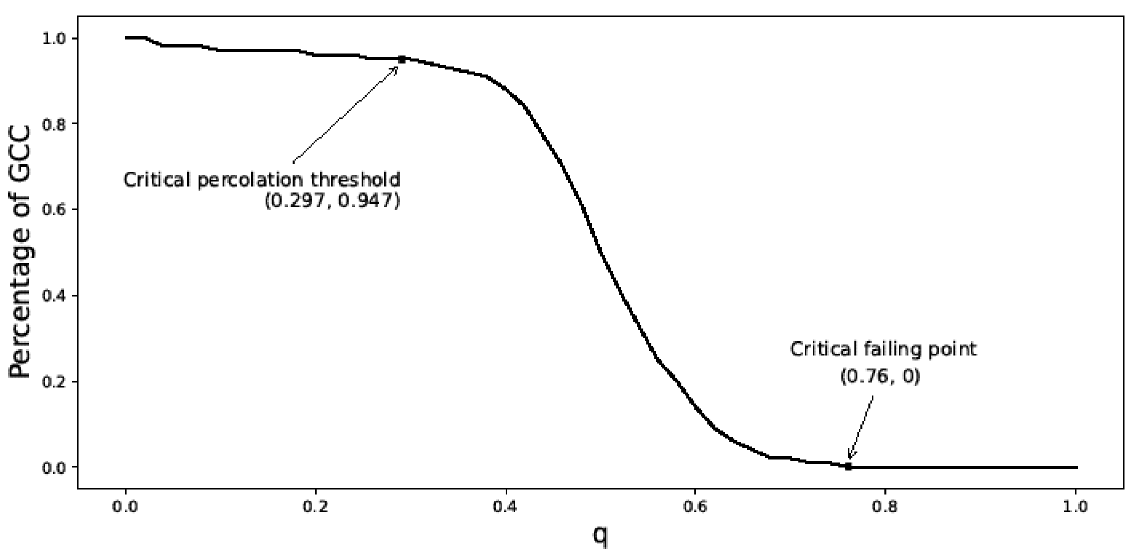


Fig. 4.9 Data-driven percolation analysis results during snowstorm

4.3.4 Active intervention with optimized traffic signal to improve traffic performance and robustness

To provide more effective intervention, it is often critical for any smart traffic system to identify the optimal time and targets to implement any active traffic intervention measure. In this section, it is the goal to study the feasibility of implementing active traffic intervention through optimizing the traffic signal at only some strategic intersections to effectively improve not only the local traffic performance, but also the overall network robustness. Toward this goal, it is the hypothesis that early intervention at only those critical intersections under the critical percolation threshold q_c will effectively improve both local traffic performance and global robustness. Such a hypothesis will be tested in the following.

As shown above, q_c=0.297 is the critical threshold for the traffic network during the snowstorm, under which the four critical intersections causing the dramatic decrease of the size of GCC have been identified with an enlarged view shown in Fig. 4.10. It is found from Figure 4.10 that some edges are removed (or "damaged") between College Avenue, Harmony Road, Horsetooth Road, and Lemay Avenue, from the perspective of percolation-based robustness assessment. Figure 4.11 shows the congestion results from the SUMO simulation of these four intersections.

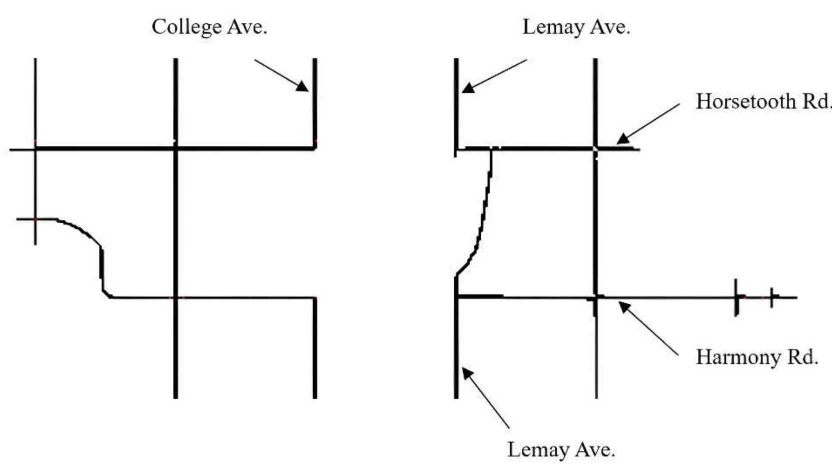
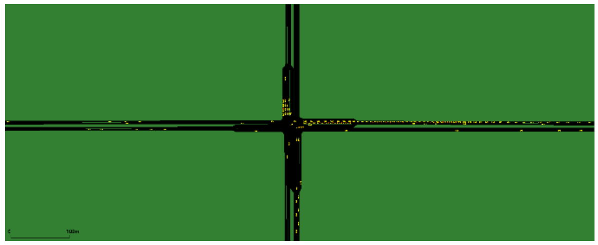
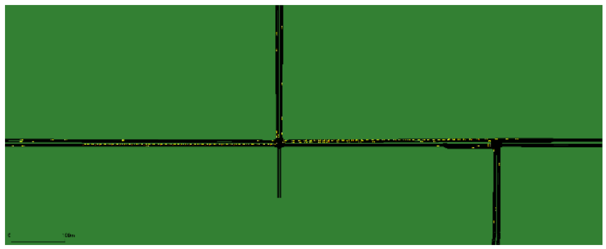


Fig. 4.10 Four critical intersections identified under q_c

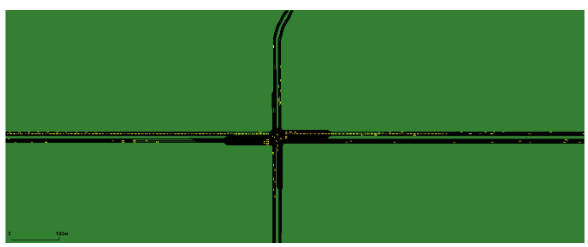


a. College and Horsetooth intersection



b. Lemay and Horsetooth intersection

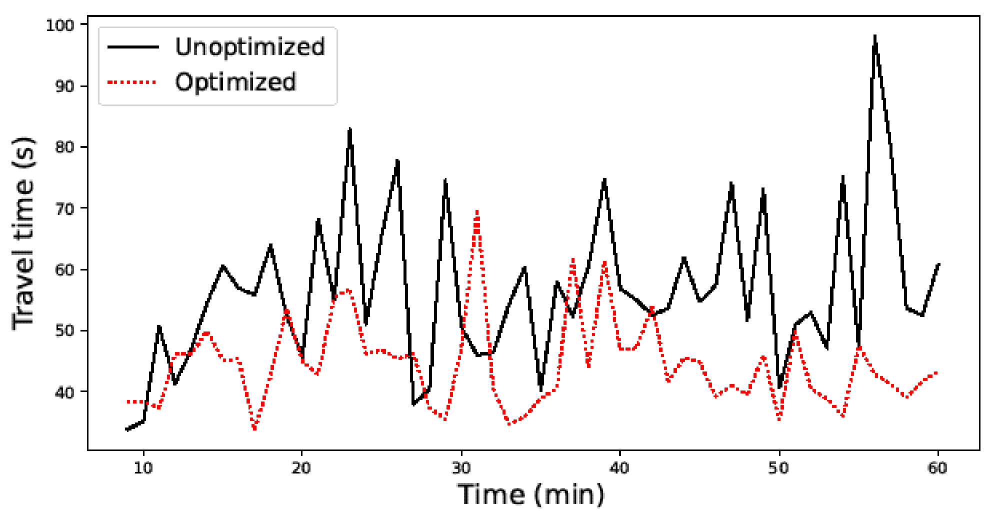
c. College and Harmony intersection



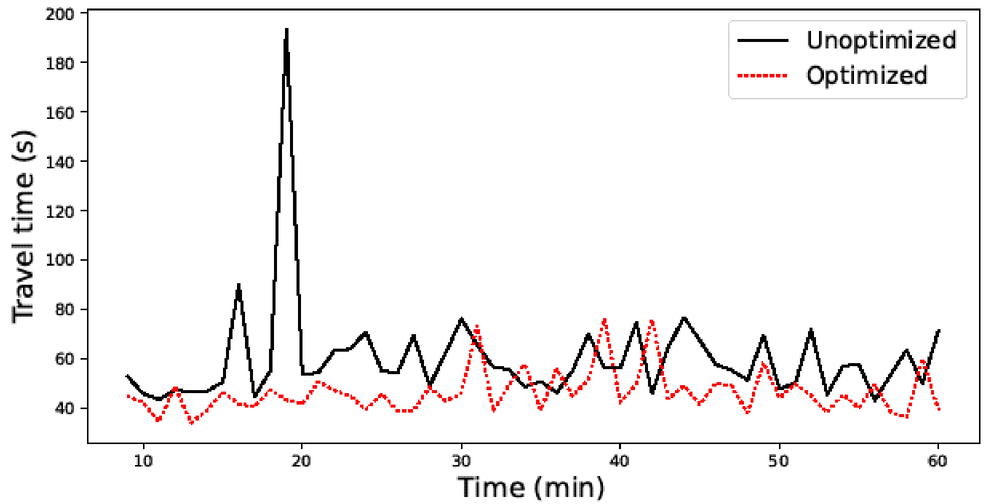
d. Lemay and Harmony intersection

Fig. 4.11 Intersection congestion results

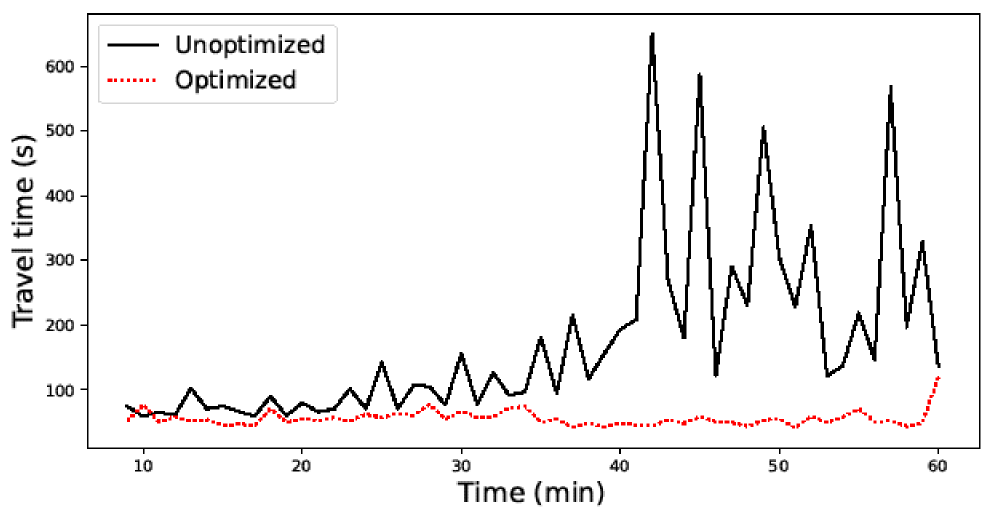
As discussed previously, the size of GCC will quickly further decrease reflecting worsen disruptions when q further increases beyond q_c. So, it is the hypothesis that an early intervention can be made at these identified strategic intersections which will "fail" as shown in Figs. 4.10 and 4.11 through optimizing the traffic signals when q_c is about to be reached. After applying QLD to the four intersections identified above, the traffic performance results at both individual intersection scale and percolation results at the whole traffic network scale are compared between those with the optimized traffic signal models and those with original and unoptimized models. Figure 4.12 shows the travel time comparisons of the four intersections starting at 9 min (initialization period for the network to be filled with vehicles) to the end point of 60 minutes. It is found that the travel time results have been considerably improved for all four intersections after the signal optimization as compared to the unoptimized results. Among all the four intersections, the most improved one was the College and Harmony intersection: the travel time after 35 minutes of simulation was dramatically increased due to the congestion with the unoptimized signal model. In contrast, after the signal optimization is applied, the travel time remained below 100s for the whole simulation period, which not only mitigates the congestion but potentially reduces the crash risks at intersections in snowy days.



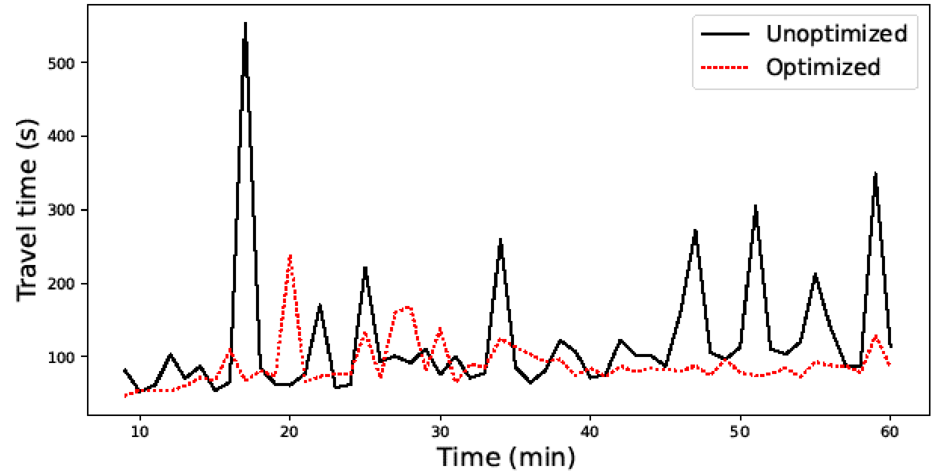
a. College and Horsetooth intersection



b. Lemay and Horsetooth intersection



c. College and Harmony intersection



d. Lemay and Harmony intersection

Fig. 4.12 Travel time comparisons at four intersections w/ and w/o traffic intervention

Figure 4.13 shows the average speed results of the whole traffic network before and after the interventions were made at the four intersections, starting from about 1000 seconds when the initialization period of the SUMO has elapsed. With the intervention, it is found in average the network traffic speed is improved by 9.3% over that before intervention. Apparently, local interventions at only four strategic intersections can effectively improve the overall traffic performance of the whole network.

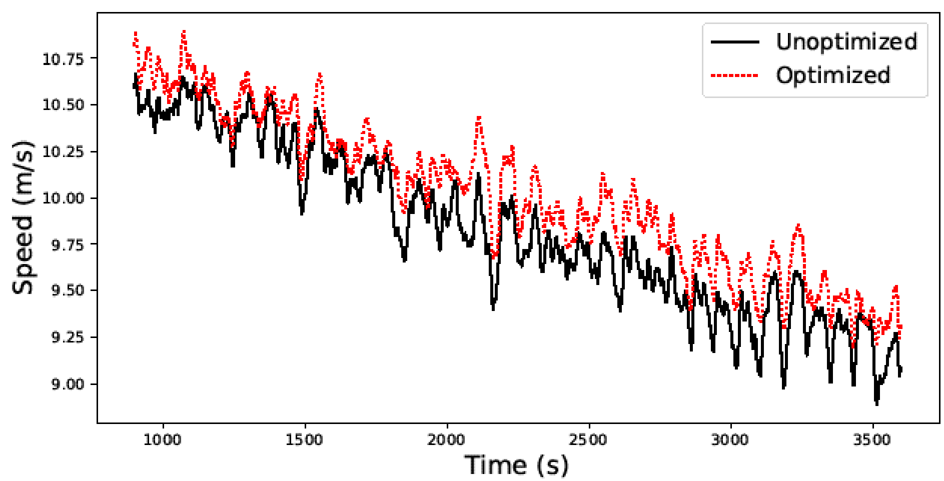


Fig. 4.13 Network average traffic speed comparison w/ and w/o traffic intervention

After the local and network traffic performance is evaluated, the robustness of the whole network is studied after the traffic interventions are implemented. Fig. 4.14 presents the percolation results of the network before and after the interventions are made at the four intersections through signal optimization, which are labeled as “unoptimized” and “optimized”, respectively. It is found that with the optimized traffic signals at the four intersections the percolation starting point, i.e., critical percolation threshold, is postponed by shifting to larger q_c values (from 0.297 to 0.379) due to the improved traffic performance of the whole network. By maintaining the GCC for longer time, the critical failing point is also postponed from 0.76 to 0.82 and the network robustness can be considerably improved. The hypothesis made earlier was found to be valid: early active traffic intervention by optimizing the traffic signal at strategic intersections identified by percolation-based resilience analysis can not only improve the traffic performance at local intersections as well as of the whole traffic network, but also the robustness of the whole network.

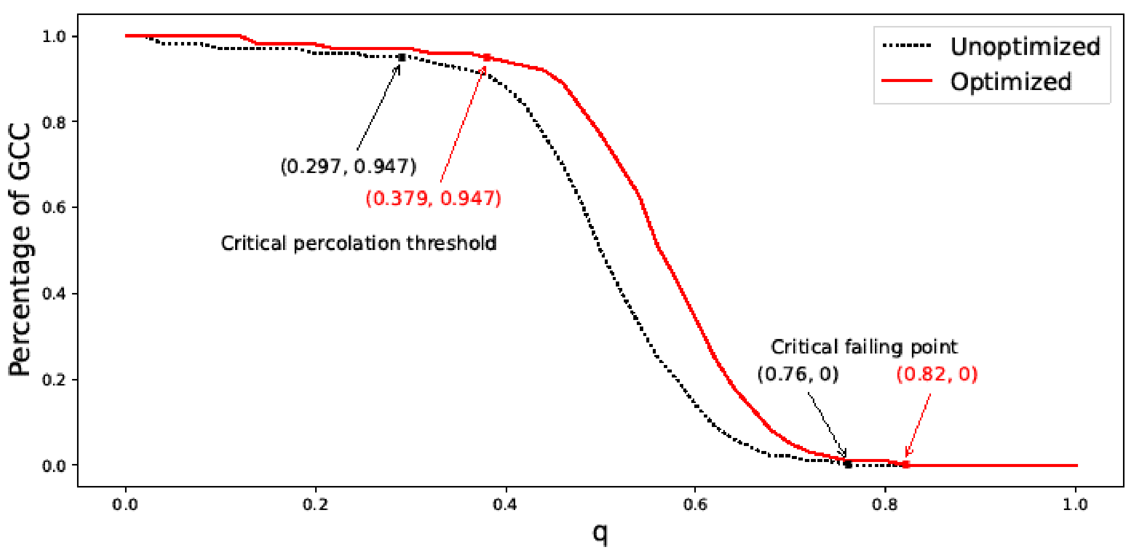


Fig. 4.14 Percolation result comparison w/ and w/o traffic intervention

4.4 Conclusion

The resilience modeling of disrupted urban traffic systems under hazards faces several major challenges, such as real data scarcity and limitations on characterizing resilience with traditional traffic performance measures and existing traffic intervention techniques. To address these challenges, this chapter proposed new resilience modeling methodology of disrupted traffic systems under natural hazards in terms of both local traffic performance and robustness at the network scale. The new methodology integrates hybrid data enhancement with SUMO and percolation-based robustness modeling to provide comprehensive characterization of resilience of disrupted traffic system. With the enhanced "real" microscopic traffic data during hazards from the calibrated SUMO traffic network model, data-driven percolation analysis can be conducted to characterize the network robustness under disruptions, which is also compared with the results from classical percolation analyses under random attacks with uniform failure probability. Based on the resilience assessment results, the study further investigated the feasibility of applying early active traffic intervention measures through optimizing the traffic signal designs at only some strategic intersections identified by the percolation analyses and at the time when the critical percolation threshold is about to emerge to improve both the traffic performance and robustness at local and network scales.

A case study of City of Fort Collins in Colorado during snowy events was made to demonstrate the methodology. The main findings include: (1) data-driven percolation analysis of traffic network with real data under hazards is preferred over the classical network percolation analysis under random attacks because of more realistic results; (2) the proposed resilience modeling methodology can provide new and valuable information in terms of resilience of disrupted traffic network at both local and network scales during natural hazards like snowstorms; (3) the percolation-based robustness results can help identify the optimal intervention moments and strategic targets (i.e., intersections) which will receive intervention through signal control optimization. By optimizing traffic signal control only at four strategic intersections with QLD algorithms, it was found that the traffic performance at intersections as well as the whole network and the robustness of the whole disrupted network under snowstorms can be significantly improved.

Although this study was demonstrated through the snowstorm events in Colorado, the new methodology and concept of early active traffic intervention can be applied to disrupted traffic networks under other hazards and at other locations by applying basic site-specific traffic data. This study tried to provide some new attempts to address several critical challenges of improving the resilience of urban traffic systems under hazards: (1) common data shortage of disrupted traffic systems under hazards; (2) comprehensive time-progressive resilience assessment of a disrupted traffic system under hazards at different spatial scales; and (3) how and when to apply effective traffic intervention such as smart traffic control techniques during hazards.

CHAPTER 5 TRANSFER LEARNING-BASED TRAFFIC SPEED FORECAST FOR URBAN TRAFFIC NETWORK DURING SNOWSTORMS[3]

5.1 Introduction

During hazards and other adverse scenarios, traffic systems experience various disruptions on infrastructures, such as bridge closure, temporary lane narrowing or closure by debris or accidents, and power outages on traffic signals, etc. (Hou et al. 2019; Hou and Chen 2020). These disruptions change over time not only with the progression of hazards, but also with the recovery efforts following hazards, such as debris removal and reopening roads and bridges. The time-progressive nature of disruptions turns the traffic system to be "dynamic" and non-stationary in terms of varying information of accessible roads, traffic capacity, and travel time during natural hazards, which can hardly be accurately predicted beforehand using traditional simulation tools. In addition, another significant and unique challenge for traffic systems during hazards as compared to normal conditions is the data availability and transferability (Ganin et al. 2019; Hou and Chen 2019). In this chapter, a robust, proactive traffic performance prediction strategy for urban traffic networks under hazards is developed. The study will firstly conduct the comprehensive traffic speed short-term forecast modeling with the DCRNN techniques and the resilience analysis of the whole network with hybrid data from normal conditions and simulations. The modeling results will provide essential knowledge for further transfer-learning. Secondly, a modified DCRNN for the snowstorm disruption is developed with two data strategies: (1) adopting snowstorm data only, and (2) applying transfer learning

[3] This chapter is adapted from a paper submitted to a journal that is currently under review (Yao et. al 2023a).

technology based on the previous model developed for normal conditions. The two strategies are compared in terms of prediction accuracy, advantages, and disadvantages. By integrating two strategies for different scenarios, a general DCRNN-based traffic forecast solution for disrupted traffic network by natural hazards is proposed to offer robust and efficient traffic forecasting by adaptively accommodating possible traffic disruptions and data availability.

5.2 Formulation

5.2.1 Short-term traffic speed forecasting with modified DCRNN

Traffic forecasting is difficult because of complex spatial dependency on road networks and nonlinear temporal dynamics under varying road and traffic conditions. Compared to normal traffic conditions with little variation spatially and temporally, the predictions considering incidents such as rush hours, accidents, or other disrupted scenarios will be much more challenging because of the nonstationary nature of traffic speeds and the difficulty of conducting long-term forecasts. Traditional knowledge-driven approaches like time series models using classical statistical methods usually rely on stationarity assumptions. In recent years, various data-driven models, especially deep learning models have been developed to conduct spatiotemporal forecasting of traffic systems, such as predicting the future time-dependent traffic speeds of a sensor network in urban areas given historical traffic speeds and the specific topology of a traffic network. Among all the models, diffusion convolutional recurrent neural network (DCRNN) has shown its excellent potential in handling the spatiotemporal time series forecasting involving nonlinearity and non-stationarity with the prediction accuracy outperforming most counterparts (Li et al. 2018). Although DCRNN has not been applied to the disrupted traffic networks by natural hazards, the strength as summarized above as compared to other peers makes people believe it could be a promising potential for such a purpose. In this study, the DCRNN structure will be adopted as the base model, which will be further modified in the following section. The basic information of DCRNN is briefly illustrated in the following.

The traffic network is represented as a weighted directed graph

$$\vartheta = (\eta, \epsilon, \mathrm{A}) \tag{5.1}$$

where,

η = a set of nodes,

ϵ = a set of edges,

A = a weighted adjacency matrix.

The traffic speed observed on traffic network ϑ is denoted as a graph signal S and $\mathrm{S}^{(t)}$represent the signal observed at time t. The traffic speed forecasting problem based on deep learning is essentially to learn a function $\psi(\cdot)$ which maps historical graph signals in time steps $\bar{T}$ to future graph signals in time steps *T* for the graph ϑ:

$$\left[S^{t-\bar{T}+1}, \cdots, S^{t}\right]_{\vartheta} \xrightarrow{\psi(\cdot)} [S^{t+1}, \cdots, S^{t+T}]_{\vartheta} \tag{5.2}$$

The spatial dependency between adjacent nodes is modeled by relating traffic speeds to a diffusion process to capture the stochastic nature of traffic dynamics. The diffusion process starts with random work on the graph ϑ with restart probability $\beta \in [0,1]$.

After developing the diffusion convolution operation of a graph signal S, a diffusion convolutional layer that maps the input S with P-dimensional features to output H with Q-dimensional features:

$$H_{:,q} = \alpha\left(\sum_{p=1}^{P} S_{:,p,*\vartheta} f_\theta\right),\ for\ q \in \{1, \cdots, Q\} \quad (5.3)$$

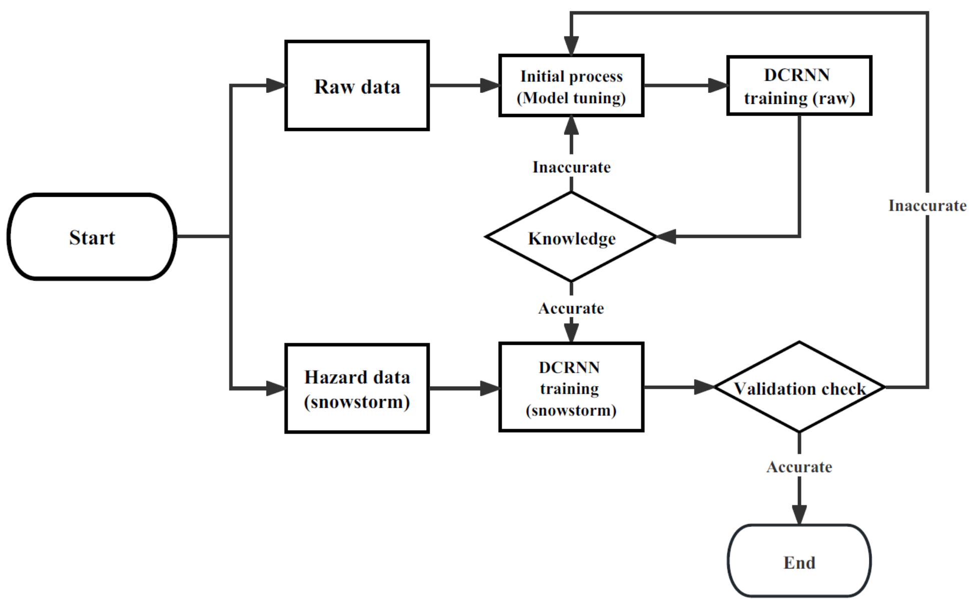
where $\{f_\theta\}$ are the convolutional filters, and θ are the parameter tensors; $*\vartheta$ denotes the diffusion convolution; α is the activation function.

Gated Recurrent Units (GRU), a variant of Recurrent neural networks (RNNs), are further leveraged to model the temporal dependency. By replacing the matrix multiplications in GRU with the diffusion convolution as defined above, the Diffusion Convolutional Gated Recurrent Unit (DCGRU) can be developed. Lastly, sequence-to-sequence architecture is applied with the encoder and decoder to conduct multiple-step forecasting. With both spatial and temporal modeling, the DCGRU is trained using backpropagation through time to maximize the likelihood of generating the target predictions as time series. More details including the model architecture can be found in Ref (Li et al. 2018).

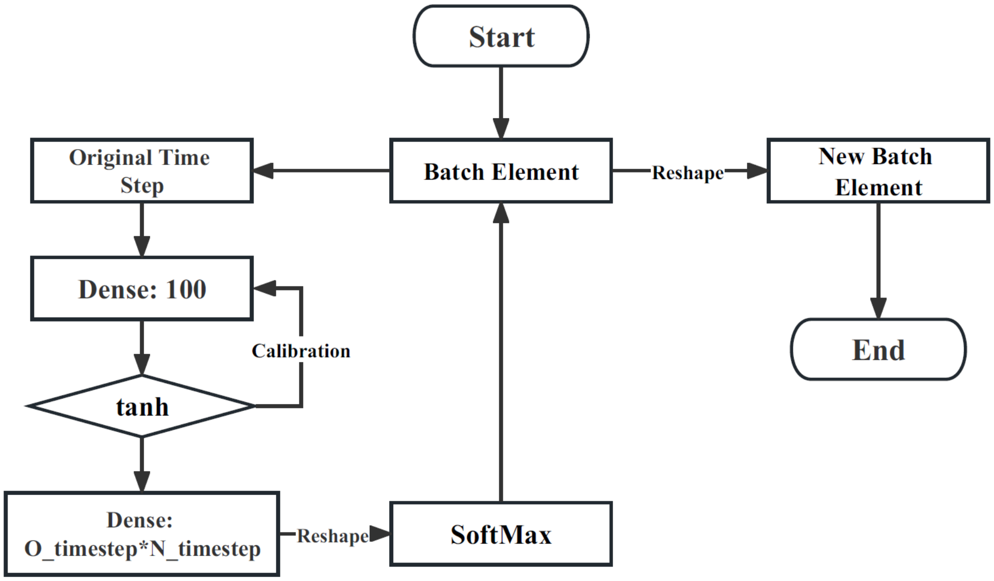
5.2.2 Transfer-learning-based forecasting model of disrupted traffic network to accommodate data scarcity

As discussed earlier, in addition to the nonstationary and "dynamic" nature of traffic data, disrupted traffic network by natural hazards usually has very limited data which can be directly applied to any typical data-driven study. Transfer learning (TL) is a machine learning (ML) research subject that focuses on preserving information obtained while solving one problem and transferring it to another similar problem. Transfer learning has been widely applied in scenarios that specific data is limited but the data for similar scenarios is abundant, and some data-driven models have already been trained. In this study, to address the data scarcity challenge which is common for disrupted traffic networks under various natural hazards, the transfer learning concept is applied to build a modified DCRNN. Specifically, the modified model will integrate the data and derived knowledge of the intact traffic network under normal conditions with limited hazard-specific data for the disrupted traffic network. The modified DCRNN starts with preliminary predictions using short-term traffic speed training results under normal conditions as the pre-trained model, based on which to carry out hazard-specific short-term traffic speed prediction (snowstorm scenario) for refined forecasting. The fundamental idea is presented in following Figure 5.1a, in which the raw data is the short-term traffic speed data in all weather conditions and snowstorm traffic data is considered hazard-specific traffic speed prediction. After the DCRNN model is calibrated functionally for raw dataset, the snowstorm traffic speed data will be applied to the calibrated DCRNN model for another phase of training. The traffic speed forecasting knowledge gained from normal (all weather) conditions will be applied to the snowstorm scenario. The result we are looking for is traffic speed forecasting in snowstorm scenarios for disruption prevention or intervention strategy to recover the traffic system rapidly. The step begins with all conditions of 50 epochs. Then, the snowstorm data only is used for another 50 epochs as non-transfer learning traffic prediction results. The final step is to pass the learning knowledge gather under normal (all weather) condition to the snowstorm scenario for the final 50 epochs. Figure 5.1b shows the design of the transfer layer for traffic speed forecasting using different timestep, which takes the data of the original timestep scale to predict weights for modifying the entire input data. The output weights have shapes of the incoming data's original timestep (O_timestep) by the target number of new timestep(N_timestep). Then SoftMax is applied along the new timestep axis. Like most models involving convolution graph, the DCRNN is typically constructed so that the number of nodes and the timesteps for input and out layers are constant. To integrate both all-weather data and snowstorm data which may have different number of nodes and time steps, the DCRNN model needs to restructure the input timestep via matrix multiplication to accommodate such needs.

For comparison purpose, another data strategy is also made which only uses limited traffic data under snowstorm to conduct the short-term time series forecasting. The results from the transfer-learning-based forecasting model will be compared to those from the snowstorm-data-only model.



a. Modified DCRNN model transfer learning design



b. The timestep transfer layer design

Fig. 5.1 Modified DCRNN workflow for traffic speed forecasting design

5.3 Demonstrative study

5.3.1 Prototype area and data

Colorado is a state in the United States known for its frequent snowstorms throughout the winter, which have historically caused substantial transportation problems in the communities. Fort Collins, Colorado, is a typical medium-sized metropolitan city with a land area of 151.51 km^2 and a population of 343,000 in 2021. Because of the large number of similar towns across the country and the ease of access to traffic monitoring data, it was chosen as the prototype community for the case study to demonstrate the proposed traffic data forecasting strategy during snowstorms. The study area is the main city road network in Fort Collins. Fig. 5.2 shows the Google Map of the study area.

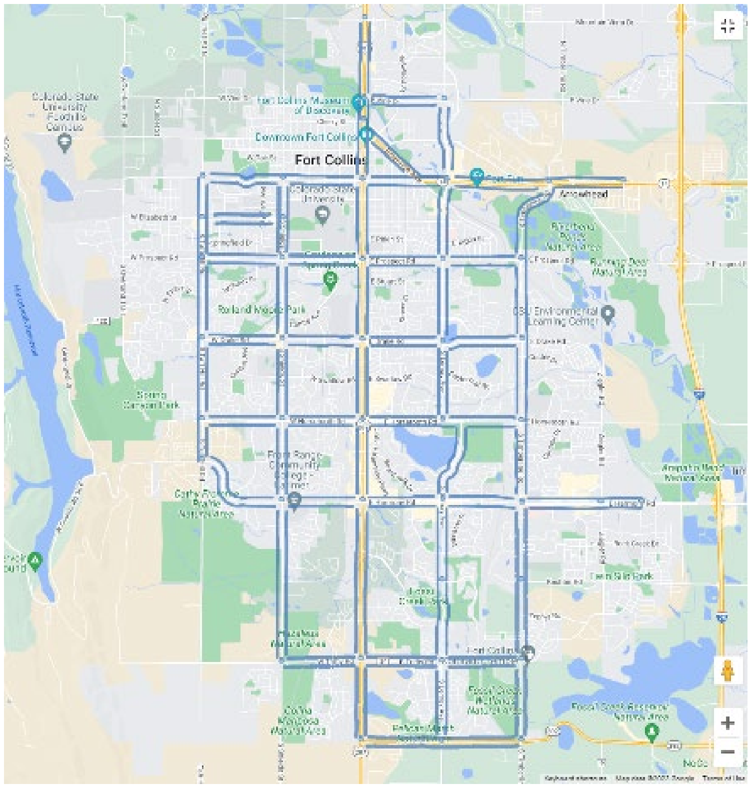


Fig. 5.2 Study area of Fort Collins (map data © 2022 Google)

Traffic data is obtained from the City of Fort Collins using Bluetooth sensor technology. The sensors are installed at the major intersections of the city, which can form multiple pairs to provide travel time and speed of each road segment at time intervals as small as every 5 minutes. The sensor layout map is outlined in Fig. 5.3 and shows the topology map of the network being studied, including the sensor pair names used in the database. The raw traffic speed data of all the pairs of the sensors between December 1, 2018, and February 1, 2019, in the city were collected for the normal (all weather) conditions. Considering all weather data has relatively slow varying patterns over time, traffic speed data of all the sensor pairs in the 15-min interval has been extracted for the short-term traffic speed forecasting. For the disrupted scenario (snowstorm), traffic speed data in the 5-minute interval of all those pairs of sensors between November 22, 2019, and November 25, 2019 has been collected to provide sufficiently refined information which varies quickly over time during natural hazards like snowstorms. Fig. 5.4 shows the snowfall and snow depth from November 24 to November 27, 2019, and it is found that the biggest snowfall happened on November 25, 2019, with 16.5 inch of snow according to the Colorado Climate Center at Colorado State University (CSU 2020). Due to sensor malfunctioning, some roads had missing data points, for which linear interpolation was conducted using the available data at the nearest time instants to derive those missing values instead of dropping the whole record. In this way, uniform time intervals of the data can be preserved. The raw data has been normalized to achieve better modeling accuracy using the Min-Max scaler provided by the Sklearn package.

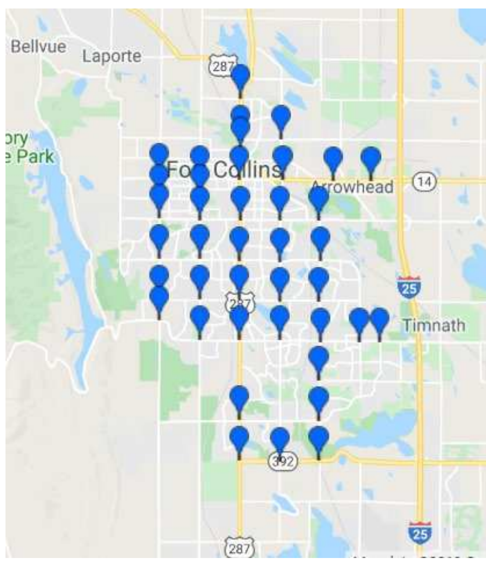


Fig. 5.3 Sensor matrix topology (map data © 2022 Google)

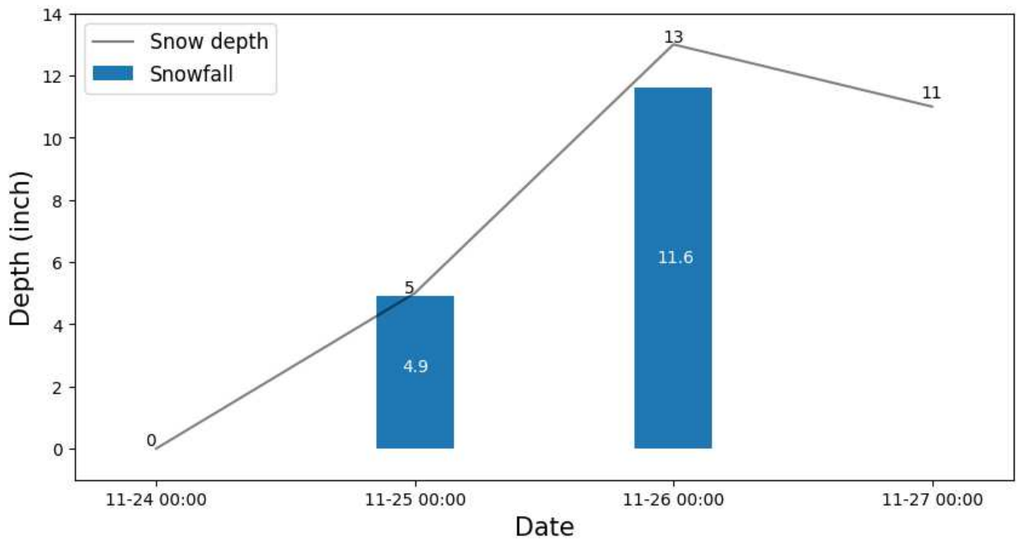


Fig. 5.4 Snowfall and Snow depth from 11-24-2019 to 11-27-2019

5.3.2 Short-term traffic speed forecasts under normal (all weather) conditions, calibration, and validation

Figure 5.5 shows the traffic speed time series data over time in normal weather conditions, which are separated into three categories: training data (80%), validation data (10%) and test data (10%). Figure 5.6 shows the data distribution over hours. And it is found that the highest traffic speed was found to be between 3 AM to 6 AM, while the lowest traffic speed happened between 3 PM to 6 PM during the afternoon peak hours.

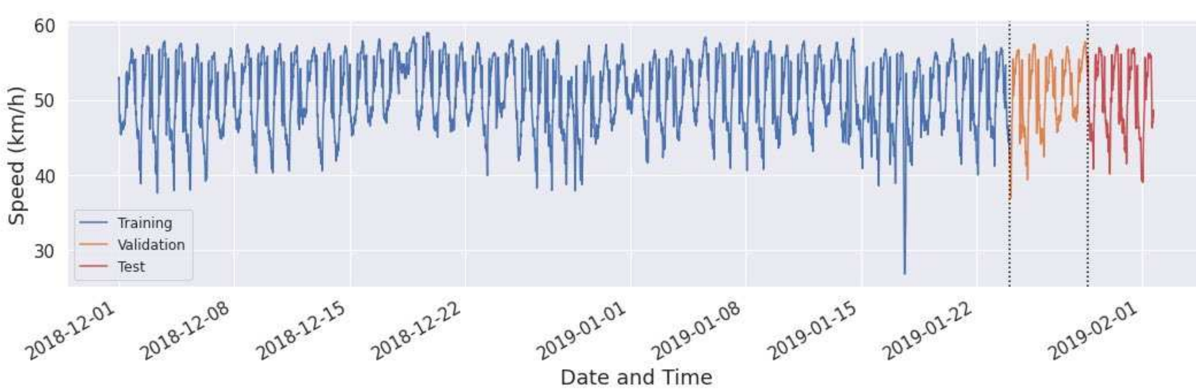


Fig. 5.5 Raw data classification

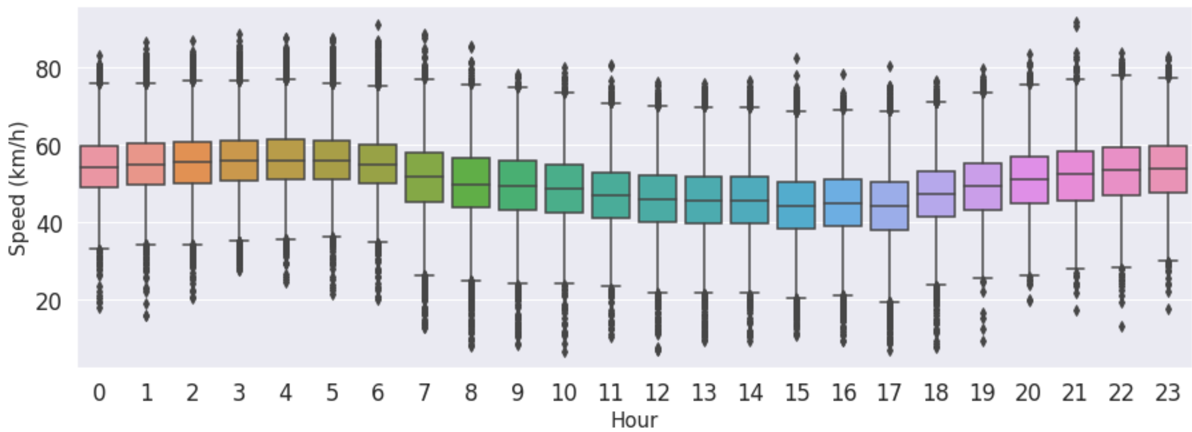


Fig. 5.6 Data distributions

In the DCRNN models, every pair or link is trained and tested separately using adjacent links and time variants as referenced features. The input timestep for prediction is 23, and the predicted timestep is 5, which means this model uses $t_1, t_2, \ldots t_{23}$ as inputs to predict $t_{24}, t_{25}, \ldots t_{28}$, then starts with t_2 and following 23 timesteps for further predictions, and so on. The validation and test parts follow the same algorithm as shown in Eq. 5.4.

$$\begin{pmatrix} t_1 \\ t_2 \\ \vdots \\ t_{23} \end{pmatrix} \xrightarrow[Predict]{} \begin{pmatrix} t_{24} \\ t_{25} \\ \vdots \\ t_{28} \end{pmatrix} \xRightarrow{New\ input\ timestep} \begin{pmatrix} t_2 \\ t_3 \\ \vdots \\ t_{24} \end{pmatrix} \xrightarrow[Predict]{} \begin{pmatrix} t_{25} \\ t_{26} \\ \vdots \\ t_{29} \end{pmatrix} \tag{5.4}$$

Figure 5.7 shows the test result of network average traffic speed forecasting based on the DCRNN model under normal conditions. According to the test result, the traffic speed prediction follows the real traffic speed trend and precise forecasting even during sudden changes in traffic speed. Figure 5.8 shows the error percentages varying over time between actual average speed and predicted average speed along with time, within a range between -7.32% and 10.12%. Furthermore, the RMSE is 0.947028, which means this knowledge from normal conditions is precise enough for further transfer learning use.

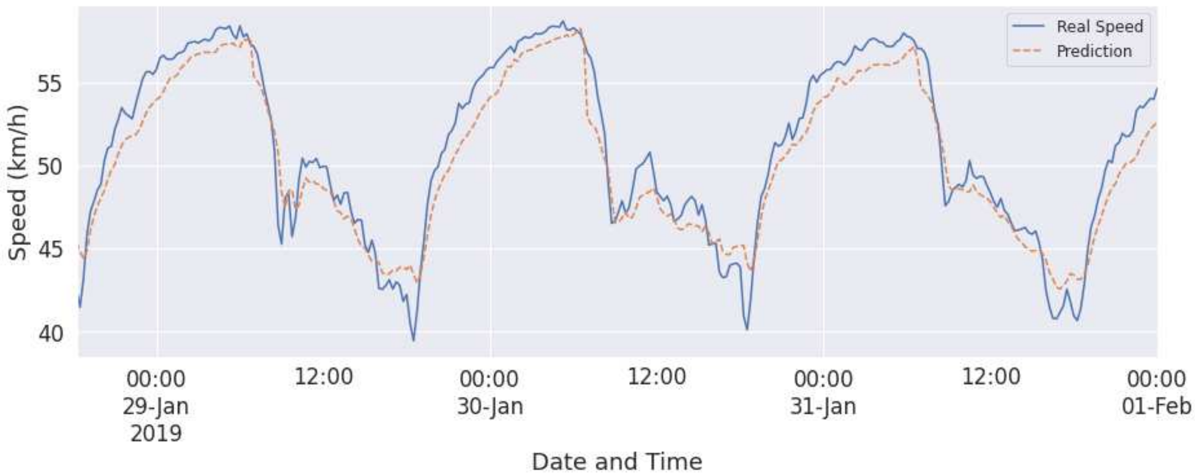


Fig. 5.7 Normal conditions forecasting test results

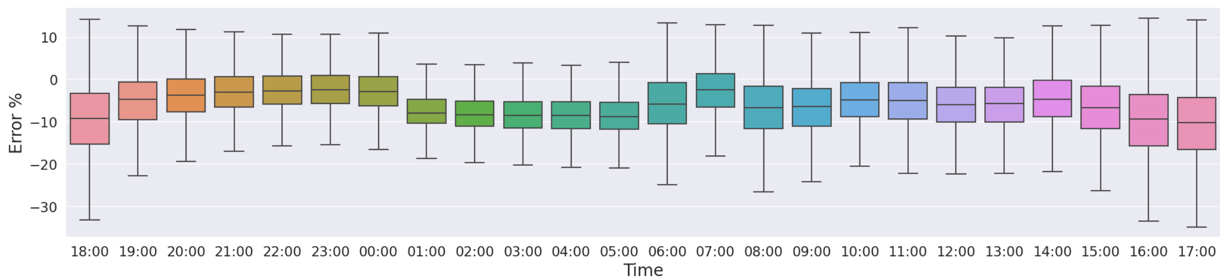


Fig. 5.8 Normal conditions forecasting error distribution

5.3.3 Traffic forecasting performance comparison with different models

The DCRNN model was calibrated and found to provide predictions with decent accuracy in the previous section. As discussed earlier, DCRNN was selected for this study simply based on some knowledge from literature about its strength on capturing non-stationary nature of time series forecasting in some existing studies. An assessment is still needed to compare the DCRNN model with other popular peers of machine learning models to demonstrate and confirm the potential advantages of DCRNN in traffic speed data forecasting. Long short-term memory (LSTM) is a popular RNN-based method for time series prediction by emphasizing the importance of modeling temporal dependency (Li et al. 2018). XGBoost is a well-known gradient-boosting library that can be used for GPU training, distributed computing, and parallelization. It is learning from the data without a specific model and does unsupervised learning. Table 5.1 presents the comparison of prediction accuracy of various approaches (DCRNN, LSTM, XGBoost) on the same dataset and training set. All approaches are assessed by commonly used metrics in forecasting accuracy estimation, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE). Figures 5.9 and 5.10 present the forecasting results and error percentage changing with time. It is found that DCRNN appears to be the best model performing traffic data forecasting in terms of accuracy in all metrics. As shown in Figure 5.9, DCRNN model can predict sudden changes more precisely because the temporal dependency becomes progressively nonlinear with variation over time. Also, DCRNN model has better performance on temporal error controlling as shown in Fig. 5.10. Therefore, DCRNN model is found to be appropriate for further snowstorm case study.

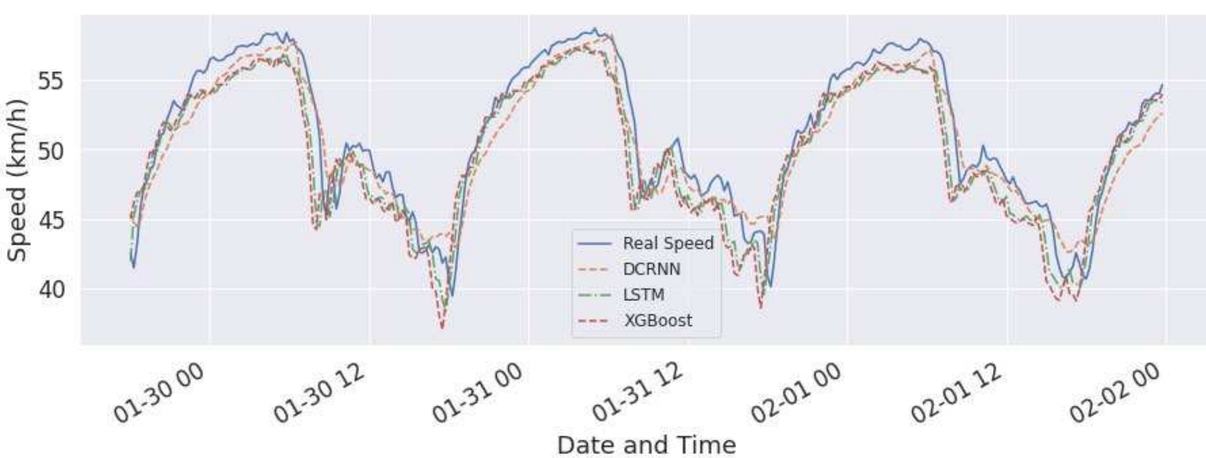


Fig. 5.9 Traffic speed forecasting comparison

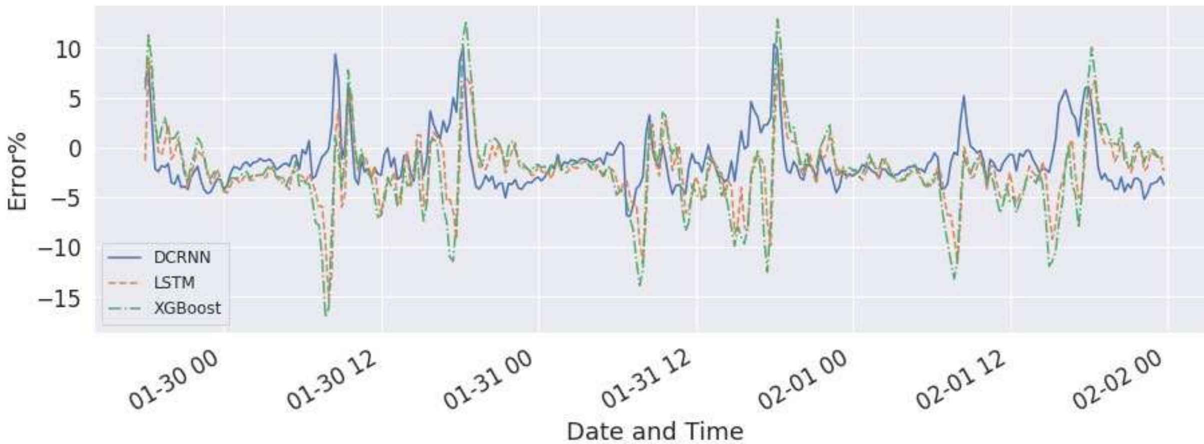


Fig. 5.10 Traffic speed forecasting error percentage comparison

Table 5.1 Forecasting accuracy comparison

	DCRNN	LSTM	XGBoost
RMSE	0.947028	1.203586	1.47466
MAE	0.810859	0.973131	1.775574
MAPE	2.59%	3.10%	5.57%

5.3.4 Traffic speed forecasting under snowstorm scenario using transfer-learning strategy

The DCRNN model has been proven to be able to predict dramatic speed changes of the traffic network during peak hour periods under normal driving conditions. Unlike normal conditions, the disruption scenarios have no sufficient precedent data or events for reference. Therefore, to predict traffic speeds under the snowstorm scenario, transfer learning is a promising technique to fill the gap between normal conditions and natural hazard conditions (snowstorms). Figure 5.11 shows the average traffic speed data in the snowstorm scenario and DCRNN learning classifications with 70% training, 15% validation, and 15% test. Figure 5.12 shows the distribution of snowstorm traffic speed data. Although the snowstorm has happened during the whole week of the selected traffic speed data, the most disrupted scenario was happening on 11-25-2019, which is included as the part of the test data.

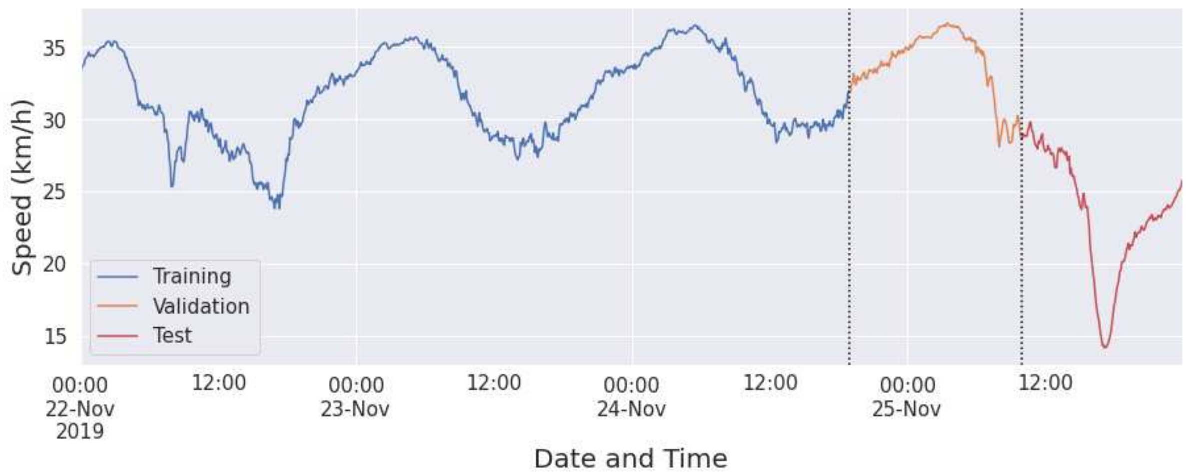


Fig. 5.11 Traffic speed data under snowstorm

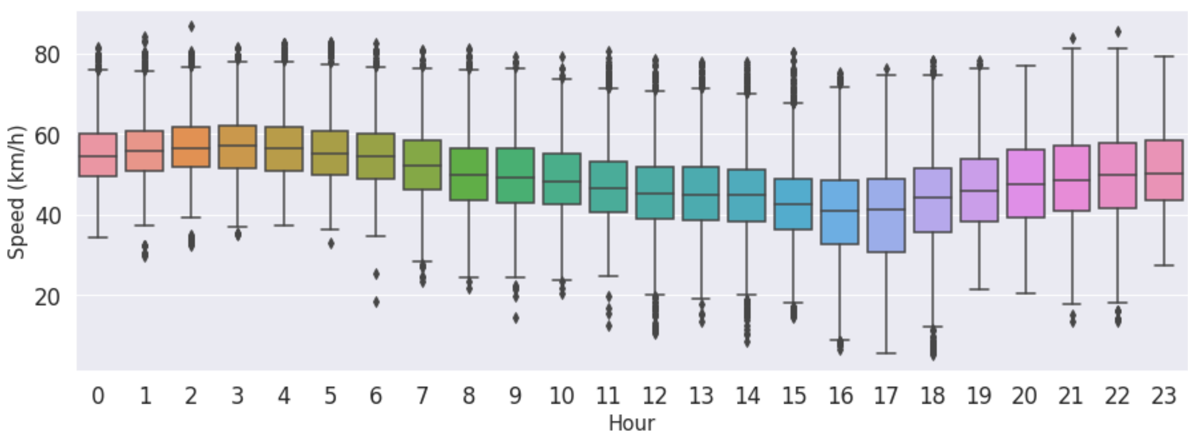
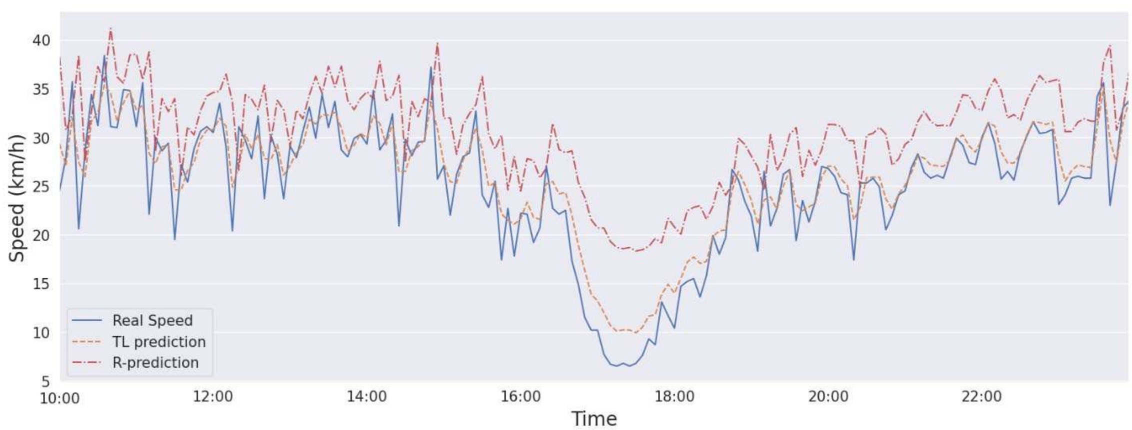
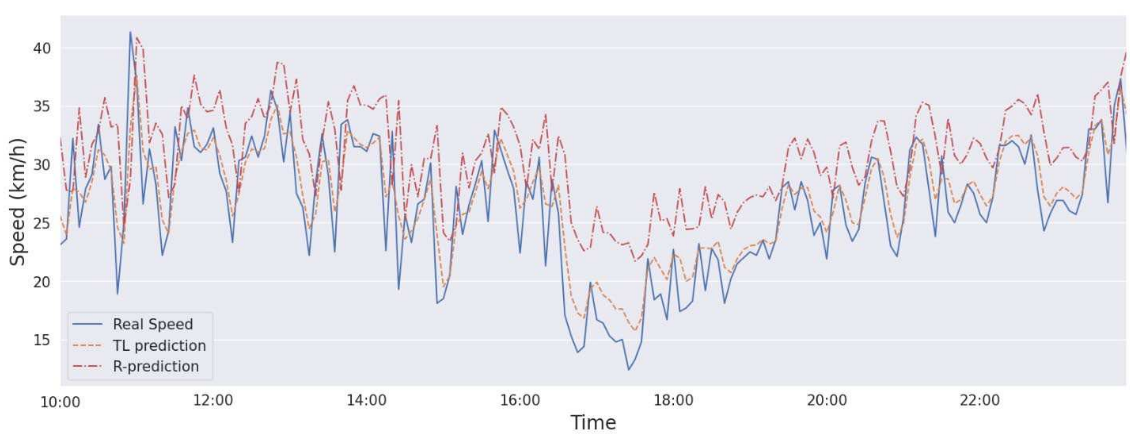


Fig. 5.12 Snowstorm data distribution

For comparison purposes, two data strategies based on the DCRNN model are studied here: the first one is to use regular learning strategy with traffic speed data under snowstorms to predict the future traffic speed time series, which is called "R-prediction" in this chapter; and the other strategy will use the transfer-learning-based strategy as introduced above, which is called "TL prediction". Figure 5.13 presents the traffic speed prediction comparison of two links (Pair 15809 and 15810) using the DCRNN model with both data strategies. From Figures 5.13a and 5.13b, the transfer learning technique makes a more accurate prediction when there are abnormal speed changes along with the time than regular prediction using snowstorm traffic data only. So, transfer learning technique is found to be able to improve the overall accuracy of the prediction, which will be helpful to more effective traffic control and intervention. The transfer learning model was built based on the model trained under normal conditions. It is likely the model developed under normal conditions can pass some realistic inherent information about the traffic network such as topology and spatial relationship to the prediction under snowstorm conditions. Such inherent information largely remains the same between the normal and snowstorm conditions, which may contribute to the improved prediction accuracy over that without such information (regular snowstorm-data-only model).



a. Pair 15809



b. Pair 15810

Fig. 5.13 Traffic speed forecasting comparison of links under snowstorm

By considering all the links of the network, Figure 5.14 displays the average speed of the whole network during a snowstorm scenario using the snowstorm data only and the transfer learning technique. Figure 5.15 presents the error variation and the time of 2 different data strategies, and it is easy to find that transfer learning offered more precise traffic speed forecasting than snowstorm data only, with the RMSE being 0. 507452 and 1.743838, respectively. Although the snowstorm data only would also provide an acceptable prediction result, the transfer learning technique can provide more accurate traffic speed prediction under hazardous conditions when historical data is not sufficient.

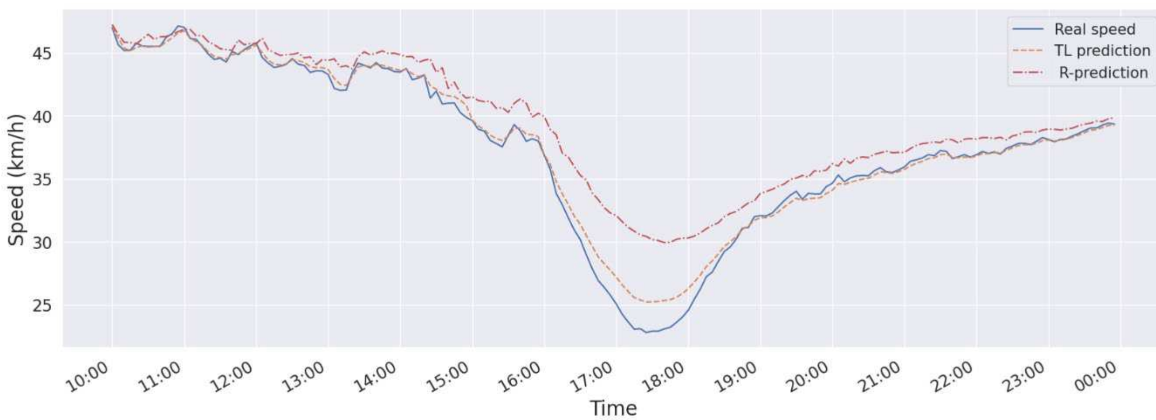


Fig. 5.14 Network average speed prediction result comparison

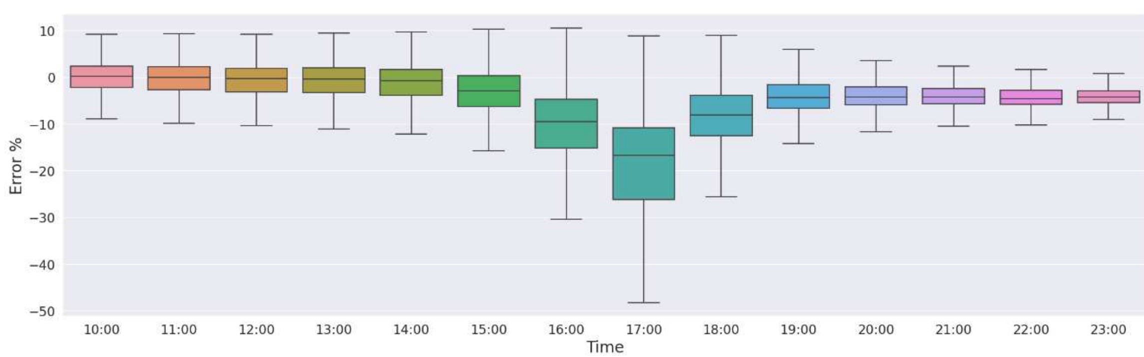


Fig. 5.15 TL forecasting error comparison under snowstorm conditions

5.4 Conclusion

Transportation systems experience significant disruptions on existing infrastructures, traffic operation and monitoring data. To carry out proactive intervention of disrupted traffic systems during hazards, efficient and accurate traffic speed forecasting of traffic speeds for the disrupted traffic systems is crucial. Short-term traffic forecasting based on time series prediction with machine learning tools has been conducted extensively in existing studies primarily under all weather conditions. Traffic speeds of disrupted traffic work under hazard are usually nonstationary and "dynamic"-varying quickly over time in a nonlinear manner. In addition, due to hazard-specific and site-specific nature of a disrupted traffic system under hazards, the available data is very scarce and has poor transferability. To conduct short-term traffic speed forecasting of a disrupted traffic network by capturing the unique challenges in terms of nonstationary and "dynamic" nature as well as the data scarcity during hazards remains a challenge.

This chapter proposed a new method based on the modified DCRNN model to address the challenges as summarized above for the disrupted traffic network under natural hazards. The new modifications include adding transfer learning technology from DCRNN learning of normal condition traffic speed data; to enhance deep learning for predicting network traffic speed under unprecedented hazard events for both prevention and intervention strategies to maintain the resilience and robustness of the traffic network.

The case studies of the City of Fort Collins in Colorado demonstrated the advantage offered by the transfer learning of the DCRNN. The main results are as follows: (1) the proposed DCRNN model can forecast traffic data precisely during normal conditions; (2) the comparison between DCRNN and other machine learning models like LSTM and XGBoost demonstrate the advantages of DCRNN to predict the whole network traffic speed more precisely; (3) transfer learning technique for hazard scenario traffic speed forecasting can provide more accurate results than hazard-specific data. Although only the snowstorm disruption was discussed in this chapter, the new methodology and concept of disrupted traffic network speed forecast can be applied to other locations and scenarios.

CHAPTER 6 DEEP LEARNING-BASED TIME-PROGRESSIVE TRAFFIC RESILIENCE FORECASTING DURING HAZARDOUS WEATHER TOWARD PROACTIVE INTERVENTION[4]

6.1 Introduction

Traffic systems are often modeled with graph-based techniques and flow-based techniques, such as traditional queuing theory and microscopic traffic simulation. Flow-based techniques, especially those in microscopic simulations, can offer detailed traffic performance information, such as the speed, time and delay of each road segment, intersection, and network. However, to provide reliable information, the flow-based models need to replicate the actual traffic network accurately and be calibrated with site-specific data (Shafiei et al. 2018). Graph theories have been widely applied to model various networks in a wide spectrum of fields encompassing natural science (e.g., mathematics, physics, biology), social science, and engineering (Newman 2018). After being converted into graphs, traffic networks can take advantage of the advances in network science to conduct basic network analyses to derive various network characteristics. Compared to flow-based studies, graph theory applications of traffic networks often ignore local or refined details of the traffic system by adopting abstracted representations, and as a result require little to no site-specific traffic data. Despite the modeling convenience, such significantly reduced data dependency also limits most existing graph-based applications to generic network analysis primarily related to the basic topological information of traffic networks, such as connectivity or topological robustness.

Various emerging technologies, such as autonomous driving, connected technology, smart intersection traffic

[4] This chapter is adapted from a paper submitted to a journal that is currently under review (Yao et. al 2023b).

management, and other Intelligent Transportation Systems (ITS) approaches, have been adopted during the last decades to construct more robust traffic systems against hazards or incidents (e.g., Ganin et al. 2019; Andronov and Leverents 2018; Yao and Chen 2022). The capability for a system to respond to disturbances like hazards or incidents is often characterized with the concept of resilience, which has gained increasing attention in the past decade. Resilience is to characterize the system behavior under disturbances or attacks, specifically the ability to provide its basic functionality as measured by robustness, redundancy, resourcefulness, and rapidity (Reggiani 2013). During the past decade, resilience-based performance assessment and mitigation of infrastructure systems including traffic networks against natural hazards have become increasingly important research topics. As discussed previously, the lack of site- and hazard-specific data has limited the progress of flow-based simulations as well as data-driven studies. Existing graph-based resilience studies fed with site-specific traffic data have demonstrated great potential on understanding recurrent congestions and congestion propagations in normal conditions (e.g., Li et al. 2021; Dong et al. 2020; Saberi et al. 2020). However, there are several major challenges to apply similar techniques to study the resilience of disrupted traffic systems under hazards. The first one is again the lack of abundant real-world hazard-specific data which can be fed into the graph-based model to provide more insightful information than basic network analysis, such as the emergence of hotspots and the evolution trends over time which are critical for any real-time and proactive intervention during hazardous events. The second challenge is that the current models developed primarily for normal conditions cannot be directly applied to derive time-progressive resilience information throughout a hazardous event. For example, in normal conditions, recurrent congestions gradually build up and change over time slowly. As a result, the percolation theory can be applied to only provide several static "snapshots" over a day to identify the hotspots of congestion and strategic road links for possible intervention. Similarly, congestion propagation over time is modeled assuming constant traffic conditions for extended periods of a day. In contrast, many factors will affect the nature of a traffic network with disruptions rather quickly during a hazardous event, such as hazard progression, evolution of specific disruptions, emergency recovery, and associated uncertainties. The fast-changing nature with uncertainties requires a "continuous video" rather than only a few "static snapshot pictures" to capture the time-progressive process of traffic congestion formulation and propagation. Such a methodology based on graph theory and real-world traffic data is not yet available for hazardous conditions.

In response to the unique challenges on short-term traffic forecasting and resilience modeling under hazardous weather events as summarized above, this study proposes a holistic time-progressive resilience performance forecasting methodology based on graph theory and real-world traffic data. Such a methodology consists of two components: (1) modified DCRNN-based short-term traffic forecasting module which has been presented in chapter 5; and (2) time-progressive resilience forecasting module integrating percolation-based robustness assessment and SIR-based congestion propagation. The novelty of such an approach over existing studies is reflected through the following aspects: (1) the modified DCRNN model based on transfer learning techniques can provide reliable traffic forecasting with limited hazard-specific data and possible data disruptions; (2) the modified percolation-based robustness assessment and SIR-based congestion propagation techniques are integrated to provide time-progressive resilience performance forecasting during a hazardous event, and more importantly critical information about when and where to conduct potential intervention to maximize the system resilience. By iterating the process over time with the new real-world data, the whole process can provide adaptive information with improved accuracy and sufficient lead time for potential decision making about proactive intervention.

6.2 Methodology

6.2.1 Percolation-based congestion characterization in spatial domain

Nodes and edges in the traffic network represent the intersections and road segments between two adjacent intersections, respectively. The average traffic speed varies during the day based on the real-time traffic volume at each edge and is usually determined using either real-life or simulated traffic data (Yao and Chen 2023). The corresponding actual speed limit is assigned for each link e_{ij}, while $r_{ij}(t)$ is a dimensionless performance indicator about the ratio between its current speed and its speed limit at time t. For a given congestion threshold q, the road e_{ij} can be classified into two categories: functional (1) when $r_{ij} \geq$ q and congested (0) for $r_{ij} <$ q:

$$e = \begin{cases} 1, & r_{ij} \geq q \\ 0, & r_{ij} < q \end{cases} \tag{6.1}$$

Percolation theory is a powerful tool to capture the development and transition process of a network under random and target attacks (Newman 2018). As for traffic networks, a road link will be regarded as congested or "failed" according to the actual traffic dimensionless performance indicator compared against the specific congestion threshold q as defined in Eq. (6.1) or based on a specific probability of congestion (or "failure") uniformly assigned to all links in the network. Under a given congestion threshold q, the "failed" (congested) links will be physically "removed" from the graph and only the functional links will remain to form a new spatial representation of the graph (traffic network). Such spatial presentation of the functional graph can provide some unique and useful insights, like the spatial distributions of the functional links, hotspots of congestion, and the critical links between several individual remaining connected sub-areas, etc.

6.2.2 Percolation-based resilience analysis

In addition, percolation analysis can also provide some useful resilience indices of the whole network. When most of the nodes/links are connected, the network can function at least partially. Thus, in percolation theory, the size of the network's largest connected component, also known as the giant component size or giant connected component (GCC) size, is commonly used to qualitatively reflect its resilience against failures (Newman 1998). A network is deemed resistant to random failures if it can withstand the loss of a significant proportion of its nodes. Since each spatial representation of the functional graph is dependent on a specific congestion criterion q, a series of spatial representations of the functional graph can be generated for different congestion criteria. A percolation index curve can be plotted to show the variations of the percolation indices with different q values. A critical congestion threshold or probability q_c can be identified when the percolation index exhibits a sudden change-indicating a critical moment for transition from the resilience (robustness) perspective. In this study, the percolation theory is applied to the traffic network under hazardous weather with two purposes: (1) to identify the congestion threshold q_c which is critical to the resilience performance, specifically the robustness of the network. Such information will guide the following temporal congestion propagation modeling; (2) to identify the critical individual links from the resilience perspective which have the priority to receive possible interventions based on the spatial presentation of the percolation analysis results.

6.2.3 SIR-based congestion propagation modeling

Short-term traffic forecasting typically will cause quickly increasing error if the predictions are too far ahead into the future, and as a result can only predict the future local traffic performance in a very short period (e.g., 5-15 minutes later) to avoid unacceptable prediction error. For proactive decision-making by stakeholders, people need to know not only the local congestion and spatial distribution in very near future moments, but also the network-level congestion propagation trend in the future with enough lead time (e.g., 20 - 60 minutes) to accommodate any practically meaningful and timely proactive decision and intervention. With limited intervention resources, people need to foresee the overall congestion formation and propagation of the whole network over time in the future and then identify the most critical moments as well as individual links for possible proactive intervention to achieve the optimal impact.

For congestion propagation, contagious processes of epidemic disease have been found promising to offer some useful insights. The popular model called SIR (S: susceptible; I: infected; R: recovered) was initially introduced by Kermack and McKendrick (1921), the main idea behind which is a mathematical hypothesis developed to explain the fast rise and drop in the number of infected people with a contagious disease in a contained community over time (Marinov and Marinova 2020). Recently, the SIR model has been applied to simulate traffic congestions with promising capabilities in understanding the transition of disrupted areas from the start to the end (Saberi et al. 2020). An empirical multi-city analysis of rush-hour traffic data was conducted using the SIR model to forecast the congested link over time (Saberi et al. 2020). If a traffic network is considered as a contained community under a specific disruption, the links adjacent to the congested links were found to be more prone to congestion (Saberi et al. 2020). After the disruption is cleared, the recovered links are those with queues already being dissipated. Therefore, the initial congested links of the network were considered as the first group of “infected people”. Recently, a hybrid analysis combining percolation process and SIR model to foresee the spread and recession of floodwaters in urban traffic networks was conducted to assist emergency managers, public authorities, residents, first responders, and other decision-makers with flood forecasting on the traffic network (Fan et al. 2020). The basic equations of the network-level SIR model which will be used in this study are introduced in the following.

For a given traffic network with N directed links under disruption scenarios, Equations 6.2-6.4 are the ordinary differential equations (ODEs) for the SIR model which describes the transition of congestion propagation in the traffic network:

$$\frac{dc(t)}{dt} = -\mu c(t) + \beta k c(t)\big(1 - r(t) - c(t)\big) \tag{6.2}$$

$$\frac{dr(t)}{dt} = \mu c(t) \tag{6.3}$$

$$\frac{df(t)}{dt} = -\beta k c(t)\big(1 - r(t) - c(t)\big) \tag{6.4}$$

where,

$c(t)$ = the portion of the congested links (=$C(t)/N$) at time t,

$r(t)$ = the portion of the recovered links (=$R(t)/N$) at time t,

$f(t)$= the portion of the functional links (=$F(t)/N$) at time t in the network.

It starts with all links being at the functional status at time $t = 0$, which means there is no congested links existing in the network, namely $C(0) = 0$. The congestion function $C(t)$ and functional function $F(t)$ define the numbers of the congested and functional links of the whole network at time t based on the congestion criterion q set in Eq. (6.1), respectively. $R(t)$ defines the number of originally congested links turning to functional links during the recovery process. There are 2 site-specific and hazard-specific parameters describing the transition of congestion propagation and recovery speed: propagation rate β and recovery rate μ. Parameter k is the effective contact with other links pointing at its upstream node, which can be calculated through Eq. (6.5).

$$k = \sum_{n=1}^{\infty} p_n \tag{6.5}$$

where, *n* is the node degree; *p* is the number of nodes with degree *n* divided by the total number of the network nodes.

Note that $c(t) + r(t) + f(t) = 1$ is always true throughout the whole process. The SIR model presented above can capture the whole process of the congestion propagation and dissipation of a particular traffic network once the propagation rate *β* and recovery rate *μ* are quantified from the specific traffic data (Saberi et al. 2020). Another parameter $R_0 = \frac{k\beta}{\mu}$ called basic reproductive number is introduced to describe the congestion spread speed. If $R_0 \leq 1$, the congestion will remain a transient local occurrence. To characterize the network-level congestion propagation such as the dimensionless congestion function $c(t)$, there are several key variables: k to characterize the network topology; β and μ to characterize the site-specific and hazard-specific traffic pattern such as congestion propagation and dissipation; and the congestion criterion *q* as defined in Eq. (6.1). With the predicted congestion function $c(t)$, the SIR model can forecast the start, peak, and end of the congestion propagation over time.

Since the two parameters *β* and *μ* are derived from the historical traffic data (Saberi et al. 2020), they will apparently become more accurate when more historical traffic data is accumulated. In normal traffic conditions, the two key parameters *β* and *μ* usually remain relatively constant over time for a given traffic condition. For hazardous events, due to the time-progressive and "dynamic" nature of the traffic data as discussed earlier, the parameters β and μ likely will vary considerably over time. As discussed earlier, the hazard-specific traffic data is limited and unique with low transferability, and therefore β and μ can only be derived from the limited real traffic data accumulated gradually with the time progression during a particular hazardous event. So, in this study, the initial values of β and μ will be firstly estimated with the traffic data under normal conditions of the same network. With the progression of the hazard, the real-time traffic data will be constantly fed to update these two key parameters in a time-progressive manner. The same critical congestion criterion q_c derived earlier in the percolation analysis will be applied here to guide the following congestion propagation modeling with the SIR model.

As discussed above, the congestion propagation can be characterized by some index such as the time-dependent dimensionless congestion function $c(t)$, with which people can have some sense about how much percentage of congested links of the whole network will be at a certain time t in the future. Apparently, the congestion function will provide network-level information about the whole process of overall congestion propagation and dissipation of all the links, rather than individual links. Such information is important for answering some critical questions by the stakeholder at the community level such as when some interventions may be needed in the future based on the overall congestion level of the whole network. It is noted that to derive the congestion function $c(t)$ with Eqs. (6.5-7), there is an inherent assumption that the values β and μ will remain constant. In other words, the SIR model can predict traffic congestion propagation with accurate results only when the traffic pattern of the network remains relatively "static" (i.e., β and μ have little variation over time). As discussed earlier, traffic under hazardous weather varies more frequently and significantly than that in normal conditions. Therefore, the prediction with the SIR model will provide less accurate results when the values of β and μ time remain the same when the hazard progresses. To deal with these challenges, the SIR model is applied in the current study under hazardous weather conditions with following consideration: (1) the accuracy from the SIR model can be improved with the frequent updating process with the new parameters (e.g., β and μ) derived from the constantly fed real-time traffic data when the hazard progresses; (2) to provide more lead time for possible intervention, the predicted traffic data into the future moments with the deep learning techniques, rather than the actual monitored traffic data, will be used to update the parameters of the SIR model; (3) it is hypothesized that although the absolute value of the congestion function at future time may not be exactly accurate at the moment because of the reasons summarized above, it can provide pretty accurate information about the general trend of the congestion propagation at the network level, particularly the forecasted critical information like future moments when the congestion may peak. Such information about the overall trend of congestion propagation as well the time when the congestion will become the worst is critical to the decision making in terms of when the intervention should be applied. Such a hypothesis will be validated in the following demonstrative example.

6.2.4 Integrated time-progressive traffic resilience forecasting toward proactive intervention

The proposed integrated time-progressive traffic resilience forecasting approach tries to provide three pieces of information: (1) what: the projected congestion function $c(t)$ of the whole network over the whole hazard period, which will be constantly updated over time with the newly derived key parameters (i.e., β and μ) based on the forecasted traffic speed data with DCRNN; (2) when: with the time-progressive $c(t)$, stakeholders can decide the optimal time for possible intervention based on the forecasted congestion function over time; (3) where: the strategic individual road links which may receive intervention will be further identified.

To make this happen, the whole iterative process includes following steps: (1) with the real-world monitored traffic data, DCRNN is firstly applied to predict short-term traffic speed forecasting of each links of the network during the hazardous event; (2) the percolation theory is applied based on the predicted traffic speed data to identify the critical congestion threshold q_c from the resilience-based analysis during the initial traffic speed dropping time point t_d; (3) the key parameters β and μ will be derived and updated based on the predicted traffic data from DCRNN. By applying the identified q_c from the percolation analysis and the key parameters β and μ, the SIR model will generate the congestion function *c(t)* over time; (4) with the constant feeding of the real-time monitoring traffic data, the future traffic speed data will be predicted continuously based on DCRNN. The newly predicted traffic data will help update the key parameters β and μ and in turn the congestion function *c(t)* with the progression of time; (5) with the time-progressive congestion function updated over time, the general congestion propagation trend is disclosed, including projected future moments which may apply intervention t_I being decided. For example, the future moment with the projected worst (peak) congestion can be a good candidate for intervention time; (6) once t_I is preliminarily decided, various preparation work can get started for coming intervention with sufficient lead time. When time gets further closer to the initial t_I , the newly updated congestion function *c(t)* in step 4 will provide the updated and more accurate short-term traffic speed forecasting, with which the SIR analysis will be able to provide the updated and more accurate t_I results; (7) once t_I is finally determined, with the spatial presentation of the percolation analysis of the network at the future moment t_I, the most vulnerable regions and strategic individual road links of the network which may receive the possible intervention can be determined. Such a process will repeat automatically in a time-progressive manner and the whole process is described in Fig. 6.1.

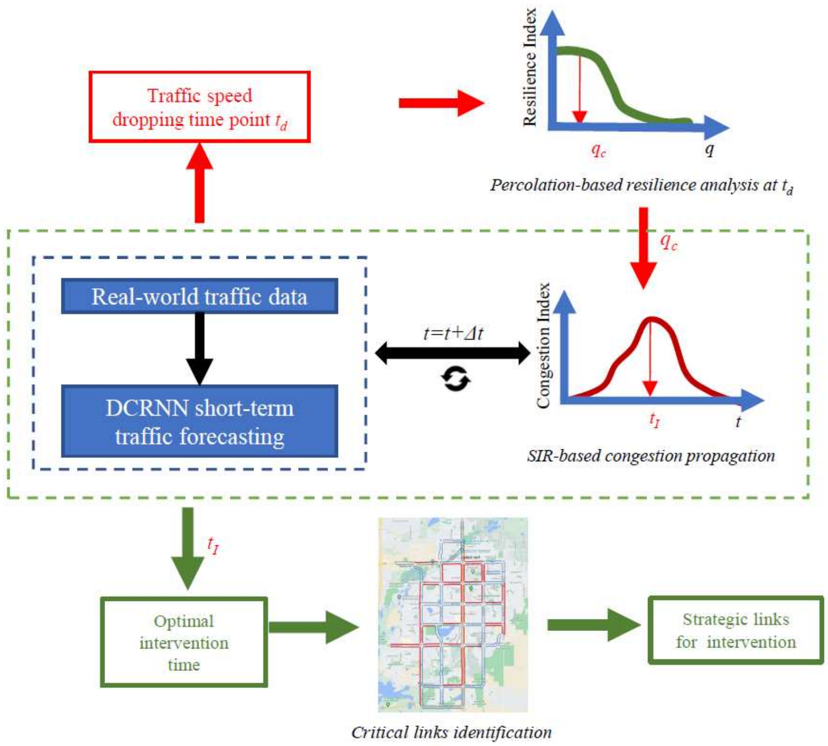


Fig. 6.1 Integrated traffic speed forecasting and time-progressive resilience indexes workflow (map data © 2022 Google)

6.3 Case study of snowstorm hazard in Fort Collins

6.3.1 Percolation-based resilience analysis

All traffic speed data from each link or pair are applied to this section to generate the percolation curve. From Fig. 6.2, it is obvious that the average traffic speed started to drastically drop after 15:00 and recovered after 21:00. Therefore, the most severe congestion of this snowstorm happened during the study period, and the traffic speed dropping time point t_d is determined to be 15:00 as the starting point, with considerable impact from the snowstorm on the traffic speed. Among all the time-dependent percolation curves, the one at time t_d will be used to derive the critical percolation point q_c. Fig. 6.2 shows the percolation curves in terms of the percentage of the size percentage of the giant connected component (GCC) with both the real monitored data and the predicted traffic data with DCRNN at t_d. The results in Fig. 6.2 suggest that the predicted results can provide pretty accurate percolation analysis results as compared to the real data. The critical percolation point q_c is found to be 0.36, under which the GCC size percentage exhibits a sudden dramatic drop in the network. The identified critical percolation point q_c will be used as the congestion index from 15:00 to 21:00 to generate the dimensionless congestion function *c(t)* with the SIR model in the following section.

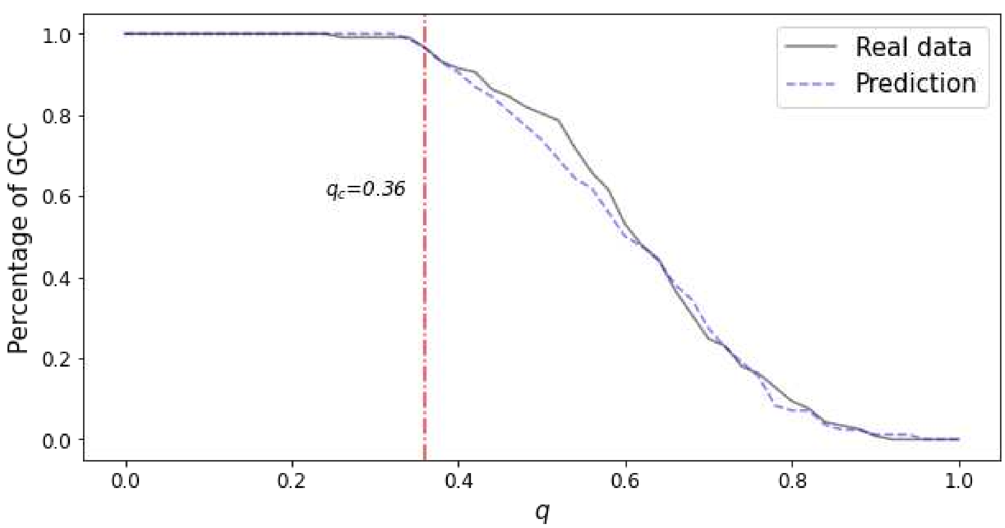
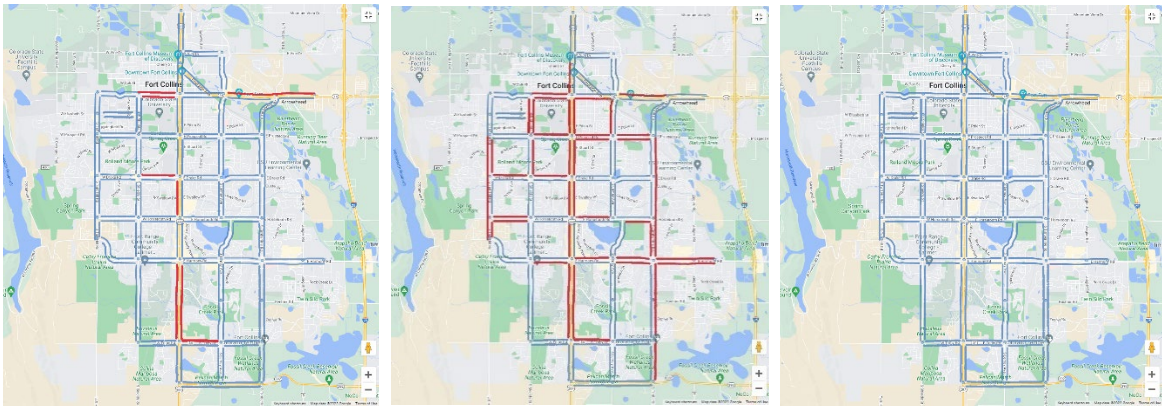


Fig. 6.2 Percolation curves and critical percolation point

Fig. 6.3 provides the spatial presentation of the congestion transition from the beginning (15:00) of the disruption (snowstorm), to the peak congestion scenario (17:10), and to the recovered period (21:00) following the predetermined percolation point q_c=0.36 using the real-time traffic data. The red links are congested, and the blue links are smooth links as shown in Fig. 6.3.



a. 15:00 b. 17:10 c. 21:00

Fig. 6.3 Congestion transition of q_c $=0.36$ using real-time data (map data © 2022 Google)

6.3.2 SIR-based congestion propagation to identify time-progressive trend

After the congestion index q_c $=0.36$ is determined from the percolation analysis, the same q_c is used for the congestion function generation with the SIR model in the following section. As discussed earlier, the accuracy of the congestion function prediction with the SIR model highly depends on the amount and quality of site-specific and hazard-specific data. In the proposed method, the real data in normal conditions will be utilized to generate the initial congestion function, which will be updated with the continuous feeding of the real monitored traffic data under hazardous conditions. Each time the new prediction results of traffic speeds are added to the model as time goes by, the SIR model will be calibrated several times to achieve the most accurate final SIR model for the traffic resilience analysis.

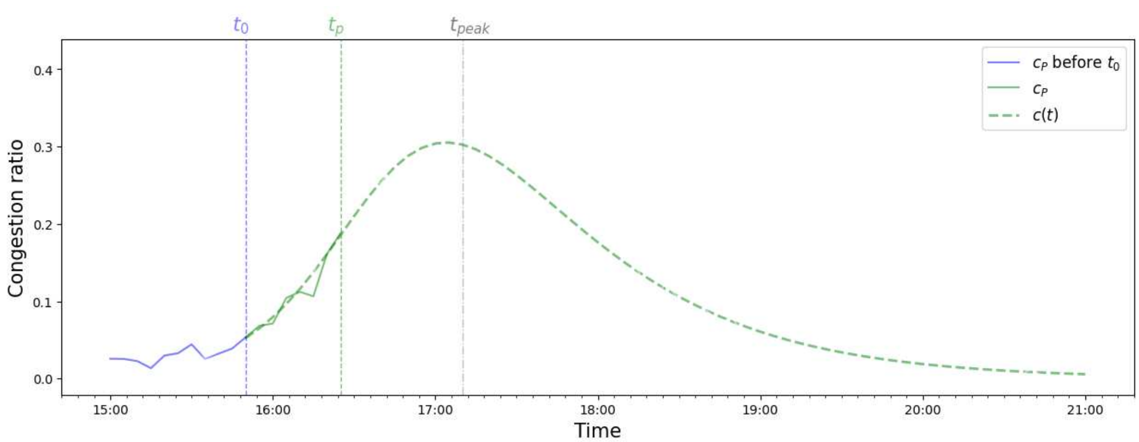
Specifically, according to the SIR model, iteration of β and μ is necessary for an accurate SIR model generation each time with the new data. To estimate the parameters of the SIR model, the ordinary least squares (OLS) method combined with a pattern search algorithm is used. The estimation is essentially conducted as a minimization problem, with the pattern search attempting to find the model parameters that minimize the root mean squared error (RMSE) being the difference between the observed and modeled *c(t)* over the whole study period (Saberi et al. 2020). The real monitored data during a hazard accumulates very slowly, which limits the accuracy of predicting the congestion function. Therefore, in the proposed model, the predicted traffic data from the deep learning, rather than real monitored traffic data, is used to derive β and μ. Specifically, the real-time traffic data is constantly fed into the DCRNN model to predict the future traffic speed by time t_p (5 timesteps or 25 minutes ahead in this study). Such predicted data serve as two purposes: (1) to estimate the updated parameters of β and μ, which will be used by the SIR model to derive the congestion function *c(t)* for the whole study period of the snow event (way beyond t_p); (2) for comparison purposes, the predicted traffic speed data by time t_p will also be used to directly derive the corresponding congestion ratios c_p (only cover up to time t_p).

Figs. 6.4(a-c) present the progression results of the congestion function *c(t)* generated through the SIR model with the predicted traffic congestion results with DCRNN at three different time points (t_p =16:25, 17:05 and 17:45). As shown in Fig.6.4a, the solid line represents the congestion ratio c_p generated from the predicted traffic speed by time t_p=16:25 with DCRNN for comparison purposes. In the meantime, the predicted traffic speed will generate the key parameters for the SIR model β and μ with the OSL method. With β and μ, the congestion curve *c(t)* (dash line) covering the whole period of congestion propagation will be generated with the SIR model with Eqs. (6.2-6.4). The starting time point for the SIR model congestion function generation t_0 is set at 15:50. The comparison between c_p and *c(t)* suggests that the SIR model can provide accurate prediction of the congestion propagation by time t_p. To assess the accuracy of forecasting the congestion propagation beyond t_p, particularly the peak congestion moment, the actual peak congestion moment derived from the real monitored traffic data as a hindcast comparison is marked on the figure as t_{peak} (at 17:10). It is found that the forecasted future peak time of the congestion curve *c(t)* from the SIR model is 17:03, which is close but earlier than the actual peak time t_{peak} (17:10). However, it is noted that such information was forecasted 25 minutes (5 timesteps) earlier than time t_p=16:25, which provides 63 minutes and 70 minutes lead time until the forecasted and actual peak time, respectively. With the pretty accurate forecasted congestion propagation trend and the congestion peak time in the future, stakeholders have enough lead time to carry out any planning and potential intervention arrangements.

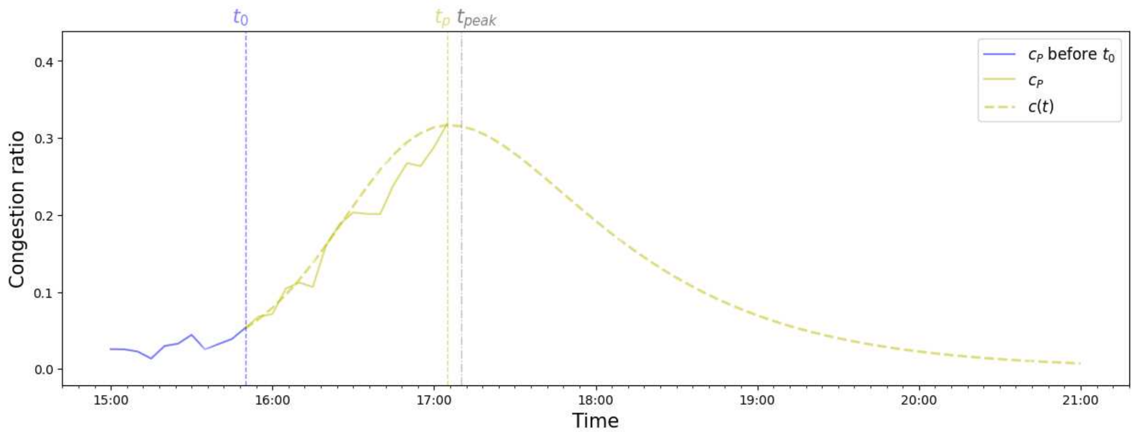
With the time progression, more real monitored traffic data will be fed into the DCRNN model. Fig. 6.4(b) demonstrates the prediction results at time t_p =17:05: the updated predicted traffic speed data from DCRNN will be used to derive new β and μ, which will be further used to generate the updated congestion curve *c(t)*. The predicted traffic speed data will also generate the congestion ratio curve by the new time t_p =17:05 for comparison. At this moment, the forecasted future peak time of the congestion curve *c(t)* from the SIR model is 17:06, which gets closer than the previous t_p - about 4 minutes earlier than the actual peak time t_{peak} (17:10). At this point, it will provide 26 minutes and 30 minutes lead time until the predicted and the actual peak time, respectively. Apparently, with the feeding of additional real-time data, the predicted peak time of the congestion function becomes more accurate with the time progression as evidenced by getting closer to the actual peak time t_{peak} derived from the real data.

In Fig. 6.4(c), when the time progresses to time t_p=17:45, which has already passed the actual peak time t_{peak}, the predicted congestion curve shows almost identical peak time as the real data, which confirms the improved accuracy with more data when time progresses. Even at this point, such information about the congestion propagation trend will still be helpful to forecasting the future trend of congestion dissipation and planning any possible emergency response and post-hazard recovery efforts as needed.

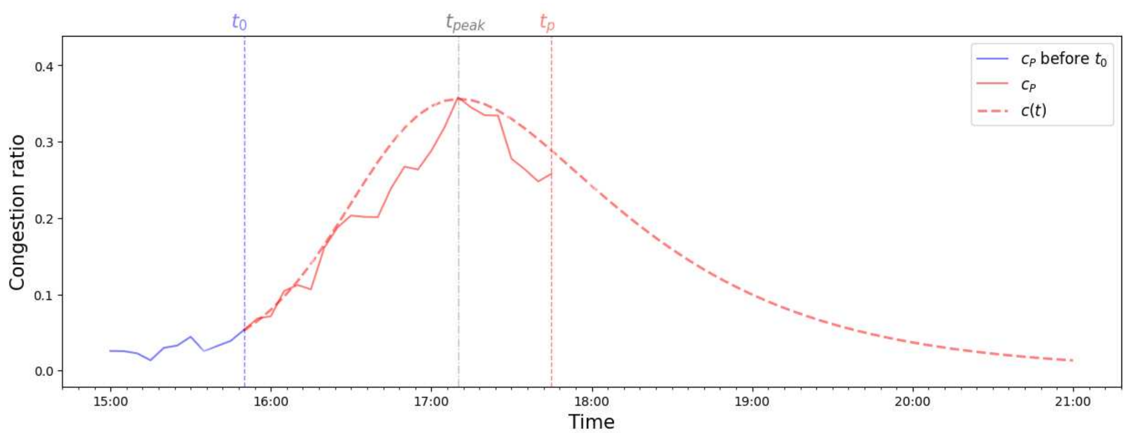
Fig. 6.5 shows the iteration results of parameters β and μ over time based on the predicted traffic data as inputs. It is obvious that the values of β and μ vary considerably over time as expected, underlying the needs and significance of updating the congestion functions of the SIR model with the new data in a time-progressive way. In Fig. 6.4, a comparison between the congestion ratios generated from the predicted traffic speed data with DCRNN and the congestion function generated from the SIR was made. Now, Fig. 6.6 makes a hindcast comparison of the final congestion function *c(t)* based on the SIR model and the congestion ratio curve c_{real} from the real monitored traffic data. It is found that the SIR model based on the traffic speed forecasting can capture the congestion propagation trend well including the peak congestion time. There is some error of the absolute magnitudes of the congestion function especially during the peak congestion moment and dissipation period and the RMSE is 0.026146.



a. t_p=*16:25*



b. t_p=*17:05*



c. t_p=*17:45*

Fig. 6.4 Progress of congestion function *c(t)* generation at different time points

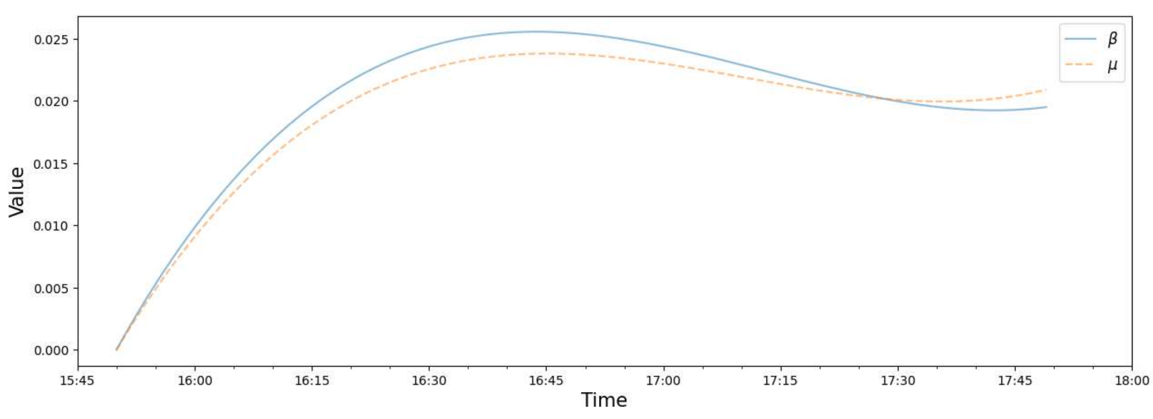


Fig. 6.5 SIR parameters iteration variation using prediction traffic data

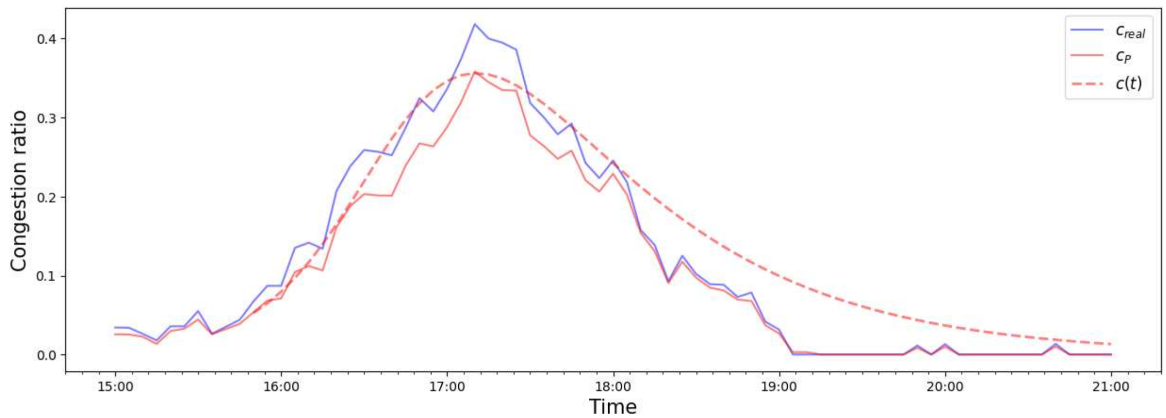
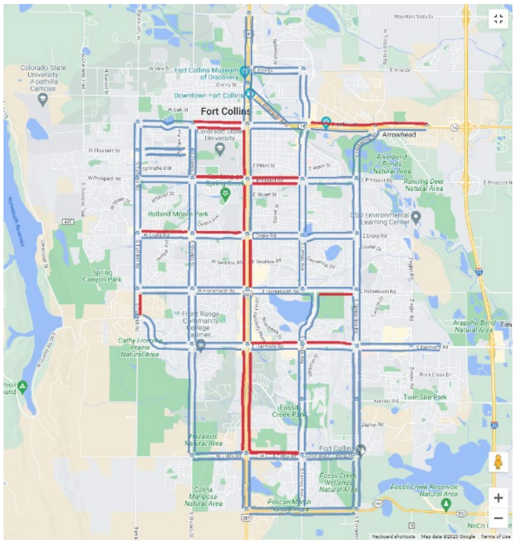


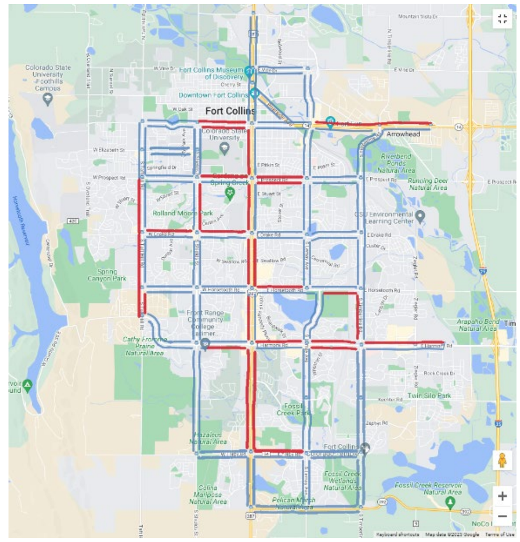
Fig. 6.6 Comparison of SIR-based congestion function *c(t)* and congestion ratio c_{real} from the real monitored data

As shown in Figs. 6.5 and 6.6, the congestion functions generated from the prediction traffic data and SIR model at different time points become more accurate and closer to reality when time progresses. The SIR-based congestion function can generally forecast the network-level congestion propagation trend well. There exists some error (-2.90% ~ 5.99%) in terms of the magnitudes of the forecasted congestion functions, likely because of the carrying over error from the traffic speed forecasting with DCRNN during the heavy snow moments as discussed earlier. However, the peak time of congestion has been predicted rather accurately (17:03,17:06,17:10, at time t_p=16:25, 17:05 and 17:45 respectively, vs. t_{peak} =17:10 in reality). This phenomenon validates the hypothesis made earlier that the congestion function based on the SIR model can capture the general trend of congestion propagation particularly when there will be peak congestion of the whole network. As discussed earlier, to forecast the general congestion trend and identify the critical time for the worst congestion with reasonable lead time is super helpful to deciding the potential intervention time t_I from the whole network perspective by the stakeholders. Depending on the decision strategy and priority by the stakeholder, which is beyond the scope of this study, t_I could be the predicted congestion peak time or other critical moments deemed necessary when the traffic congestion evolves.

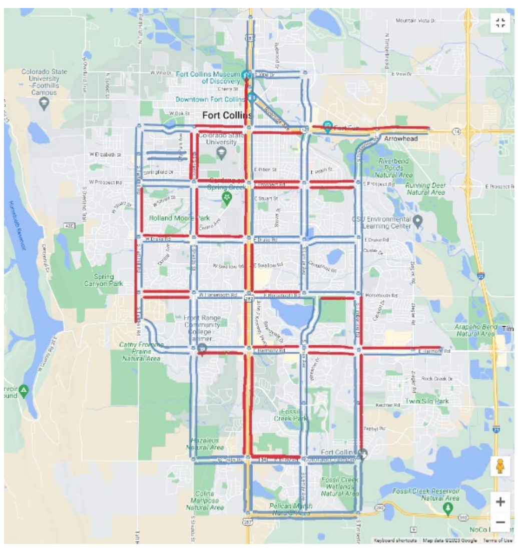
6.3.3 Identification of critical linkage for potential intervention

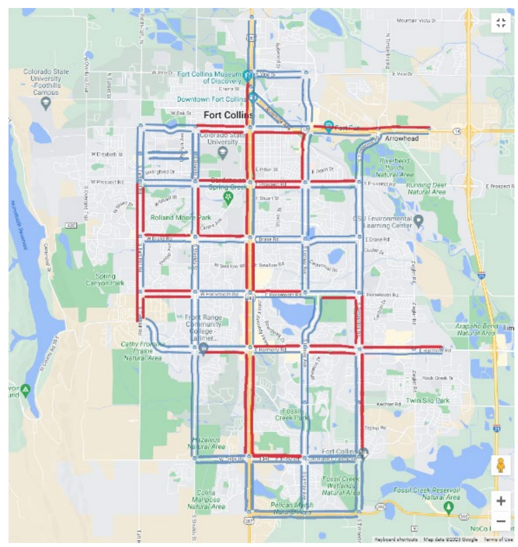
Once the potential intervention time t_I is decided based on the congestion propagation simulation with the SIR model, the next step is to determine individual strategic links which should receive potential intervention. In this section, the spatial presentations of the percolation analysis results using the predicted traffic speed data at time points t_p =16:25 and t_p =17:05 following the congestion criteria in Eq. 6.1 are made in Fig. 6.7. In Fig. 6.7, the spatial presentations of the percolation analysis results with the predicted data are compared with those based on the real monitored traffic data at the same time under the critical percolation point $q_c=0.36$. As shown in Fig. 6.7a, at time point t_p =16:25, all the identified "future" critical (congested) links from the prediction indeed become congested later according to the real data, except there are 2-3 links later found congested which were not successfully forecasted. It shows the proposed approach can also offer decent congestion forecasting at the link level to provide accurate guidance of individual strategic links which may deserve interventions based on the forecast. At time point t_p = 17:05 (Fig. 6.7b), most of the "future" congested links identified from the prediction are same as those from the reality, suggesting improved accuracy of the forecasted traffic speeds with more real data being fed over time.





a. t_p =16:25 prediction b. t_p =16:25 reality





c. t_p =17:05 prediction d. t_p =17:05 reality

Fig. 6.7 Prediction congestion links map at t_1 and t_2 (map data © 2022 Google)

6.4 Conclusion

Transportation systems experience various disruptions during hazardous weather events, causing significant challenges in predicting traffic efficiency, resilience performance, and applying any informed mitigation efforts. This study is conducted in response to the challenges of forecasting time-progressive traffic speed and resilience performance under hazardous weather and the need of investigating the feasibility of carrying out possible proactive intervention. The proposed approach integrates the deep learning traffic speed forecast, percolation-based resilience modeling, and the SIR congestion propagation modeling to offer a power tool to forecast both the time-dependent traffic congestion and resilience performance at both link and network levels during a hazardous weather event.

Such an integrated methodology bears great potential to assist the stakeholders to not only foresee the "future" traffic congestion as well as resilience performance at both link and network levels, but also make the informed decision with sufficient lead time about possible proactive intervention, emergency response, and recovery. Proactive intervention can be made with information about identifying the "future" optimal intervention moments t_I and individual strategic links which have the priority of receiving possible intervention with sufficient lead time. Moreover, because the critical links were identified based on the percolation-based resilience (robustness) analysis results, such a strategy of targeting at only a few most critical links can effectively improve the resilience of the whole network.

CHAPTER 7 SUMMARY AND FUTURE STUDIES

7.1 Summary and conclusions

The contributions and findings of this dissertation are summarized in the following, which correspond to Chapter 2 to 6:

Chapter 2 of the dissertation compares CORSIM and SUMO microscopic traffic simulation for research purposes. CORSIM is used to study the MAX route and Harmony intersection in terms of traffic performance and signal control. By comparing different traffic control plans, the most appropriate traffic signal plan for MAX route is identified, which achieves the best travel time savings while minimizing impacts on Harmony Road traffic. However, CORSIM's parameter variation is limited for research purposes. SUMO has been applied to successfully study a typical urban traffic network, including traffic performance and signal control plans. A new traffic signal control algorithm using DPS and TraCI control is proposed, showing clear advantages over traditional methods in terms of average speed, time loss, waiting time, and the number of arrived vehicles. SUMO was finally selected as the main simulation platform for the following chapters.

Chapter 3 introduces a new adaptive traffic signal strategy that combines dynamic phase selection (DPS) and queue length dissipation (QLD) for disrupted scenarios with incidents at a single intersection. DPS skips unused phases during incidents to reduce queue lengths and improve overall traffic performance. QLD determines optimal green times through signal timing optimization. The proposed DPS+QLD strategy aims to enhance the resiliency of intersections against disruptions by reducing queue lengths, minimizing traffic loss time, and restoring intersection mobility quickly.

Chapter 4 presents a new resilience modeling methodology for disrupted traffic systems under natural hazards. This methodology integrates hybrid data enhancement with SUMO and percolation-based robustness modeling. It characterizes the resilience of disrupted traffic systems by analyzing local traffic performance and network-scale robustness. The study investigates the feasibility of early active traffic intervention measures through optimized traffic signal designs at strategic intersections to improve traffic performance and robustness.

Chapter 5 addresses the challenge of conducting short-term traffic speed forecasting for disrupted traffic networks under natural hazards. The proposed method modifies the DCRNN model and incorporates transfer learning technology to predict network traffic speed during unprecedented hazard events, aiding prevention and intervention strategies for maintaining traffic network resilience and robustness.

Chapter 6 integrates deep learning traffic speed forecasting, percolation-based resilience modeling, and SIR congestion propagation modeling to forecast time-dependent traffic congestion and resilience performance during hazardous weather events. This integrated methodology assists stakeholders in foreseeing future traffic congestion and resilience performance, enabling informed decisions on proactive intervention, emergency response, and recovery. Proactive intervention can be implemented based on identified optimal intervention moments and strategic links with sufficient lead time.

7.2 Future study directions

Although the dissertation discussed the urban traffic network resilience modeling from traffic speed forecasting to critical road segment identification, and the adaptive intersection interventions under snowstorm hazard, there are still room and potential perspectives could be studied and improved in the future.

7.2.1 Traffic signal adaptive intervention

In Chapter 3, comparative investigations of the three traffic signal control plans (i.e., fixed, adaptive and DPS+QLD plans) suggest that the proposed traffic signal control plan DPS+QLD exhibits superior performance than the other two plans in terms of quickly dissipating the queue and improving the overall intersection efficiency and potential safety performance. There are, however, still some limitations of this study such as only a single intersection was studied, and the arrival flow rate remained constant for the whole simulation. In future studies, more realistic traffic with various arrival flow rates and multiple intersections on a corridor may be studied to provide more insightful findings.

7.2.2 Percolation-based resilience modeling

Chapter 4 tried to provide some new attempts to address several critical challenges of improving the resilience of urban traffic systems under hazards: (1) common data shortage of disrupted traffic systems under hazards; (2) comprehensive time-progressive resilience assessment of a disrupted traffic system under hazards at different spatial scales; and (3) how and when to apply effective traffic intervention such as smart traffic control techniques during hazards. This study has great potential to be extended in the future by addressing the limitations in this study: (1) it only investigated the early traffic intervention when the critical percolation threshold with GCC appears due to the scope limit of the feasibility study. More comprehensive studies of different intervention moments and corresponding strategies would be interesting topics to explore in the future; (2) only one snowstorm event was investigated as a case study. More comprehensive studies of multiple snow events over years may provide more insightful and comprehensive findings specific to the urban region being studied.

7.2.3 Traffic speed forecasting

Chapter 5 demonstrated the advantage offered by the transfer learning of the DCRNN. The main results are as follows: (1) The proposed DCRNN model can forecast traffic data precisely during normal conditions. (2) The comparison between DCRNN and other machine learning models like LSTM and XGBoost demonstrates the advantages of DCRNN to predict the whole network traffic speed more precisely. (3) Transfer learning technique for hazard scenario traffic speed forecasting can provide more accurate results than hazard-specific data. Although only the snowstorm disruption was discussed, the new methodology and concept of disrupted traffic network speed forecast can be applied to other locations and scenarios. Based on the proposed new model, more extensive research, and studies of traffic speed forecasting under different types of disruption will be considered and implemented in the future.

7.2.4 Time-progressive traffic resilience forecasting

In Chapter 6, the case study of a snowstorm event in the City of Fort Collins has demonstrated the proposed approach with satisfactory results and promising potential. This study has some room for future improvements: although the state-of-the-art deep learning techniques based on the transfer learning and DCRNN has demonstrated decent prediction accuracy, the prediction error during the moments experiencing sharp speed reduction during the severe snow was unexpectedly large. Though the increased error was largely due to the exclusion of the related training data, more advanced deep learning algorithms may be explored to further advance the forecasting accuracy of time-progressive traffic efficiency and resilience performance.

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