An Adaptive Traffic Vehicle Routing Framework

During Big Public Events

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# Table of Contents

Abstract ................................................................................................................................. v

1. Introduction .......................................................................................................................... 1
   1.1 Research problem ............................................................................................................ 3
   1.2 Research approach .......................................................................................................... 8
   1.3 Contribution ..................................................................................................................... 10
   1.4 Thesis structure .............................................................................................................. 11

2. Literature Review ............................................................................................................... 12
   2.1 Real-time traffic information collection ............................................................................ 12
   2.2 Real-time vehicle routing ............................................................................................... 14
   2.3 Traffic prediction ............................................................................................................ 16
   2.4 Participatory and adaptive traffic routing ...................................................................... 18

3. Adaptive Traffic Routing .................................................................................................. 21
   3.1 Framework ..................................................................................................................... 21
   3.2 Study area, network and travel plan data ......................................................................... 22
   3.3 Traffic density and travel time calculation ..................................................................... 25
   3.4 Adaptive traffic routing ................................................................................................. 28
      3.4.1 Adaptive traffic route planning .................................................................................. 28
      3.4.2 Simulation system ..................................................................................................... 30
   3.5 Traffic density updating ................................................................................................. 31

4. Experiments and Results ................................................................................................... 34
   4.1 Experiment environment ............................................................................................... 34
   4.2 Experiment design .......................................................................................................... 35
4.2.1 Different number of vehicles ................................................................. 39
4.2.2 Different scenario stages: “black hole” and “volcano” .............................. 40
4.2.3 Different vehicle dispatch directions ........................................................ 43

5. Conclusion and Future Work ........................................................................ 45
  5.1 Conclusion ................................................................................................. 45
  5.2 Future direction ......................................................................................... 47

References ........................................................................................................ 50
Abstract

One of the most ubiquitous transportation problem is real-time vehicle routing. Previous work leveraged both real-time (e.g. vehicle location and velocity) and historical traffic data (e.g. street traffic count within a certain amount of time) collected from traffic sensors and road cameras, to facilitate vehicle routing. However, one type of data, vehicle travel plans, were commonly ignored. Travel plans are the data which describe: 1) the origin a vehicle is from; 2) the destination it is heading to; and 3) the time it plans to leave from the origin. The travel plan data is valuable for vehicle routing because current travel plans from vehicles could cause corresponding traffic congestion somewhere in the network sometime in near future, which is defined as “butterfly effect” in this thesis. Therefore, we could improve future travel plans by avoiding the anticipated traffic congestion spots predicted by these known travel plans. Due to the fact that the state-of-art work tends to route each vehicle independently without considering such “butterfly effect” among vehicles, this paper proposed an adaptive traffic routing framework which would fully use traffic plan data to improve real-time routing and mitigate traffic congestion.

Additionally, the state-of-the-art work failed to make a comprehensive study of vehicle routing during big public events (e.g. a football game in a stadium or a movie in a theater), where there are two phases, including the “black hole” phase caused by a large number of vehicles heading to the same destination before the public event begins, and the “volcano” phase when vehicles leave from the event spot and drive to different directions after the event. While previous work may focus on addressing either the black hole phase or the volcano phase, none have attempted to study the two phases together. Therefore, this paper develops a new framework which can handle both phases at the same time.
To perform vehicle routing, traditional approaches widely use A* algorithm, which didn’t consider the influence of the travel plans (i.e., the butterfly effect). Therefore, a time-dependent adaptive traffic routing algorithm, which consistently updates the traffic conditions with current travel plans, is implemented and integrated in a traffic simulation system, known as MATSim, within the proposed framework. To demonstrate the feasibility and effectiveness of this adaptive traffic routing framework, a series of experiments are conducted based on the MATSim system. The experiment results show that our framework is able to leverage the butterfly effect among vehicles for vehicle routing. The framework can also handle a large number of vehicles for both the black hole phase and the volcano phase. Our framework outperformed the traditional A* routing algorithm in both phases, with approximately 15% and 45% performance improvement, respectively, in all experiments.

**Keywords:** Real-time vehicle routing; Adaptive traffic routing; Big public event; Traffic Simulation
1. Introduction

Urban expansion has influenced human life in many ways, and traffic congestion is one of the most significant consequences to our human societies. People in big cities such as San Francisco and New York suffer from the high congestion level. People not only waste their time in waiting for the traffic, but also spend more on gas bills. Public health is also threatened by the traffic-induced air pollution (Kunzil et al., 2000).

To deal with such a high traffic congestion level, traditional, static, non-adaptive navigation systems are no longer suitable. Instead, real-time routing is preferred in the latest intelligent transportation systems including Google Maps. The goal of real-time routing is to find the optimal vehicle route from an origin to a destination in a traffic network with dynamic traffic conditions, weather conditions and etc. (Haghani & Jung, 2005). Real-time routing takes advantage of multiple data resources such as weather conditions and real-time road traffic information. Using such information, the vehicle navigation and routing system can better navigate vehicles to avoid heavy traffic and therefore decrease traffic congestion level within the traffic network.

While city-scale traffic congestion could be mitigated by the real-time routing approach, the traffic congestion level still can become extremely high around a certain spot (i.e. traffic hotspot) in certain situations. Examples include a large number of people going to the theater to watch a new movie and leaving the theater after the movie. As a consequence, the theater becomes the traffic hotspot, before the movie begins and after the movie ends. Highly congested traffic can paralyze such hotspot regions and propagate the congestion to other areas of the network. In such situations, any vehicle in the network could play a significant role and are highly correlated to the traffic systems shown as Figure 1, defined as
traffic butterfly effect in this thesis. Any vehicle can impact the road densities (i.e., the number of vehicles in a road) of the traffic network and the road densities in turn can determine the routing decisions for each individual vehicle (i.e., a routing algorithm would select roads with low densities to achieve shortest travel time for a vehicle). Additionally, traffic in one area of the network can propagate to other areas of the network (Kamarianakis & Prastacos, 2005; Long et al., 2008). For example, if many vehicles plan to go to the same destination (the hotspot point depicted as the red dot node in Figure 1 right), the area around the destination is expected to experience heavy traffic congestion (presented as the red lines in Figure 1 right). Therefore, subsequent vehicles following these vehicles with the same travel plans will take a lot more time to arrive at the destination in comparison to their travel time when there is not too much traffic in the area. Moreover, vehicles with different destinations but have to travel the congested region would be also influenced. As a result, more vehicles could contribute to the traffic congestion, which in turn further propagates the congestion region from the hotspot area to its surrounding areas.

Therefore, all vehicles are correlated by influencing each other’s routing decisions dynamically in the situations discussed earlier. However, conventional real-time routing approaches often cannot mitigate such traffic pressure because they only consider each vehicle independently without taking into consideration the impact of other vehicles and the corresponding traffic propagation effect to the network. Therefore, it is important to find an alternative approach to mitigate and prevent extreme traffic congestions by leveraging such correlation relationship as shown in Figure 1.
1.1 Research problem

The fundamental research question this thesis addresses is how to leverage the correlation among vehicles in vehicle routing to mitigate and avoid traffic congestion. Current studies route vehicles independently where every vehicle tries to choose the optimal route for itself. However, these routes might not be optimal at the network system level. In this case, we propose an adaptive vehicle routing framework to plan routes for vehicles. This framework can dynamically update the traffic density based on each vehicle’s current routing decision, consistently predict future traffic within the network, and therefore adaptively mitigate traffic congestion by routing vehicles to alternative routes based on the awareness of the existence of other vehicles and their routing decisions. As a result, the routes for vehicles derived from our approach may not be optimal for each individual vehicle, but optimal at the system level, which help mitigate the extreme congestion instead. In other words, vehicles do not always choose the shortest routes to their destinations but adaptively select some sort of sub-optimal routes and eventually improve the traffic network efficiency.
Such a framework can be useful to handle many real-worlds traffic situations where there are a large number of vehicles involved with similar travel plans (e.g., having the same origins or destinations as shown in Figure 1 right). Some of the examples would be traffic congestions produced by big public events such as a graduation commencement, a new movie, or a basketball game. Big public events in this thesis context are defined as two phases, including (1) “black hole” phase (Figure 2 Left), similar to the traffic corridor situation (Golias, 2002; Mahmassani & Jayakrishnan, 1991): a large number of vehicles head to the same destination; (2) “volcano” phase (Figure 2 Right), which can also be called evacuation scenarios (Hamza-Lup et al., 2008; Wang et al., 2013; Wolshon et al., 2005): a large number of vehicles at a certain location enter the traffic network and head to different directions.

The volcano phase often comes after the black hole phase. For example, if there is a new movie between 7pm to 10pm, people from all over the city drive to the theater before 7pm, which results in the black hole situation. In this case, the black hole is the theater and people from all directions drive towards it. The closer to the black hole, the higher the traffic congestion level is supposed to be. After the movie ends at 10pm, people leave the theater at almost the same time. A large number of vehicles leaving from the theater is like the volcano eruption phenomenon. In this case, the theater is the volcano and the traffic congestion level will get extremely high near the volcano center.
To sum up, both “black hole” and “volcano” phases would cause serious traffic problems. Therefore, this thesis takes big public event as a case study to validate the proposed framework and to demonstrate that our framework is capable of alleviating traffic congestion during such events. The traffic congestion level influences the travel time of each vehicle from the origin to the destination. Meanwhile, the average travel time of the vehicles within the network reflects the traffic congestion level. Correspondingly, to prove its efficiency, the proposed framework aims to shorten the average vehicle travel time of all involved vehicles heading to the black hole and leaving from the volcano.

Currently, only limited research focuses on the real-time routing problem during big public events. To deal with the routing problem occurring before such an event (i.e. the black hole problem), scholars mostly relied on real-time traffic information sharing either through radio broadcasting (Emmerink et al., 1995; Helbing 2001) or in-vehicle navigation system.
(Arnott et al., 1991; Mahmassani & Jayakrishnan, 1991) to reduce traffic congestion. To address the routing problem after the big public event (i.e. the volcano problem), researchers tend to focus on evacuation planning by developing sophisticated evacuation algorithms and transportation policies (Hamza-Lup et al., 2008; Wang et al., 2013; Wolshon et al., 2005). In other words, these previous research concentrated either on the black hole scenarios (Arnott et al., 1991; Emmerink et al., 1995; Helbing, 2001; Mahmassani & Jayakrishnan, 1991) or the volcano scenarios (Hamza-Lup et al., 2008; Wang et al., 2013; Wolshon et al., 2005). However, these two scenarios are correlated during big public events since volcano scenarios happen after black hole scenarios. Thus, it is worth discussing the two scenarios together and finding a general solution to address the common problems (e.g. extreme traffic congestion) in these scenarios.

In addition, none of these research works (Arnott et al., 1991; Hamza-Lup et al., 2008; Mahmassani & Jayakrishnan, 1991; Wang et al., 2013) leveraged volunteered geographic information (VGI) as a data source to understand the real-time traffic conditions in their simulation systems while routing vehicles. Traditionally, researchers relied on the real-time traffic data captured by city infrastructure (e.g. road cameras; Del & Pernici, 2005) and on-boarded Global Positioning System (GPS) devices for vehicle routing (Hull et al., 2006). However, they did not fully utilize another data source, volunteer drivers, who can contribute real-time traffic data (e.g., car accident and road congestion information) for data collection. Over the last decade, VGI emerges as a new approach to collect traffic information for supporting real-time routing (Wilkie et al., 2014). VGI has become popular due to the rapid development of location-based services and the explosion of the mobile network industry. VGI was first introduced in 2007 (Goodchild, 2007) when Web 2.0
techniques had already made a sufficient amount of data sharing and distribution activities through the Internet. OpenStreetMap is among the earliest VGI applications to collect geographic data contributed by thousands of volunteers. VGI collected from different collaborative platforms has been utilized in a variety of fields, such as species identification (Deng et al., 2012), disaster management (Huang and Xiao, 2015), and transportation management (Fire et al., 2012). With VGI, collaboration on solving geographical problems becomes more possible. Researcher can acquire VGI data provided by volunteering individual users. In the vehicle routing context, traffic related VGI can be easily collected to facilitate vehicle routing.

At the same time, mobile networking is becoming even more popular and mobile devices become our major tools to access and share information. With the dramatic proliferation of location-based services, massive data gathering from mobile devices can provide real-time traffic information and facilitate decision-making processes such as vehicle routing (Mohan et al., 2008) and smart transportation planning (Wilkie et al., 2014). Leveraging mobile VGI to improve real-time routing quality would help drivers avoid unnecessary traffic congestion and thus reduce traffic hotspots. A more efficient traffic network system also has the potential of reducing greenhouse gas emissions caused by traffic congestion. In short, mobile VGI could potentially promote a more energy-efficient and clean transportation system (Li et al., 2012).

Another issue of the previous studies is using grid-like or small-scale artificial networks to perform traffic simulations to validate their proposed approaches (Arnott et al., 1991; Emmerink et al., 1995; Mahmassani & Jayakrishnan, 1991). However, in the real-
world, traffic networks are much larger and complex, and therefore cannot be well represented by such small-scale artificial networks.

To sum up, much more work should be done regarding the research gaps mentioned above. This thesis is therefore trying to expand the literature by proposing an adaptive traffic vehicle routing framework, which is able to mitigate and avoid traffic congestion for both scenarios (i.e. black hole and volcano) together during big public events. Our framework can utilize the predictions of future traffic based on the awareness of all vehicles within the network to adaptively route vehicles away from traffic congestion.

Additionally, travel plan VGI is utilized within our proposed framework. As discussed above, VGI is becoming popular in these years and has become a powerful technology for geographical data collection in transportation field (Li et al., 2012; Mohan et al., 2008; Wilkie et al., 2014;). Comparing to traditional data collection methods, it is faster, cheaper, and easier to scale up. Finally, a real world large-scale network (i.e. City of Madison) is used as our study area, and our traffic simulation and performance validation of the proposed approach is based on this relatively large-scale network.

1.2 Research approach

This research aims to propose an adaptive traffic routing framework to address the extreme traffic congestion introduced by a large number of vehicles with similar travel plans within a network system using public events as an example. During these events, people tend to drive towards or from the same event location around the same time, which results in heavy traffic congestion near the event region. To provide a promising solution to solve the traffic problem above, this framework is able to dynamically predict the future traffic by
Knowing the existence of vehicles and associated route decisions in the network based on the travel plan data voluntarily contributed by each individual vehicle.

Similar work along this line would be participatory routing (PR; Dresner & Stone, 2004; Hull et al., 2006; Karimi, 2014; Wilkie et al., 2014). PR collects information from individual vehicles to make routing decisions. Such information includes but is not limited to vehicle trajectory data (Hull et al., 2006), travel plan data (Dresner & Stone, 2004; Wilkie et al., 2014), and real-time traffic accident report (Karimi, 2014). PR emerges as a new approach to support vehicle route planning (Wilkie et al., 2014; Dresner & Stone, 2004). For example, Wilkie et al. (2014) employed travel plan data collected from mobile devices to generate routes which can reduce total traffic congestion level in the network. However, their system failed to work under situations where the travel plans are expected to produce large volume of traffic jam in a certain spot, e.g. black hole and volcano scenarios (Wilkie et al. 2014). This research makes an initial effort to leverage the awareness of vehicle existence in the traffic network to alleviate traffic congestion levels under both black hole and volcano situations.

In our framework, we utilize vehicle travel plan data from volunteers to dynamically predict the future traffic to better route vehicles. Traditionally, two basic types of data used for a real-time routing system are: 1) the basic traffic network and 2) the street traffic condition. However, vehicles travel plans are helpful to improve real-time routing (Wilkie et al., 2014). When the routing system knows the travel plans of all vehicles, it will be able to predict future traffic hotspots and thus route vehicles away from those spots. In order to collect such travel plans, we take advantage of VGI as the data collection approach. Through
installed navigation applications, the travel plan data can be easily collected from users’ mobile devices.

The proposed study first collects travel plans from all vehicles. Then these plans are used in the framework by a time-dependent routing algorithm to compute routes for the vehicles. There are two major components in the framework: 1) use the current road traffic densities of the network to compute route for a vehicle; and then 2) update the traffic densities using the route computed. Subsequent vehicles will then use the updated densities to compute their optional routes and update the traffic densities as well.

Finally, a series of simulation experiments are performed, using the planned routes as input, to evaluate the effectiveness of the method for both black hole and volcano scenarios. A baseline A* routing algorithm (Wilkie et al., 2004), which is commonly used in traditional routing approaches and only takes individual vehicle’s travel plan as input without awareness of other vehicles within the traffic network, is also developed in the experiments to compute routes for performance comparison. The expected result is that our proposed adaptive traffic routing framework reduces traffic congestions comparing to traditional approaches using the baseline A* routing algorithm in both the black hole and volcano scenarios.

1.3 Contribution

There are three major contributions of this thesis work: 1) In this research, an adaptive traffic routing framework is proposed to solve extreme traffic congestion problems during public events and many other real-world situations with extreme traffic congestions caused by vehicles with similar travel plans. Unlike traditional approach, the framework can deal with both the black hole and volcano scenarios within a public event. Experiment results (Section 4) prove its effectiveness and great potential to benefit the real-world vehicle
routing and navigation system by mitigating traffic congestion level. 2) This thesis utilizes travel plan VGI as the data source in the proposed method. It fills the gap that previous works did not use vehicle travel plans as a prospective VGI data type on solving traffic congestion problems. and 3) In our framework, the time-dependent routing algorithm is used that took advantage of the awareness of all vehicles within the network to predict future traffic and adaptively route vehicles away from traffic congested areas.

1.4 Thesis structure

The rest of the thesis is divided into 4 sections. Section 2 reviews the current work on related fields. Section 3 describes the research methods with 5 subsections. Section 3.1 provides the overview of the methodology along with the workflow of the proposed framework. Section 3.2 defines the study area and describes the data sources. Sections 3.3 to 3.5 illustrate how to utilize travel plan data to facilitate vehicle routing. Section 4 demonstrates the simulation environment and different experiments designed and followed by the result discussions. Section 5 concludes this thesis work and discusses possible future directions.
2. Literature Review

2.1 Real-time traffic information collection

Traditional approaches to obtain real-time traffic information for real-time routing highly depend on the street infrastructure such as traffic camera and vehicle detection loops. Through these sensor networks, real-time traffic can be monitored with a high accuracy (Coleri et al., 2004). Due to the expensive installation and maintenance cost of such street infrastructures, efforts are made to seek alternative approaches for real-time traffic monitoring and vehicle routing.

Hull et al. (2006) designed and implemented a distributed mobile sensor computing system called CarTel. The system collects various types of data through pre-installed devices on vehicles. These devices interact with the server by opportunistic networking (e.g. Wi-Fi and Bluetooth) for both data collection and real-time routing. The system is able to handle intermittent network connectivity by using a specially designed database. However, the required device installation process is the biggest obstacle for their system to scale up. It is much less convenient than installing a software application on a mobile device (e.g., smartphone). For example, applications, such as Uber and Google Maps, can easily be installed on users’ mobile devices and updated from time to time to improve the system functions. Opportunistic networking is also unstable and less prevalent comparing to cellular networks (e.g. 3G or 4G) used by mobile devices.

Mohan et al. (2008) tracked the movements of automobiles on streets by pre-installed GPS devices to derive traffic information as the replacement of the traditional street infrastructure approaches. However, this method also highly relies on those pre-installed vehicle GPS devices to track automobile movements. Pre-installed GPS devices are
expensive and thus impractical in ways similar to street infrastructures mentioned above. For example, it is difficult to uninstall those devices when the vehicle owners want to stop the service, and this might also raise privacy concerns. Maintenance of the software and hardware components of the devices is also inconvenient and expensive (Li et al., 2012).

In recent years, with the prevalence of smartphone and wireless network, mobile VGI is widely used in many fields, including vehicle navigation (Bakillah et al., 2014), traffic control (Jariyasunant et al., 2011), and real-time traffic monitoring (Krause et al., 2008; Wilkie et al., 2014). The low-cost and decentralized nature of VGI has attracted much attention on leveraging VGI to improve routing quality. Among these works, VGI was collected in image formats through mobile social applications (e.g. Flickr) and processed by sophisticated image segmentation algorithms to extract traffic networks and update the routing system when a change happens such as road construction (Karimi, 2014). However, it is very difficult to track the changes in traffic network in real-time because it requires immediate update such as reports by volunteering witnesses or change detection by road cameras.

Other researchers collected GPS trajectories through mobile VGI to derive real-time traffic (Bakillah et al., 2014). GPS trajectories are a series of GPS coordinates generated by moving vehicles. With location-based service enabled, mobile devices are able to collect GPS trajectories from the users. The GPS trajectory data is then used to derive vehicle location and speed information thus generates a real-time traffic map. However, deriving such data requires collecting and processing a large volume of spatial-temporal GPS data.

This thesis did differently by collecting travel plans of individual vehicles to derive future traffic conditions. Comparing to pre-mentioned data (e.g. images and GPS trajectories)
collected from mobile devices, this approach is more promising since people these days tend to utilize their mobile applications for navigation and route planning. Therefore, collecting the travel plan data is much easier and less expensive. On the same time, it is much convenient to process such data.

2.2 Real-time vehicle routing

With the widely available real-time traffic information collected from different sources as discussed earlier, real-time routing is possible and was first introduced by Dantzig and Ramser (1959) for the vehicle dispatching problem. However, only limited work was conducted on real-time routing under extremely heavy traffic conditions. Additionally, to my best knowledge, the approaches used in these work, are used to handle either (a) black hole or (b) volcano scenarios.

(a) Black hole scenario

Mahmassani et al. (1991) developed a framework to investigate the effectiveness of in-vehicle real-time traffic information strategies on reducing traffic in a congested traffic corridor (i.e., black hole scenario). However, their primary focus was on using in-vehicle navigation systems. Therefore, the system could only respond to traffic changes but not prevent traffic congestions in advance.

Emmerink et al. (1995) discussed the effectiveness of information provision to drivers on the performance of the traffic networks with recurrent congestion. They used driver behavior models along with real-time vehicle en route information to reduce traffic congestion. However, the experiments they conducted are in a small-scale network with only 18 nodes and 27 links. Therefore, whether the method can perform well in the real world complex situations is highly questionable.
(b) Volcano scenario

Hamza-Lup et al. (2008) proposed two traffic evacuation algorithms to provide efficient and rapid responses to natural and human-related disasters by effectively dispatching involved vehicles away from the disaster regions (i.e., volcano scenario). Both algorithms methods are efficient on automatically generating evacuation plans with excellent evacuation speed. However, the algorithms require only one or several evacuation exit points as the routing destinations. They did not consider the situation where each vehicle needs to evacuate to a different destination (e.g. home), which much complicates the evacuation planning process.

Chen et al. (2008) evaluated a staged evacuation strategy using agent-based modeling and proved its effectiveness for areas where the population density is high. In their study, residents in different evacuation zones are organized to evacuate in order according to the location of the zones in the affected area. However, their method is only limited to grid structure traffic network, which is of limited use for complex non-grid networks.

To sum up, none of these studies address the black hole and volcano scenarios at the same time. This is because these two types of scenarios require different types of data as input. For the black hole scenarios, the required input is usually real-time traffic-related information (Emmerink et al., 1995, Mahmassani et al., 1991); for the volcano scenarios, the evacuation destination and the disaster/event spot are required (Chen et al., 2008; Hamza-Lup et al., 2008). However, our approach is independent of such input data. With the travel plans as input, it can produce routing for different situations. In this thesis, an adaptive traffic routing framework is introduced to leverage the travel plan data and traffic simulation experiments are conducted to compare the effectiveness of the framework on the two
scenarios together. Additionally, this study is conducted on a real urban network (i.e. City of Madison) rather than on some artificial non-real networks. The framework proposed in this thesis not only responds to real-time traffic in a timely fashion but also prevents future traffic jams. Last but not the least, this thesis fully considers different variations (e.g. different number of vehicles, different scenario stages, and different vehicle dispatch directions; details are in Section 4) of the two scenarios mentioned above.

2.3 Traffic prediction

Real-time traffic monitoring is not enough for traffic management and planning. Congestion could be very serious, especially in an urban traffic network, which should be avoided in advance. Therefore, traffic prediction, which is to forecast traffic volume of road segments within a traffic network (Smith & Demetsky, 1997), becomes a popular topic within the transportation field.

Most researchers used time-series models for traffic prediction. Min et al. (2011) introduced a method for traffic speed and volume prediction using a multivariate spatial-temporal autoregressive model. The basic idea of the model is that the traffic condition on a road segment is affected by the immediate past traffic situations on a certain number of neighboring links. Their work differs from other studies (e.g. Kamarianakis & Prastacos, 2005), which only consider the distances between links but ignore the connectivity between links. For example, two links may have small distances but are actually unreachable to each other (e.g. they are parallel with each other). Additionally, spatial correlations between the highway upstream links and their neighboring links in the network are considered in their model. They used historical speed data to calculate the reachability, in a certain time interval,
between links to represent the spatial relationship. Experiments show that the model can predict traffic volume and speed with a very good accuracy on 5-minute interval over 1 hour.

Smith et al. (2002) compared an autoregressive integrated moving average (ARIMA) model with nonparametric models, including a nearest neighbor model, to predict 15-min expressway traffic. The result shows that the ARIMA model performs better than nonparametric models.


Markov model is also used in relevant research for traffic prediction. Qi and Ishak (2014) used Hidden Markov Model (HMM) to predict freeway traffic during peak hours. The data were collected from real-time traffic monitoring street infrastructures (detective loops) over a 6-year period in every 30 seconds. Their HMMs output the most likely sequence of traffic conditions over a short time period. Schnitzler et al. (2014) combined a Gauss-Markov model with Gaussian process to predict traffic in Dublin city using historical data.

To sum up, these works all utilized historical traffic data to predict future traffic conditions on the same traffic network. The assumption of these works is that historical traffic pattern is not much different from the future traffic pattern. However, in the real-
world, traffic is complex and in some cases the patterns displayed in historical traffic data do not exist in future traffic.

This thesis differs from the previous research by using volunteer vehicles’ travel plans for traffic prediction. Rather than predicting traffic based on historical traffic data, the thesis uses users’ real-time travel plans to predict short-term traffic conditions. The updated traffic conditions are then used by the system to route other vehicles. This approach provides more realistic modeling about the around-the-corner traffic because: 1) in this approach, there is no assumption for the underlying traffic patterns which can be erroneous to predict future traffic; and 2) traffic plan data represents vehicles’ planned actions in the future thus can be used to infer how the future traffic might be in the network.

2.4 Participatory and adaptive traffic routing

Participatory routing is becoming popular in recent years. The core idea of such work is to allow vehicles within the routing system participate in the vehicle routing process. Each individual vehicle influences the traffic network a bit and eventually impacts other vehicles.

Rutger et al. (2011) introduced a novel approach for anticipatory vehicle routing. They used a decentralized delegate multi-agent system which was inspired by ant behaviors. The ant agents representing vehicles collaborate in the system by communicating with each other to share traffic and route information via the sensor devices installed on the network links. Although this collaborative mechanism among agents can mitigate traffic congestion ahead of time, it requires expensive infrastructure installation on both personal vehicles and street infrastructures.

Guo et al. (2014) introduced the concept of “Mobile Crowd Sensing” (MSC) evolved from “participatory sensing” (Burke et al., 2006) where the citizen power of large-scale
sensing is leveraged through mobile devices. MCS involves both explicit (i.e. the users intend to contribute data) and implicit (i.e. the users intend to do some other online activities but also contribute some sort of data) user participation and collects data from both mobile sensors and mobile social networks. Several research trends are discussed in the paper such as the hybrid mobile networking which combines both infrastructure-based and opportunistic network. Interactions among users are also discussed as a potential way of improving data quality in MCS.

Wilkie et al. (2014) proposed a novel idea of participatory route planning (PRP), which takes advantage of MCS to form an efficient cooperative routing system. The idea is built on the work of “Self-Aware Traffic Route Planning” (Wilkie et al., 2011) and synthesizes the idea of “participatory sensing” (Burke et al., 2006). The system calculates travel routes for the vehicles based on the real-time traffic conditions and existing routes planned for other participants (i.e. vehicles) within the network. The method accounts for the fact that a planned route for a vehicle will cause a small traffic increase on the route at a certain time in the future. The authors also conducted a series of experiments to validate their approach using a microscopic traffic simulator, SUMO. In their simulation, they simulated three scenarios: 1) single-source, single-destination; 2) multiple-source, single-destination; and 3) multiple-source, multiple-destination. However, they did not consider the scenarios of single-source, multiple-destination such as people exiting a theater after a movie ends. Additionally, the system cannot handle highly congested traffic because of the limitation of the simulation system.

To sum up, there are several limitations of the current participatory research. Firstly, they did not well integrate the prediction of future traffic by leveraging the awareness of all
vehicles within the traffic network into vehicle route planning process. Secondly, these work failed to consider the traffic propagation within the network as previously discussed. Moreover, although the authors illustrated how real-time sensor data can be incorporated to the system, they did not demonstrate how historical traffic data can be utilized.

This thesis seeks to build on the current participatory routing studies and proposes an adaptive traffic routing framework to overcome these limitations. Within the adaptive traffic routing framework, the traffic propagation is recognized and the prediction of future traffic is integrated based on the awareness of existing vehicles in the traffic network. In addition, comparing to current participatory routing, this thesis utilizes sophisticated traffic simulations to investigate the effectiveness of adaptive traffic routing for solving extreme traffic congestions under big public events. This thesis also demonstrates how to incorporate historical traffic data (e.g. traffic density) with real-time traffic plan data.
3. Adaptive Traffic Routing

3.1 Framework

Figure 3 below shows the overall workflow of this thesis work. The workflow includes four integrated components:

- Network and travel plan data: In this research, traffic network data is first processed into the format that can be used by the simulation system. Then travel plans of black hole and volcano scenarios are generated within the study area.

- Traffic density and traffic time calculation: Traffic density distribution is used to calculate link travel time (i.e. the time for a vehicle to traverse a street link) according to Greenshiled’s (1934) traffic flow theory. The link travel time for each link is then used by the time-dependent routing algorithm (below) to compute routes for the vehicles with different travel plans.

- Time-dependent routing: Given a set of travel plans of different vehicles, a time-dependent routing algorithm is applied to compute the optimal route for both stage scenarios. The algorithm is implemented and integrated to the selected traffic simulation system (MATSim). The output of the algorithm is the planned routes for all travel plans.

- Traffic density updating: Whenever a route is planned by the time-dependent routing algorithm, the route is then used to update the traffic density distribution. The updated density distribution is then used to compute routes for subsequent travel plans.
Figure 3. Workflow of the proposed adaptive traffic routing framework

3.2 Study area, network and travel plan data

The study area (Figure 4) is a 20 km by 12 km rectangular region located in the southwestern part of the City of Madison. The Madison ACM theater, which is the center of the region, is chosen as the spot to study black hole and volcano traffic scenarios because it is a public gathering place with high population density under certain events. In 2013, the Madison population is estimated to be 243,000 inhabitants (United States Census Bureau, 2013). The city has witnessed a population boom over the past two decades, growing approximately 27% of its population from the year of 1990 to 2013 (United States Census Bureau, 2013). This population boom resulted in a rapid growth and investment on public entertainment facilities including public theaters. Correspondingly, such the rapid growth in
the area also brought an added pressure on the city’s traffic system and calls for more attention than ever.

![Study area map](image)

**Figure 4. Study area map**

The raw traffic network data is provided by the Madison Area Transportation Planning Board\(^1\) in shapefile format. The network represents the Dane Country roads updated to 2014. A user-defined coordinate system is used where the origin is at 43°04'10.3"N, 89°25'20.0"W, the center area of Madison. The road within the study area is extracted from the entire network.

---

\(^1\) [http://www.madisonareampo.org/](http://www.madisonareampo.org/)
The data is then converted to nodes and links in Extensible Markup Language (XML) format, which is the required format in the MATSim traffic simulation system. The simulation system is introduced in Section 3.4.2 and used to conduct traffic simulation experiments in Section 4. Networkx\(^2\) and lxml\(^3\) libraries are used for the data conversion process. Networkx, a library for the creation, processing, and study of the structure, dynamics, and functions of complex networks in Python language, is used to read in the traffic network shapefile; lxml, a Python package for manipulation XML and HTML, is then used to create and write the network to specified XML format. Attributes of the nodes and links in the XML file are listed in Table 1.

**Table 1.** Selected attributes of the nodes and links in the network XML file

<table>
<thead>
<tr>
<th>Network Element</th>
<th>Attribute Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Node</td>
<td>id</td>
<td>The node id</td>
</tr>
<tr>
<td></td>
<td>x</td>
<td>The x coordinate</td>
</tr>
<tr>
<td></td>
<td>y</td>
<td>The y coordinate</td>
</tr>
<tr>
<td>Link</td>
<td>from</td>
<td>The origin node’s id</td>
</tr>
<tr>
<td></td>
<td>to</td>
<td>The destination node’s id</td>
</tr>
<tr>
<td></td>
<td>capacity</td>
<td>The maximum capacity of the link (units: car/one hour)</td>
</tr>
<tr>
<td></td>
<td>freespeed</td>
<td>The allowed maximum speed of the link (units: meter/second)</td>
</tr>
<tr>
<td></td>
<td>length</td>
<td>The real length of the link (unit: meter)</td>
</tr>
</tbody>
</table>

---

\(^2\) https://networkx.github.io/  
\(^3\) http://lxml.de/
The travel plan data is generated for both the black hole and volcano stage scenarios. Each plan has an origin and a destination with a pair of coordinates. For the black hole scenario plans, the destination is set to the theater and the origin locations are randomly picked within the study area. The volcano scenario plans are generated using the black hole scenario plans by switching origin and destination locations.

3.3 Traffic density and travel time calculation

Initially, the traffic density (i.e., the number of vehicles within a certain time interval on a street) for all street links is set to zero by default. Given a street link $e$, its traffic density at time $t$ is defined as $\rho_e(t)$, which can be derived based on a normal distribution with mean $\bar{\rho}_e(t)$ and variance $\bar{\rho}_e(t)$. Then the traffic density updating component introduces in Section 3.5 will calculate and update the values of $\bar{\rho}_e(t)$ and $\bar{\rho}_e(t)$ for this street link.

To associate density with travel time, the Greenshield’s (1934) fundamental diagrams (Figure 5) are used. In the diagram, $u$ is traffic speed (unit: meter/second), $q$ represents traffic flow rate (unit: car/second), and $k$ stands for traffic density (unit: car/meter). The maximum speed $u_f$, is reached when the traffic density is zero; the maximum density $k_j$ is reached when the traffic speed is zero, as a signal when the road is completely congested. When the traffic flow rate is at its maximum value $q_c$, the traffic network reaches its full capacity (maximum flow rate) where the traffic speed is $u_c$ and the density is $k_c$. These relations can be defined as:

$$u = \frac{u_f}{k_j}(k_j - k)$$ (1)
$k_j = 2k_c$ \hspace{1cm} (2)

$u_f = 2u_c$ \hspace{1cm} (3)

**Figure 5.** Greenshield’s fundamental diagrams relating traffic density ($k$), speed ($u$) and flow rate ($q$).
According to the fundamental relation of traffic flow theory, we can also know that
\[ k_c = \frac{q_e}{u_c}. \]
Thus, we can derive the following equation to compute, at a specific timestamp \( t \), a link \( e \)'s travel speed \( u_e(t) \) given the traffic density \( \rho_e(t) \):

\[
u_e(t) = u_{e,f} - \rho_e(t) * \frac{u_{e,f}}{4 \cdot q_{e,c}}
\]  

(4)

where \( u_{e,f} \) indicates the maximum travel speed on the link \( e \). Since link capacity is already given as \( C_e \) (unit: car/one hour) in our data as introduced in in Table 1, the maximum flow rate of link \( e \) \( (q_{e,c}) \) can be derived as:

\[
q_{e,c} = \frac{C_e}{3600}
\]  

(5)

Therefore, the travel time \( \tau_e(t) \) to traverse the link \( e \) at a specific timestamp \( t \) can be calculated as:

\[
\tau_e(t) = \frac{l_e}{u_e(t)} = \frac{l_e}{u_{e,f} - \rho_e(t) * \frac{u_{e,f}}{4 \cdot q_{e,c}}}
\]  

(6)

Using the first-order Taylor expansion theory, \( \tau_e \) can be represented using its estimated mean \( \overline{\tau}_e(t) \) and variance \( \overline{\tau}_e(t) \), which in turn can be derived by the traffic density mean \( \overline{\rho}_e(t) \) and variance \( \overline{\rho}_e(t) \) values of the link. As a result, the values of \( \overline{\tau}_e(t) \) and \( \overline{\tau}_e(t) \) can be computed by:
\[
\tau_e(t) = \frac{l_e}{u_{e,f} - \bar{\rho}_e(t) \cdot \frac{u_{e,f}^2}{4 \cdot q_{e,c}}}
\] (7)

\[
\tau_e(t) = \left( \frac{d\tau_e(t)}{d\rho} \left[ \bar{\rho}_e(t) \right] \right)^2 \bar{\rho}_e(t)
\] (8)

3.4 Adaptive traffic routing

3.4.1 Adaptive traffic route planning

To enable adaptive traffic route planning, a time-dependent A* routing algorithm (Wilkie et al., 2011) is utilized and implemented. The core idea is that whenever a route is planned for a vehicle, the future traffic will become a little more congested when the vehicle traverses the route planned. As shown in Figure 6, after a route is planned from the origin node \(s\) to the destination node \(g\) (Figure 6 Left), the traffic density of each link along the path all increases by one. As a result, the subsequent vehicles with the same origin and destination might obtain a different route derived based on the new traffic densities in the network (Figure 6 Right).

![Figure 6](image_url)

**Figure 6.** The schematic diagram illustrating the time-dependent routing algorithm
The algorithm (Figure 7) computes the optimal route between the origin node $s$ and the destination node $g$ at timestamp $t_0$. Instead of storing a single cost value for each node $u$ in memory, the algorithm requires to store both the mean $\bar{\tau}_u$ and variance $\sigma^2_\tau$ of the travel time of the current-best route from the origin node $s$ to $u$ (line 1). Initially, the values are infinity for all nodes, except for the origin node, which are set as zero instead (line 1). The algorithm starts from the origin node (line 2) and then expands the route to one of its neighboring nodes (i.e. the best candidate). A loop is used to search all the neighboring nodes to find the most suitable candidate (line 8-15). We continue to expand the route (line 3) from the chosen node till reaching the destination. A condition check is performed to stop the algorithm when the destination is found (line 6-7).

The heuristic value $\bar{h}(u)$ represents the low-bound estimation of the mean travel time from node $u$ to the destination node $g$, and $h^2(u)$ represents the low-bound estimate of the variance travel time from $u$ to $g$ (line 4). In this study, $\bar{h}(u)$ is the Euclidean distance between node $u$ and the destination node $g$ divided by the largest speed limit in the whole traffic network. $\bar{h}(u)$ is set to be zero for all nodes. $\omega$ is the weight parameter (line 4). The travel time mean $\bar{\tau}_e(t_0 + \bar{\tau}_u)$ and variance $\sigma^2_\tau(t_0 + \bar{\tau}_u)$ to traverse link $e$ can be computed using the equations for $\bar{\tau}_e(t)$ and $\sigma^2_\tau(t)$ derived in Section 3.4 (line 9-10).

```
TRAFFICA*(s, g, t_0)
   1: \forall u \in V : \bar{\tau}_u \leftarrow \infty; \sigma_\tau \leftarrow 0; \bar{\tau}_e \leftarrow 0
   2: OPEN \leftarrow \{s\}
   3: \textbf{while } OPEN \neq \emptyset \textbf{ do}
   4: \quad u \leftarrow \text{arg max}_{u \in OPEN} \{ \bar{\tau}_u + \bar{h}(u) + \omega(\bar{\tau}_u + \bar{h}(u)) \}
   5: \quad OPEN \leftarrow OPEN \setminus \{u\}
   6: \quad \textbf{if } u = g \textbf{ then}
   7: \quad \quad \textbf{return}
   8: \quad \textbf{for each edge } e = (u, v) \text{ in } G \textbf{ do}
   9: \quad \quad \mu \leftarrow \bar{\tau}_e(t_0 + \bar{\tau}_u)
10: \quad \quad \sigma \leftarrow \sigma_\tau(t_0 + \bar{\tau}_u)
11: \quad \quad \textbf{if } \bar{\tau}_u + \mu + \omega(\bar{\tau}_u + \sigma) < \bar{\tau}_v + \omega\bar{\tau}_v \textbf{ then}
12: \quad \quad \quad \bar{\tau}_v = \bar{\tau}_u + \mu
13: \quad \quad \quad \bar{\tau}_v = \bar{\tau}_u + \sigma
14: \quad \quad \quad \textbf{add } (u, v) \textbf{ to } OPEN
```

3.4.2 Simulation system

Traffic simulation, defined as the mathematical modeling of transportation systems using computer software, is commonly used to explore the traffic congestion problem (Dornbush & Joshi, 2007; Jain, 1996; Mo & Walrand, 2000). Right now, a variety of traffic simulation systems are developed to support transportation management and research, such as SUMO\(^4\), Aimsun\(^5\), and VisSim\(^6\). In this study, a microscopic traffic flow simulation system, MATSim (Multi-Agent Transport Simulation), is selected to simulate the black hole and volcano stage scenarios within the selected study area and test the feasibility of the proposed framework. MATSim is an open source project started by Nagel (2004) intended for transportation planning modeling.

Comparing to other popular traffic simulators (e.g. SUMO, Aimsun, VisSim, and TRANSIMS), MATSim is more suitable for our study. First of all, MATSim is open-source that allows researchers to extend it on their own needs. Secondly, the modularity of MATSim, based on the loose coupling and high cohesion software design principle, is flexible and extendable so that developers can easily adjust the source code without worrying much about the system design and software architecture-related issues (Maciejewski & Nagel, 2011). Finally, MATSim implements a cost-efficient simulation mechanism which enables it to scale up to large scenarios without sacrificing much performance.

In recent years, MATSim has been applied in many research studies to leverage traffic simulation for solving traffic planning and transportation problems. Ciari et al. (2010)

\(^5\) [https://www.aimsun.com/](https://www.aimsun.com/)
\(^6\) [http://www.vissim.com/](http://www.vissim.com/)
used MATSim to estimate the car sharing demand in the urban area of Zurich, Switzerland. Dobler (2009) implemented a within-day replanning for MATSim where the vehicles within the network are able to modify their daily travelling plans and routes. Schroeder et al. (2012) presented in MATSim a multi-agent transport model to facilitate complex logistic decision.

 Integrating the time-dependent routing algorithm to the MATSim system, we can produce routes according to the vehicle travel plan inputs for both black hole and volcano scenarios. In this research work, a traditional A* routing algorithm is also implemented in the MATSim system to generate different routes with the same travel plan data. The two sets of routes are then compared and analyzed in Section 4.

3.5 Traffic density updating

Each time a route is computed by the routing algorithm, the traffic densities of the links along route will be increased a little. Therefore, the density functions \( \bar{\rho}_e(t) \) and \( \bar{\rho}_e(t) \) for these links should be updated. After a route is planned, we get a path \( \pi = (e_1, e_2, \ldots, e_n) \), where \( n \) is the total number of links the vehicle will visit to reach the destination, \( e_1 \) represents the starting link from the origin node, and \( e_n \) is the link whose ending node is the destination node. and the distributions \( \tau_u \sim \mathcal{N}(\bar{\tau}_u, \bar{\tau}_u) \) of the travel time from the origin node \( s \) to each node \( u \) along the path. The probability that the vehicle is on the link \( e_i = (u, v) \) at time \( t \) can be computed as:

\[
q_e(t) = Pr(u) \cdot Pr(v') = \int_{-\infty}^{t-\tau_0} pdf_{\tau_u}(t) dt \cdot \int_{t-\tau_0}^{+\infty} pdf_{\tau_v}(t) dt
\] (9)
where $Pr(u)$ presents the probability the vehicle arrives at node $u$ before time $t$, $Pr(v')$ stands for the probability that the vehicle leaves nodes $v$ after time $t$, and $t_0$ is the start time of the vehicle, $pdf$ stands for probability density function.

According to the traffic density definition, the density of a link $e$ is the number of vehicles on the link divided by the length $l_e$ of the link. Therefore, given the previously calculated density mean and variance for a link and the probability that a vehicle will be on this link at a specific timestamp $t$, their current values can be updated using the formulas respectively:

$$\bar{\rho}_e(t) \leftarrow \bar{\rho}_e(t) + \frac{q_e(t)}{l_e}$$  \hspace{1cm} (10)

$$\tilde{\rho}_e(t) \leftarrow \tilde{\rho}_e(t) + \frac{q_e(t)(1 - q_e(t))}{l_e^2}$$  \hspace{1cm} (11)

Therefore, if the $q_e(t)$ is equal to 1, which means the vehicle will definitively be on this link, then density mean will be incremented by $\frac{1}{l_e}$. Since the time axis is discrete, only a finite number of $\bar{\rho}_e(t)$ and $\tilde{\rho}_e(t)$ are calculated for each $e$. The most likely period that the vehicle is on the link is between $(t_0 + \tau_u, t_0 + \tau_v)$. The period is cut into multiple pieces with a time interval factor $\alpha$, which represents how frequent we update the traffic density. It is an adjustable variable that can be any positive value. If we use a small value for $\alpha$, we will obtain a better modeling of the network traffic. However, more computing resource (e.g., memory) will be consumed while running the routing algorithm. If we employ a large value, we can save our computing resource but running the risk of losing traffic condition details.
For example, if we use 1 hour as the interval and the traffic within the hour increases first and then decreases to the same level, our traffic model would incorrectly assume that the traffic does not change within the hour. In our study, we set the interval to 15 seconds, which is a cost-efficient value without losing much traffic details. Hence, the sequence of $t$ values selected to update $\bar{\rho}_e(t)$ and $\bar{\rho}_e^{'}(t)$ is listed as:

\[
(t_1, t_2, \ldots, t_n) = \left[ \frac{t_0 + \bar{\tau}_u}{\alpha} \cdot \alpha, \frac{t_0 + \bar{\tau}_u}{\alpha} \cdot \alpha + \alpha, \ldots, \frac{t_0 + \bar{\tau}_u}{\alpha} \cdot \alpha + k \right] \cdot \alpha \]

\* $\alpha, \ldots, \left[ \frac{t_0 + \bar{\tau}_v}{\alpha} \right] \cdot \alpha$

(12)
4. Experiments and Results

4.1 Experiment environment

The experiments are conducted with the MATSim traffic simulation system, which is deployed on Amazon Elastic Compute Cloud\(^7\) (EC2). Amazon EC2 is the core part of the Amazon’s web services\(^8\) (AWS) and provides scalable computing capacity in the cloud (Huang et al., 2010). Amazon EC2 is popular among researchers because of its outstanding elasticity, low cost, and high security level (Li et al., 2013). It has been used in various research fields including environmental science (Huang et al., 2013), genetic research (Lee et al., 2012), and computer science (Li & Venugopal, 2011).

First we developed and integrated our proposed adaptive traffic routing method in the MATSim simulation system using Java language. The input to the system is a series of travel plan files in XML format. The output for each travel plan is the planned routes for the vehicles in the plan. We can then calculate the average travel time of these routes. The entire Java program (containing the simulation system) is then exported to a runnable Java Archive (JAR) file to easily run the pre-designed experiments for performance test and evaluation purposes on our Amazon instance.

Next step is to launch our EC2 instance and deploy our routing system to the instance. To launch an instance on EC2, we need to first specify an Amazon Machine Image\(^9\) (AMI) which provides required information (e.g. memory; operating system) for the instance. In this project, a public AMI with Linux operating system is selected. After the instance is successfully loaded, the next step is to login to the remote EC2 instance through secure shell.

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\(^7\) [https://aws.amazon.com/ec2/](https://aws.amazon.com/ec2/)
\(^8\) [https://aws.amazon.com/](https://aws.amazon.com/)
(SSH) using the private SSH key file generated when you launched the instance. Then we transferred the JAR program to the instance using SFTP, which stands for SSH File Transfer Protocol, via a free software Cyberduck\textsuperscript{10}. The last step is to run the JAR program with the experiments on the instance and record the results.

4.2 Experiment design

As a proof-of-concept study, a series of experiments are conducted to demonstrate how the research problem is addressed in our system. The experiments consist of comparing the performance of the adaptive traffic routing algorithm against the baseline A* routing algorithm in various scenarios. In these experiments, there are several factors involved, including vehicle number, which is the total number of vehicles to be simulated, scenario stage, representing whether the scenario is at black hole or volcano stage, and vehicle dispatch direction (from 0 to 360 degree), which defines how the vehicles are heading towards to the predefined hotspot in the network. Specifically, the following experiments are designed to test the feasibility and effectiveness of our proposed adaptive traffic routing.

- Different number of vehicles: the purpose of this experiment is to test the performance of our proposed adaptive traffic routing and scalability of the system in handling a large number of vehicles. In this experiment, we use 360 degree as the vehicle dispatch direction and black hole as the scenario stage, but increase the vehicle number from 200 to 4400 as shown in Figure 8. The spots in these figures represents vehicle origins, and the star represents the destination location. With an increasing number of vehicles, the traffic in network is expected to increase and it is supposed that the average trip duration

\textsuperscript{10} https://cyberduck.io/
for the vehicles will increase as well. Therefore, this experiment could be a good example to test the scalability of our framework.

Figure 8. Different number of vehicles (360 degree vehicle dispatch direction; black hole scenario stage)

Note: The figure only shows part of the travel plans from 200 to 1800 vehicles. Travel plans with over 2000 to 4400 vehicles are not shown here.

- Different scenario stage: the purpose of this experiment is to demonstrate how this study addressed both the black hole and volcano scenarios together. In this experiment, 360 degree is utilized as the vehicle dispatch direction and the number of vehicles used to test for both black hole and volcano scenarios ranges from 200 to 4400.
• Different vehicle dispatch direction: In black hole scenarios, all vehicles would head to the hotspot (e.g., theater) from different directions. The collective directions could be in various ranges, from 0 to 360 degree as shown in Figure 9. For example, if the direction is 360 degree (Figure 9 (h)), vehicles are scattered all over the network space; if the direction is 180 degree (Figure 9 (d)), all vehicles are distributed in the east side of the theater. A routing system might respond differently when the dispatch direction is different: a smaller degree of dispatch direction might result in heavier traffic. Therefore, the purpose of this experiment is to examine the consistency of the proposed routing algorithm in response to situations where vehicles do not scatter uniformly in the network. In this experiment, we use black hole as the scenario stage and 1000 as the vehicle number, but increase the vehicle dispatch direction from 45 to 360 degree, with 45 degree as the incremental interval.
**Figure 9.** Different vehicle dispatch directions (from 45 to 360 degree vehicle dispatch direction; black hole scenario stage; 1000 vehicles)

For each experiment, a travel plan, a description file in XML format to describe the simulated vehicles with each vehicle having an origin, a destination and departure time should be supplied as the input for MATSim traffic simulation system. While different vehicles might be assigned with different origins or destinations depending on the scenario stage, i.e., origins (destinations) are the same for the volcano (black hole) scenario stage and different for the volcano (black hole) scenario stage, the departure time is always the same for all vehicles.

To test the improvement of the proposed framework, two different sets of routes are generated by the two routing algorithms, including traditional A* routing algorithm and our adaptive traffic routing algorithm. The number of routes equals to the number of vehicles in the travel plan file. For each route, there is an expected vehicle travel time, which represented how long the vehicle will take to traverse the route. For each of the two route sets, we could compute the average vehicle travel time (AVTT) to represent the performance of the routing algorithm. The less the average vehicle travel time is, the better the algorithm performs. In order to reduce the impact of the computer system (e.g., the computer may perform differently at different time, especially in the cloud server where computer resources are shared by multiple users), each experiment is performed ten times, and we calculated the average of AVTT. This average travel time (ATT) represents the average time vehicles travel from their origins to destinations.

We use ATT to compute the improvement ratio $\beta$, which is the improvement of our proposed approach against the A* traditional routing approach. $\beta$ is defined as:
\[ \beta = \frac{ATT(\text{traditional approach}) - ATT(our \ approach)}{ATT(\text{traditional approach})} \] (13)

where \(ATT(\text{traditional approach})\) is the ATT derived from the traditional A* routing method and \(ATT(our \ approach)\) is the ATT generated by our adaptive traffic routing algorithm.

4.2.1 Different number of vehicles

This experiment aims to check how our proposed framework performs under situations where there is a large volume of vehicles involved in the traffic network. Therefore, in this experiment, we increase the vehicle number from 200 to 4400 as shown in Figure 8. The vehicles are equally distributed in the traffic network and all plan to departure from the home (origin) at 6PM to the theater, which locates at the center of the network. These experiments reflect the real world situation that people from all over the city drive to the theater for a new movie.

The result of the simulation can be seen in Figure 10. The line with triangles shows the average vehicle travel time (ATT) of all vehicles from the origin to the destination using the traditional A* routing method, and the line with dots represents our adaptive traffic routing approach. The line with squares is the improvement ratio.

Observing from the Figure 9, the average travel time increases with the increasing number of vehicles for both the traditional method and our approach. However, our routing algorithm results in less travel time than the traditional method. It can also be noticed that the improvement ratio rises rapidly with the rising of vehicle number when there are not many vehicles. It reaches the peak with \(\beta = 0.43\) at about 1000 vehicles. After that, the ratio
smoothly decreases and finally converges with the value around 0.25 when there are over 4000 vehicles, because the traffic network reaches its full capacity and the alternative routes provided by our adaptive traffic routing algorithm cannot help much with mitigating the congestion situation.

![Improvements on different number of vehicles: "black hole" scenario](image)

**Figure 10.** Improvements on different number of vehicles on black hole scenario (360 degree vehicle dispatch direction)

### 4.2.2 Different scenario stages: “black hole” and “volcano”

In this section, experiments are conducted to see how our proposed routing algorithm works for both black hole and volcano scenario stages. In Section 4.2.1, 22 experiments (from 200 to 4400 vehicles) are conducted for black hole scenario. Similarly, the same
number of experiments (Figure 11) are conducted for volcano scenario, where for each vehicle the origin (e.g. home location) now becomes the destination and the destination (e.g. theater) becomes the origin. These experiments reflect the real world situation that people flood out of the theater when the movie is over. We can see from Figure 11 that our approach reduces the average travel time comparing to the traditional A* algorithm by a factor of 0.236 on average. The improvement ratio increases with the increasing number of vehicles simulated in the network, and slows down the increasing trend when there are over 1000 vehicles. After that, the improvement ratio stays at a relatively stable level within the range of 0.2 to 0.285. Similarly, this is because that the traffic network is heavily congested with many vehicles involved (more than 1000) and even the alternative routes provided by our algorithm cannot help reduce the travel time.
**Figure 11.** Improvements on different number of vehicles on volcano scenario (360 degree vehicle dispatch direction)

Figure 12 compares the improvement ratio with different number of vehicles under the two scenarios: black hole (line with triangles) and volcano (line with dots). In general, we can see that the improvement is larger in black hole scenario than in volcano scenario. This is caused by the fact that there is more traffic congested spots in black hole scenario than the volcano scenario. The reason is that in both the scenarios vehicles leave their origins at the same time. In black hole scenario, the origins (i.e. people’s homes) are different; while in volcano scenario, the origins (i.e. the theater) are the same. Therefore, in black hole scenario, since the distances between the origins to the destination (i.e. the theater) are varied depending on where the people live, vehicles are expected to arrive at the theater at different times. In this case, some vehicles, especially those close to the theater, are less likely stuck in traffic jam by reaching the theater much earlier, therefore contributing to the overall traffic improvement. On the other hand, in volcano scenario, all people leave the theater at the same time, which can easily paralyze the whole network area around the theater in a short time. In this situation, there is not much alternative routes can help since all exits from the theater are congested. We also observe in Figure 12 such a huge difference of the improvement ratio between the black hole and volcano scenarios when there are not too many vehicles. This is because when only a small number of vehicles involved, these vehicles, which are not in traffic jam and therefore have short travel time, would count much more while deriving the average travel time in black hole scenario than that of volcano scenario. It is also interesting to observe that both the two scenarios reach the peak improvement ratio at about 1000 vehicles and stays stable with over 4000 vehicles. This is
because that all these experiments use the same traffic network with the same network capacity. Therefore, it is reasonable to observe such similar bottlenecks in both black hole and volcano scenarios.

Figure 12. Improvements under black hole and volcano scenario stages (360 degree vehicle dispatch direction)

4.2.3 Different vehicle dispatch directions

In this section, we test the consistency of our routing algorithm in situations where the vehicles scatter nonuniformly in the traffic network, which is often the case in the real world. Figure 13 shows the improvement for the black hole scenario with 1000 vehicles heading to the hotspot under different directions. The line with triangles represents the average travel time using traditional A* routing algorithm; the line with dots is the average
travel time using our approach. We can find that our time-dependent routing outperformed the traditional method for all vehicle dispatch direction scenarios. It can also be observed that the improvement ratio (the line with squares as markers) is relatively stable with a value around 0.42. This result indicates that our approach is quite consistent with different vehicle dispatch directions and independent of the vehicles origin directions.

**Figure 13.** Improvements on different vehicle dispatch direction (1000 vehicle; black hole scenario stage)
5. Conclusion and Future Work

5.1 Conclusion

This thesis proposes an adaptive traffic routing framework to facilitate vehicle routing and mitigate extreme traffic congestion introduced by a large number of vehicles with similar travel plans. Example situations would be massive vehicles participating a big public event, which is defined to include two phases in this study: the black hole phase and the volcano phase. The two phases correspond to the scenarios where people head towards from their homes to a location (e.g. theater) before the event (i.e. the black hole phase) and leave the location to their houses after the event (i.e. the volcano phase). Unlike traditional approaches which only focused on one of the two phases, our proposed framework is able to address the traffic congestion problem for both phases together.

One type of VGI data, vehicle travel plans, which are contributed by vehicle drivers using the mobile devices and were ignored by the current approaches, is leveraged in our framework. This source of information is useful for vehicle route planning because individual travel plans could cause “butterfly effects”: the routes planned based on previous travel plans of vehicles could trigger the changes of the subsequent traffic and thus can influence the route decisions of the future vehicles, which are made on real-time based on the new traffic condition.

Additionally, a time-dependent A* routing algorithm is utilized and implemented in our framework for vehicle route planning. Given a travel plan, our framework first uses the algorithm to calculate the best route for the plan. Then the planned route is used by the traffic density updater in our framework to update the future traffic density of the street segments (or network links) along the route. The traffic density is then converted to link travel time
using the traffic flow theory. After that, the framework will use the updated link travel time to compute routes for subsequent travel plans and update traffic density accordingly.

In order to demonstrate the feasibility of the proposed framework, an adaptive traffic routing system was implemented based on MATSim, a popular traffic simulation system, and three experiments were designed and performed, one with varying numbers of vehicles, one with different scenario stages and another with varying vehicle dispatch directions. By increasing the number of simulated vehicles in the routing system through the first experiment, we found that our framework is able to handle a large number of vehicles with limited impact on the system performance. The “different scenario stage” experiment demonstrated that our framework is able to mitigate traffic congestion in both black hole and volcano scenarios. Finally, our “different vehicle dispatch direction” experiment proved that our framework performs consistently no matter where the vehicles are coming from.

During our experiments, we noticed that: 1) Our framework performs best with around 1000 vehicles in the network and the improvement ratio on average vehicle travel time decreases after 1000 vehicles and then becomes stable when there are over 4000 vehicles; when there are not many vehicles, the collaboration between vehicles is limited. This explains why we found that the improvement ratio increases with the increasing number of vehicles. When the number of vehicles continues to increase, the traffic network becomes too congested to gain benefits from vehicle collaboration, which is the reason why we observe a decrease in the improvement ratio. 2) Selection of the public event location matters. Initially we chose a sport stadium as the location for the big public event. However, we found that there are two large bodies of water on the north and east sides of the stadium. They impacted our third experiment where vehicles should be able to come from all
directions. Therefore, we changed the location to the theater to re-conduct the experiments.

and 3) Selection of the time interval parameter is important. In our traffic density updater, we recorded the traffic density of each network link at different timestamps. Because of the limited amount of computing resource we have, we can only maintain a finite number of timestamps for each link. For example, for a certain link, if we want to update its traffic density every second for one hour, we will need to store 3600 records for this single link. Considering there are thousands of links in the network, it is not feasible to use one second as the time interval to update link traffic density. Therefore, we need to determine an appropriate time interval between these timestamps. The time interval we used is 15 seconds because we found that the improvement ratio does not increase much if we use smaller intervals and the ratio falls rapidly with larger intervals.

While the proposed framework uses the issue of traffic congestion during big public events as an example, its applications go beyond this specific situation. Especially, with the increasing popularity of mobile devices and the rapid development of advanced wireless network, adaptive traffic routing will have much more usage in the future to deal with complex traffic situations.

5.2 Future direction

Due to the limited amount of time and resources, there are still several limitations in this study and more effort could be dedicated to further improve the framework. Four major limitations and possible future directions are:

Routing optimization: In our simulation, we did not implement any optimization mechanisms for route planning. For example, if several vehicles with different departure origin locations plan to go to the same destination, there might be several alternative routes
the vehicles can take. Different route solutions for these vehicles can be performed by iterating and combining all possible routes for each vehicle to maximize the framework’s improvement ratio. Because of limited amount of computing resources (i.e. memory), we can also set up an appropriate objective value (i.e. we will stop the iteration if the improvement ratio exceeds the value). In this case, more experiments should be conducted to find a reasonable optimization strategy.

**Make simulation more realistic:** In our simulation system we assume that all vehicles participate in informing the system of their travel plans through the mobile devices. However, in a more realistic situation, not all vehicles in the network will provide their travel plans. These vehicles nonetheless influence the network traffic density. Hence, a possible future direction is to take such vehicles into consideration and integrate these vehicles into our simulation model to produce more realistic results. Additionally, in our experiment design for the black hole scenario, we assume all vehicles leave their homes at the same time. However, in reality, people plan their trips ahead of time based on the distance of their locations (e.g. homes) to the destinations. The closer they live to the theater, the later they will leave their houses and drive towards the theater. Therefore, one near future work to be done is to estimate the departure times of the vehicles based on their home locations to generate more realistic travel plans for simulation.

**Validate with real-world data:** In our experiments, the vehicle travel plans are generated by our simulation system. Therefore, another improvement that can be made is to analyze and validate the proposed framework on real-world traffic data. In this case, a mobile application can be developed and deployed on vehicles to collect real-world travel plan VGI data. Then we would perform similar experiments with the collected real-world data to
validate our framework. However, there are some challenges including the difficulty of VGI data collection from the public, the various quality issues of VGI data, and the massive data computing challenges in real-time context (Flangagin & Metager, 2008). Therefore, there is still much work needed to be done to provide enough incentives for VGI participation and take privacy issues into considerations.

**Synthesize multi-source data for routing:** In the real-world, traffic systems are complex, dynamic, and impacted by many factors, such as weather conditions, real-time traffic events (e.g., car accidents), road construction, and drivers’ behavior preferences (e.g. an aggressive driver might choose to use a shortcut instead of waiting in traffic). Integrating such information into the routing system would improve the routing quality significantly (Emmerink et al., 1995; Pacifici et al., 2010). Therefore, a possible future direction would be to design a more sophisticated system to collect multi-source information in a real-time fashion, and also develop an improved routing algorithm to synthesize the data to perform more realistic routing.
References


