Predicting the duration and impact of the non-recurring road incidents on the transportation network

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SINGAPORE

**PREDICTING THE DURATION AND IMPACT
OF THE NON-RECURRING ROAD INCIDENTS
ON THE TRANSPORTATION NETWORK**

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**Interdisciplinary Graduate School
Energy Research Institute @ NTU**

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TRANSPORTATION NETWORK**

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A thesis submitted to the Nanyang Technological University
in partial fulfillment of the requirement for the degree of
Doctor of Philosophy

2019

Statement of Originality

I hereby certify that the work embodied in this thesis is the result of original research and has not been submitted for a higher degree to any other University or Institution.

20.05.2019

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Supervisor Declaration Statement

I have reviewed the content and presentation style of this thesis and declare it is free of plagiarism and of sufficient grammatical clarity to be examined. To the best of my knowledge, the research and writing are those of the candidate except as acknowledged in the Author Attribution Statement. I confirm that the investigations were conducted in accord with the ethics policies and integrity standards of Nanyang Technological University and that the research data are presented honestly and without prejudice.

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Authorship Attribution Statement

This thesis contains material from five papers published in the following peer-reviewed journal and conference proceedings where I was the first and corresponding author.

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The contributions of the authors are as follows:

- Prof. Justin Dauwels provided the initial project direction, co-designed the study, guided throughout the project, and helped in revising the manuscript.
- I pre-processed the data, developed the models, and prepared the manuscript.
- Dr. Muhammad Tayyab Asif helped in writing the codes and revising the manuscript.

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- Dr. Muhammad Tayyab Asif provided feedbacks throughout the project and helped in revising the manuscripts.
- Dr. Ulrich Fastenrath provided guidance in the interpretation of the results.
- Dr. Hongliang Guo helped in revising the manuscripts.
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- I wrote the codes, performed the analysis, and prepared the manuscript.
- Yuanzheng Zhu pre-processed the data and edited the manuscript.

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Abstract

Non-recurring incidents such as accidents, vehicle breakdowns, etc. are leading causes of severe traffic congestion in large cities. Consequently, anticipating the impact of such events in advance can be highly useful in mitigating the resultant congestion. However, availability of partial information or ever-changing ground conditions makes the task of forecasting the impact particularly challenging. In this thesis, we propose adaptive ensemble models that can provide reasonable forecasts even when a limited amount of information is available and further improves the prediction accuracy as more information becomes available during the course of the incidents. Furthermore, we consider the scenarios where the historical incident reports may not always contain accurate or complete information about the duration and length of congestion due to the incidents. To mitigate this issue, we first quantify the effective duration and queue-length of the incidents by looking for the change points in traffic state (average traffic speed and flow data) of the individual upstream links and then utilize this information to predict the duration and queue-length of the incidents. The prediction models forecasts the values continually with elapsed time until the end of the incidents to comprehend the temporal dynamicity.

We compare the performance of different traditional regression methods in predicting the duration, and the experimental results show that the Tree-bagger outperforms other methods. The overall MAPE value averaged over all incidents improves by 50% with elapsed time. On the other hand, we build a queue-length prediction model using a Long Short-Term Memory neural network which incorporates the updated traffic data and various spatiotemporal features as inputs. At the start of the incident, the proposed model has a mean error value of 73.7%, which reduces to 45.6% after one

hour of prediction.

Moreover, we are interested in not only predicting incidents' impact but informing the drivers about the current and future traffic state is also our area of concern. Currently, in order to inform or alert the commuters about the traffic situation during the road incidents, several LED displays, better known as variable message signs or VMS messages, have been installed by the LTA on the expressways of Singapore. Therefore, apart from building the predicting models, this thesis also aims to evaluate the impact of VMS displays on the overall traffic distribution of Singapore whether these displays are really helpful to the drivers or not. To this end, the incidents data and their corresponding VMS messages are collected from the two busiest expressways of Singapore, namely Pan Island Expressway (PIE) and Central Expressway (CTE). The analysis shows that approximately 14% of the vehicles change their direction after the VMS messages have been activated.

Lastly, since Singapore is a tropical country having a significant amount of rainfall throughout the entire year, the weather condition has a noticeable impact on the traffic of Singapore. Therefore, we also aim to analyze the influence of rainfall on traffic incidents if the frequency of these incidents, especially accidents, increases after rainfall or not. Therefore, the rainfall data acquired from the National Environmental Agency (NEA) of Singapore is analyzed to investigate the correlation between the occurrence of traffic incidents and rainfall. Overall, the obtained results support the hypothesis that the frequency of traffic incidents is higher during rainfall as compared to dry periods. Moreover, the frequency is the highest after rainfall. Besides, it is observed that traffic speed and flow decrease by 10.14% and 3.88% respectively during rainy weather.

Overall, this thesis aims to help avoid incident-induced traffic jams by designing the urban traffic prediction models. Thus, the cost of time and fuel can be saved, which will benefit the national economy as a whole.

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List of Acronyms

LTA	Land Transport Authority
NEA	National Environmental Agency
ITS	Intelligent Transportation System
NDW	National Data Warehouse for Traffic Information
SVR	Support Vector Regression
MLP	Multi-Layer Perceptron
ANN	Artificial Neural Network
PeMS	Performance Measurement Systems
RVM	Relevance Vector Machines
CART	Classification And Regression Tree
PCA	Principal Component Analysis
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
VMS	Variable Message Signs
AYE	Ayer Rajah Expressway
BKE	Bukit Timah Expressway
CTE	Central Expressway
ECP	East Coast Parkway
KJE	Kranji Expressway
KPE	Kallang-Paya Lebar Expressway
MCE	Marina Coastal Expressway
PIE	Pan Island Expressway
SLE	Seletar Expressway
TPE	Tampines Expressway
IoT	Internet of Things

Chapter 1

Introduction

Intelligent Mobility plays an important role in driving the economic growth of a nation. Due to the major development in urbanization and the expanding population, traffic congestion has become a critical problem in metropolitan cities. Like all other major cities, Singapore is also facing a similar problem of congestion with its land scarcity and huge vehicle population. Traffic congestion happens whenever the demand exceeds the maximum capacity of a road. Therefore, to make optimum use of the road network capacity, Intelligent Transport Systems (ITS) are often employed to cope up with this situation efficiently. Using advanced sensor technologies, the real-time traffic information is collected from large transportation networks [3] and utilized in various applications such as route guidance, congestion avoidance, traffic control and management, etc. [4] [5].

Traffic jams can be broadly classified into two categories: 1) Recurrent peak-hour congestion which happens during rush hours (usually twice a day - once in the morning and once in the evening) of every weekday when most of the people commute to or from their workplaces, and 2) Non-recurring congestion due to traffic incidents such as accidents, vehicle breakdowns, etc. Partial or entire closure of road lanes owing to these incidents brings about the reduction in traffic capacity resulting in congestion [6]. Moreover, since average traffic volume is higher during the peak-hours, the chance of occurrence of the traffic incidents is also higher. Consequently, the incident-induced congestion may sometimes coincide with the peak-hour congestion resulting in acute traffic jams on the roads. Therefore, in this thesis, we have

developed data-driven traffic prediction models which can help in reducing the overall traffic jams caused by the non-recurring incidents.

In this chapter, we explain the motivation and objective of the research performed in this thesis. In the end, we mention the contributions of this work and provide the outline of the thesis.

1.1 Motivation

The unexpected occurrence of non-recurrent traffic events causes about 25% of traffic congestion on the arterial roads and even a higher proportion for urban expressways [7]. According to the 2012 Urban Mobility Report [8], traffic congestion leads to a total cost (in terms of wasted time and fuel) of about 121\$ billion in the US in 2011, which is approximately 1% of the GDP of the country. Moreover, the non-recurring incidents lead to more economic losses because of its unpredictable nature. Therefore, anticipating such events in advance can be highly useful in mitigating the resultant congestion. However, since these types of incidents are non-recurrent and unplanned, the probability of occurrence of these incidents is hard to forecast. Therefore, Intelligent transport systems (ITS) are more concerned about minimizing the severity of congestion after the incidents have already happened. Nowadays traffic management authorities implement modern technologies in different cities in order to solve transportation problems efficiently and make road travel safer and faster.

The two integral systems of ITS are Traffic Information Management System (TIMS) and Dynamic Routing Guidance System (DRGS). Both of these systems play a vital role because TIMS is responsible for real-time data acquisition of traffic parameters like speed, the number of vehicles passing by, weather condition of the roadway, etc., and DRGS helps the commuters to dynamically choose the routes by providing information on network traffic

and other possible routes to be taken. However, Dynamic Routing Guidance is possible only when the prediction of the impact of incidents is carried out using the traffic information available from Traffic Information Management System. The two techniques used for traffic prediction are either based on simulation or data-driven. In a simulation-based approach, traffic prediction models which would predict the future state are designed based on some theoretical models. This approach needs some expertise to build the network traffic simulation. On the other hand, data-driven models can be built for prediction using historical or real-time data-sets [9]. In this thesis, we have developed a data-driven traffic prediction model which can help in reducing the overall traffic jams caused by the nonrecurring incidents on the expressways of Singapore. It forecasts the congestion propagation in the network which enables to estimate travel times and to determine route guidance schemes. The traffic route guidance system can then guide the drivers to take an appropriate alternative route in order to avoid the traffic jams and reach the destination with minimal loss of time.

Apart from the predictive solutions, there are several other new technologies to assist the drivers in the occurrence of an incident. For example, the Land Transport Authority (LTA) has installed the new age Variable Message Signs (VMS displays) with modern technologies (such as graphics and more colours) on the expressways of Singapore. These LED road traffic signs notify the drivers about any kind of disruption in traffic, such as accidents, obstacles, roadworks, etc., and therefore helps in rerouting the vehicles. Nowadays, VMS system is an integral part of Dynamic Routing Guidance System. Therefore, traffic management authorities from several smart cities have been investing a significant amount of resources to install the VMS displays in different places. As such, they are interested to investigate if their investment is impactful or not. In this context, this thesis aims to provide a quantitative measure of the effectiveness of VMS messages

on the drivers. based on these assessments, traffic operators can plan their further actions. For example, if the percentage is lower than the expectations, the awareness about this technology among the drivers needs to be increased. On the other hand, the traffic operators may plan to install VMS in the arterial roads as well, which will benefit the entire city as a whole. Moreover, we know that rainfall and traffic incidents are correlated to each other. However, whether the frequency of incidents is higher after rainfall compared to that during rainfall or not is still an open question. In this context, this thesis aims to address this issue by comparing the frequencies of different types of incidents during rainfall and after rainfall in Singapore. Based on this analysis, the traffic management authorities may take preventive measures to reduce the possibility of occurrence of the incidents, for example displaying warning messages to the drivers even after rainfall, etc. Moreover, this study provides a quantitative measure of correlation between rainfall and incidents which indicates that rainfall can be a potential feature for predicting the possibility of occurrence of an incident. Therefore, the motivation behind these quantitative analyses is to help the traffic network operators in improving the overall road infrastructure of the modern cities.

1.2 Objectives

This thesis primarily aims to find potential solutions for mitigating the effect of non-recurrent road incidents more efficiently. The objectives of this research are as follows:

1. **Building a real-time adaptive dynamic traffic prediction model:** Since the most common causes responsible for traffic congestion except the peak hour rush are accidents or crashes, vehicle breakdowns, roadworks, obstacles, poor environment, etc., a significant part of this work has focused on constructing a dynamic traffic

prediction model which can forecast the duration and impact of the road-incidents. The regression model incorporates real-time traffic information including the network features such as the expressway, number of lanes, etc. and human mobility patterns such as morning and evening peak hours, weekday/weekend, etc. along with traffic speed and flow data and performs the prediction in a moving horizon manner until the end of the incidents. Moreover, our model is adaptive to the availability of the features since the model is able to perform a reliable prediction even when a smaller feature-set is available.

2. **Providing measures of confidence associated with the prediction:** Although the regression models can perform the prediction with reasonable precision, the prediction performance may vary considerably from one incident to another. Hence, another objective of this study is to provide some measures of confidence associated with the forecast values of the target variable. Such measures can prove to be highly useful in planning a real-time response. Therefore, we apply Bayesian approaches which give error bars as the measurement of uncertainty for the individual incident.
3. **Evaluating the effectiveness of VMS technology:** In order to provide information, warning, or alert to the commuters about the current traffic situation during the road incidents, several LED displays, better known as variable message signs or VMS messages, have been installed by the LTA on the expressways of Singapore. The objective of this thesis is to evaluate the immediate impact of VMS on the overall traffic distribution of Singapore in response to accidents and obstacles. To this end, we analyze the incidents data and their corresponding VMS messages collected from the two busiest expressways of Singapore, namely PIE and CTE. The central argument of

this analysis is that if the average traffic flow of the exits increases significantly compared to that of normal days, it demonstrates the impact of the VMS messages on the drivers behavior.

4. **Analyzing the effect of rainfall on traffic incidents:** Since the vehicles are more prone to incidents during rainfall because of low visibility, wet roads, etc., the primary objective of this study is to determine if the frequency of traffic incidents, especially accidents, increases during rainfall or not. Moreover, the effect of rainfall may exist even after it stops raining because there may be a higher probability of a breakdown or crash at that time due to lack of the drivers' carefulness. Therefore, we analyze the rainfall data acquired from the National Environmental Agency (NEA) of Singapore to investigate the correlation between the occurrence of traffic incidents and rainfall. Overall, the obtained results support the hypothesis that the frequency of traffic incidents is higher during rainfall as compared to dry periods. Moreover, the frequency is the highest after rainfall.
5. **Exploring the rainfall effect for different expressways:** Since Singapore is a tropical country having a significant amount of rainfall throughout the entire year, the weather condition has a significant impact on the traffic of Singapore. Therefore, we compare the traffic speed and flow of rainy days with that of dry days for different expressways to analyze the effect of rainfall even when there is no traffic incident. Based on the routes and locations of different expressways, the traffic speed and flow vary considerably from each other. For example, the expressways in the west part of Singapore like PIE and AYE are more affected. On the other hand, KPE comprises a long underground tunnel, which alleviates the effect of rainfall for this expressway.

1.3 Contributions

The contributions of this thesis in the context of minimizing the impact of traffic incidents are explained below.

In the past, most of the studies related to incident impact prediction did not incorporate the real-time traffic data in their analysis [10] [11] [12]. Although a few other studies considered real-time data, however the proposed models did not include any mechanism to provide updated predictions based on online streaming data [13] [14]. Conversely, apart from the spatial, temporal, and geographical features, we have considered the real-time traffic data of high resolution in our analysis. Also, the prediction has been performed sequentially with elapsing time over the entire span of the incident.

Moreover, the feature-sets used in the state-of-the-art prediction models were fixed, whereas our model can flexibly incorporate features as incident and traffic data gradually become available. Therefore, our model is more befitting for practical implementation since, in practice, our feature-set can be adjusted at different time instants based on the availability of the features. Moreover, our system is proposed to work even when multiple features are missing. It is likely that for some incidents important features are missing for the entire duration of the incidents. However, our model will still perform the prediction with the available information only.

Although a number of studies performed traffic prediction (prediction of speed or flow) using deep learning methods [15] [16], to the best of our knowledge, none of the previous studies considered the deep learning architecture for predicting the impact of the road incidents. In this thesis, we aim to predict the spread of incident-induced congestion using the LSTM network. Moreover, we build a single LSTM network where we render the inputs with a varying number of time-steps at different instants for training the model and apply the same model for performing the prediction dynamically till the incident ends. Thus, instead of having independent regression model at each

instant, we build a single model which is trained with different batches of data together. Here lies the novelty of our model.

Apart from that, the resolution of traffic data is another important factor in data-driven prediction models. In previous studies [17] [18] [19], the resolution of the traffic data is coarse (15 minutes or 1 hour) compared to the resolution of our data (5 minutes). Therefore, our model is able to understand the subtle changes in the impact of incidents more accurately.

In the context of analyzing the impact of VMS, a number of studies conducted different kinds of surveys on the drivers asking whether they follow the messages or not [20] [21] [22]. However, these surveys may be biased by the false positive responses from the drivers. On the other hand, several other studies carried out field observations to understand the impact of VMS [23] [24] [25]. Although the results obtained from the field studies are more accurate and unbiased, they are difficult and sometimes expensive to arrange and control. Therefore, most of these studies do not have a comprehensive data-set. In this thesis, we have adopted a data-driven approach for analyzing the effect of VMS, which has not been attempted before. Therefore, this analysis is not localized to any particular area of the city. Moreover, we have not derived the results based on any survey or personal interaction; instead we employ the historical traffic flow data recorded by sensors. Therefore, our analysis is free from the response bias.

Last but not the least, many a time rainfall leads to different types of traffic incidents, such as vehicle breakdown, accidents, crashes, etc. in Singapore. Therefore, we compare the frequencies of incidents during rainy weather with the frequencies of dry weather. Although the previous studies investigated the correlation between rainfall and traffic incidents [26] [27] [28] [29], none of these studies have compared the rate of incidents during rainfall with the incident rate after rainfall. Considering the fact that incidents may happen even after the rainfall due to lack of carefulness of the drivers, we

address the open question of whether the rate of occurrence of the incidents is higher during the rainfall or after rainfall in this thesis.

1.4 Outline of the Thesis

The remainder of this thesis is structured as follows. In Chapter 2, we review previous relevant research works on different topics related to non-recurring traffic incidents, such as incident duration and queue-length prediction, the effect of rainfall on incidents, and the use of VMS technology. In Chapter 3, we discuss the problem of predicting the incident duration, propose different machine learning algorithms for prediction, and build models for real-time application. Chapter 4 presents the queue-length predicting models using different machine learning methods and deep learning techniques. In Chapter 5, we assess the effectiveness of a new technology named Variable Message Signs (VMS) for the expressways of Singapore. Chapter 6 includes the data-driven analysis of the impact of rainfall on the traffic parameters and the correlation between rainfall and traffic incidents. Finally, Chapter 7 elaborates on the conclusions obtained from the research performed in this thesis and suggestions for the future work.

Chapter 2

Literature Review

In this chapter, first we introduce different traffic data collection techniques. Next, we review the literature related to the prediction of incident duration and impact. Besides, we also explore the studies on the use of VMS technology in different urban areas. Finally, in the last section, we discuss the studies regarding the adverse effect of rainfall on road traffic.

2.1 Data Collection

The collection of real-time traffic data was the foremost goal in the previous decade [29]. Accurate and reliable traffic data collection has always been essential for the traffic-related applications to ensure better navigation [30]. Moreover, the reliability and efficiency of the predictive models depend on the accuracy of the real-time data-sets [31].

2.1.1 Conventional in situ technologies

The traditional traffic data collection technologies are broadly classified into two categories:

- Intrusive methods,
- Non-intrusive methods.

Intrusive methods have been used for many years. They primarily include different types of sensors that record data and are placed on the side of a road. On the other hand, non-intrusive techniques are based on remote observations and have recently appeared to be very favorable.

We now describe different types of intrusive methods below [32]:

1. **Magnetic loops:** This is one of the most commonly employed methods for collecting traffic data. A magnetic field is produced by loops which are kept inside the road in rectangular forms. A counting instrument is kept on the road-side to which data information is passed. Life expectancy of this type of device is short because of possible damage by heavy vehicles; otherwise, it is usually not affected by foul weather. For the past several years, this method is employed in different countries of Europe. The major disadvantage of this method is its high cost.
2. **Pneumatic road tubes:** The roads and lanes are embedded with rubber tubes in pneumatic Road tube method to detect pressure changes from vehicles' tires passing over them. This is recorded in another device located along the road-side. Disadvantages of this technique are limited road coverage and the effect of the change in traffic condition or weather which may affect the readings.
3. **Piezoelectric sensors:** Piezoelectric sensors are another variety of sensors which transform mechanical energy into electrical energy. Deformity caused to the piezoelectric products results in the variation of potential difference among electrodes.

Next, we discuss different non-intrusive methods as follows [32]:

1. **Manual counts:** This is the most traditional method which involves mechanical count boards, electronic count board system, tally sheets, etc. Automated counts like vehicle occupancy rate, vehicle classification, etc. are best studied by this method, which is otherwise difficult, even by trained personnel.
2. **Passive and active infra-red:** This method radiates infra-red from the base area to detect the vehicle type and speed based on radiation policy. One drawback of this method is the inability to perform in

foul weather and also limited coverage of road and lanes.

3. **Passive magnetic sensors:** In this method, magnetic sensors are usually embedded under the roadbed. The number of vehicles, their type, and speed are recorded by the sensors. However, for the closely spaced vehicles, the differentiation of these sensors is poor.

2.1.2 Floating Car Data (FCD)

The most recent technology which has been employed in many countries nowadays is the floating car data method. Every vehicle is equipped with a mobile phone or GPS which acts as a sensor and collects the traffic data, such as car speed, location, travel duration, etc. on the road network. The data thus collected by the individual sensor are sent to a central processor. After the data have been collected, the useful information like traffic status, route guidance, etc. is distributed to the commuters and drivers on the road. FCD provides us with real-time and high-quality traffic data to the existing technologies and has become a crucial part in the development of new Intelligent Transportation Systems (ITS) since it is very reliable and efficient, and provides better safety for the drivers. There are broadly two types of Floating Car Data:

- GPS based FCD,
- Cellular FCD.

GPS based FCD has been commonly used these days although a limited number of cars are equipped with this system. The major limitation of this system is that it suffers high equipment cost compared to cellular FCD.

On the other hand, the mobile phones present in a vehicle can be used as traffic probes to collect the data, which are termed as Cellular based FCD. These mobile phones need to be switched on to calculate the traffic data over a particular road segment. This approach is particularly suitable for urban areas due to the antennas being placed in shorter distances. This system

is more advantageous in the sense that it does not require any specialized device to be installed in the cars or any hardware to be placed along the road-side. Hence, it is cheaper than loop detectors and also quite accurate. The installation is much more convenient and also easy to maintain. The major drawback of this approach is that sophisticated algorithms are needed in order to fetch the information and use this high-quality data before being re-transmitted to end-users.

2.2 Prediction of Incident Duration

Traffic incidents can severely disrupt the flow of traffic in the already congested large metropolitans. The uncertainty in forecasting the impact of traffic incidents arises due to the challenges associated with predicting the duration of that particular event. Accurate forecast about the duration of such events can prove to be highly invaluable for traffic management authorities, logistics and taxi companies, as well as for motorists traveling in that area. Therefore, incident duration prediction has remained an active research problem for the last three decades in the area of transportation studies. In this section, we briefly discuss the relevant studies and highlight their strengths and limitations.

In earlier years, most of the studies applied simulation-based theoretical modeling for traffic prediction. For example, Golob *et al.* [33] built log-normal models of incident duration by considering more than 9000 accidents caused by trucks in 2 years that happened on freeways in Los Angeles. Chung *et al.* [34] also applied a log-logistic model to fit the incident data from Korean Freeways. Moreover, Hojati *et al.* [12] implemented Weibull and log-logistic distributions with fixed as well as random parameters. However, all these studies developed static models which did not incorporate real-time traffic conditions.

Later, a few studies found that incident duration can be better approximated if separate static models are fitted to different stages of the incidents. For example, Ruimin *et al.* fitted different statistical models for each stage of the traffic incident, such as dispatch time, clearance time, etc. [35], and subsequently built a mixture model combining the distributions, namely, generalized gamma, Weibull, and log-logistic for different incident clearance methods [36]. Similarly, Nam *et al.* [37] designed three separate statistical models for reporting time, response time, and clearance time respectively using maximum likelihood estimation. However, in practice, the information about the distinct stages of traffic incidents may not always be available. Moreover, the prediction of the entire incident duration is more useful to the drivers since the impact of the incident exists in the road network throughout the entire duration [12].

In recent years, various data-driven modeling algorithms, such as Support Vector Regression (SVR) [38], Artificial Neural Networks (ANN) [39], etc. have been applied for predicting the duration of traffic incidents. For example, Valenti *et al.* [40] applied different machine learning methods for this purpose, and they observed that Support Vector Regression/ Relevance Vector Machines (SVR/RVM) perform well for predicting the long duration, and Artificial Neural Networks (ANN) are more suitable for the short duration.

An important consideration in predicting the incident duration is the comprehensiveness of the data-set. Some of the earlier works did not include essential features in their analysis. For example, Wu *et al.* [38] did not consider the blockage of lanes, shoulder lane, etc. in the feature-set for analyzing the incidents from the Netherlands. Moreover, Lopes *et al.* [41] applied ANN in a sequential model containing four neural networks with incremental inputs. However, their data-set was highly homogeneous because they focused on only a single highway in Portugal. Besides, several studies

did not include traffic data in their analysis. For example, Pereira *et al.* [42] studied the incidents from Singapore; however, they did not consider traffic data in the feature-set. Moreover, Lin *et al.* [10] introduced a combination of M5P tree and hazard-based duration model for predicting incident duration. Nevertheless, they also did not include traffic data in their study.

Furthermore, a number of studies have analyzed the impact of incidents by incorporating real-time traffic data albeit in a limited manner. For instance, Yuye *et al.* [39] explored real-time traffic data for predicting the impact of incidents; however, they considered traffic speed only as a categorical feature. He *et al.* [43] also studied the relationship of various external factors with the duration of the incidents. However, they considered the average values of traffic data at two instants only; before and after the incident detection. Therefore, these studies did not perform a sequential prediction of the incident duration.

Moreover, most of the studies assumed traffic flow to be the most important metric for estimating the traffic congestion. For example, Golob *et al.* [44] fitted linear regression models between traffic flow and the incidents in their analysis, and Skorput *et al.* [45] built a mathematical model to detect the incidents based on the inward and outward traffic flow. On the contrary, we not only analyze the variations in upstream and downstream traffic flows but also consider speed as a covariate to model the impact of incidents in a more comprehensive manner.

Apart from that, the resolution of traffic data is also an important factor in data-driven traffic prediction models. Khattak *et al.* [18] introduced an online tool named iMiT which can dynamically predict the incident duration, secondary incident occurrence, and the associated delays. For this purpose, they worked with the traffic flow data available from the Hampton Roads Areas. However, the resolution of their flow data is 15 minutes, whereas the traffic flow data used in our work are recorded at 5-minute interval.

Moreover, Ma *et al.* [19] researched on the prediction of freeway incidents' clearance time in USA. Although they obtained competitive results using the Gradient Boosting Decision Trees method, the resolution of their traffic volume data is too coarse (1 hour), which is not sufficient to understand the subtle changes in the impact of incidents accurately.

In addition to that, most of the previous studies assumed that the dataset provided by the traffic management authorities are completely accurate. For example, Khattak *et al.* [18] relied on the incident report provided by HRTOC for their analysis. However, the reported incident duration may incur a measurement error, since there might be a delay in reporting the incidents by HRTOC after they occurred. By contrast, we perform the prediction of both reported incident duration (according to the incident reports) and effective incident duration (computed based on the impact of the incidents in the neighboring upstream links) and provide a comparative analysis in the thesis.

Besides, the feature-sets used in the prediction models of the earlier studies were fixed, whereas our model can flexibly incorporate features as incident and traffic data gradually become available. Therefore, our prediction gets more refined with elapsing time.

Lastly, Adaptive network-based fuzzy inference system (ANFIS) has been considered to perform efficiently of late since it combines the efficiency of the fuzzy model in handling the uncertainty with the prediction accuracy of artificial neural network method using back-propagation [46]. For example, Tang *et al.* [47] predicted the lane changing behavior of the drivers using this model. Besides, Eleni *et al.* [48] proposed an approach to predict the incident duration based on Fuzzy-Entropy Neural Network. They considered the uncertainties arising from late clearance of the incidents or the possibility of occurrence of the secondary incidents; therefore, the fuzzy model is more suitable for them. However, they did not mention the error values of

incident duration prediction in their study.

In the following, we summarize the previous studies related to incident duration prediction in Table 2.1.

Table 2.1: Summary of the previous studies related to incident duration prediction.

Literature	Methodology used	Research gap
Hojati <i>et al.</i> [12]	Weibull and log-logistic distributions	Built static models without any real-time traffic data.
Ruimin <i>et al.</i> [35]	Distinct models for each stage, e.g., dispatch time, clearance time, etc.	1) Information about distinct stages are not always available. 2) Prediction was not updated sequentially.
Khattak <i>et al.</i> [18]	Theoretically based deterministic queuing model	1) The resolution of traffic flow data is 15 min. 2) Relied only on incident reports, which may incur measurement error.
Qing <i>et al.</i> [43]	Hybrid tree-based quantile regression	1) Used traffic data only before and after the incident detection. 2) Prediction performed once; at the beginning of incident.
Wu <i>et al.</i> [38]	Support Vector Regression method	Important features, e.g., blockage of lanes, carriageways, shoulder lane, etc. are missing.
Pereira <i>et al.</i> [42]	Text-analysis approach	Did not incorporate traffic data; only incident features.
Yuye <i>et al.</i> [39]	Multivariate decision tree, neural network, etc.	Considered traffic speed as a categorical feature.
Lin <i>et al.</i> [10]	Combination of M5P tree and hazard-based duration model	Did not include traffic data in their study.
Lopes <i>et al.</i> [41]	Combination of Neural Networks	Only a single highway was considered, hence lack of variety in the data-set
Ma <i>et al.</i> [19]	Gradient Boosting Decision Trees	1) Traffic volume data are coarse (resolution 1 hour). 2) Did not perform sequential prediction.
Wei <i>et al.</i> [49]	Artificial neural network model	1) The training and test data-sets are too small to build a robust model. 2) Not adaptive to the availability of features.

We now discuss the earlier studies where Bayesian methods have been used for traffic prediction. Van *et al.* [50] applied neural network in Bayesian framework to predict travel times with confidence intervals. However, neural network algorithms tend to converge on local minima rather than global minima, whereas Support Vector Regression method does not suffer from this drawback. On the other hand, Ahn *et al.* [51] predicted traffic flow in highways of Korea using BSVR approach. However, they did not predict the duration of non-recurrent incidents in their work, which is the main area of concern in this thesis.

2.3 Prediction of Queue-length of the Incidents

Modeling and estimation of traffic congestion has been one of the most active research areas in the field of urban transportation for the past years. In this section, we will briefly discuss related research works in this area.

The problem of traffic forecasting has been addressed from two different perspectives: (1) simulation (model) based and (2) data-driven based. Simulation models are built to simulate the network behavior and predict the future conditions [52]. These methods, however, suffer from exhaustive calibration and scalability [53]. On the contrary, data-driven models involve free-calibration. These methods include time-series analysis and machine learning techniques.

In the past, most of the studies explored simulation-based theoretical modeling for analyzing the impact of the incidents. For example, Long *et al.* [54] employed the cell transmission model (CTM) to simulate the traffic jam at the microscopic level. Liu *et al.* [11] proposed a traffic shock wave model and simulated different superposition situations of shock waves for the road network. Raktim *et al.* [55] also developed a simulation model to design a freeway service patrol program for incident management. However, none of these studies dealt with the real-time traffic data. Hence, the performance of these models may degrade when used in real-time applications. Moreover, the spatial transferability of these models may be compromised as well. Later, Kong *et al.* [56] proposed a traffic flow prediction method using the floating car trajectory data-set. The floating car data have certain limitations, such as it generally represents a sample of data, which is a subset of total traffic. Therefore, this sample has to be a good representative of the entire population of cars. Moreover, the credibility of the data-set largely depends on other influences, such as the accuracy of the map, turning the

device on timely, etc.

Nowadays traffic management authorities regularly update the traffic information on their websites collected from a variety of sensors, making the real-time traffic data more readily available for research purposes. A comprehensive overview of the data-driven methods is provided in [57]. In general, most of the studies consider the current and past traffic data from the particular link only where the incident happened to predict future values [58] [59]. Additionally, some studies incorporate the information from neighboring links also [60], which improves the prediction performance of the models. Sheu *et al.* [61] developed a real-time model to predict the time-varying traffic states of the lanes, such as lane-changing fractions, queue-lengths, etc. However, their study primarily concentrated on the intersections, with a single upstream-downstream link pair. Similarly, Miller *et al.* [62] also considered only one upstream-downstream link pair around the incident location, which may fail to capture the spread of the congestion entirely. In real-life scenarios, the congestion can spread over more than one upstream link. Besides, more than one lane may be blocked during the incidents, which was not considered in these studies.

Moreover, a number of studies analyzed either traffic speed or flow data in their analysis. For example, Yang *et al.* [63] considered only traffic volume data for predicting the congestion, which may result in false alarms when the traffic volume (number of cars) is low without any congestion, such as off-peak hours or midnight, etc. Yuye *et al.* [39] also worked on real-time traffic data from Singapore; however, they also investigated traffic speed only, that too as a categorical feature. Similarly, Shahabi *et al.* [13] also analyzed traffic speed data only for accident impact prediction. On the contrary, to make our method more robust to the outliers, we consider both traffic flow and speed values recorded by the sensors for estimating and predicting the queue-length.

A few other studies considered real-time data, however, the prediction is not updated with online streaming data. For example, Miller *et al.* [62] and Florido *et al.* [14] did not take the online streaming traffic speed and flow data into account. Besides, Shahabi *et al.* [13] proposed a prediction model although the predictions are not refined by the online streaming data. In contrast, since the length of congestion at a particular instant depends on the instantaneous traffic state of the road, the temporal variation of incidents' impact is difficult to predict without the updated traffic data. Similarly, Chung *et al.* [64] analyzed the spatiotemporal impact of incidents on the network using the time and location of the accident, and information from the loop detector. Therefore, this method is applicable for any road where accident data are available, and loop detectors are installed. However, their model can capture only the one-time impact of the incident. Usually, in real-time an incident is always followed by a growing/shrinking pattern of traffic.

The spatial and temporal resolution of traffic data is another important factor. Shahabi *et al.* [13] explored the incidents on the freeways of Los Angeles, where the sensors are 0.5 miles away from each other. Since the spatial resolution of their data-set is coarse, they applied interpolation method to obtain finer traffic data-set. In our work, the links are 50 – 150 meter long, and there is a sensor located at the end of each link. Therefore, we analyze the traffic data with a finer resolution.

In another work, Yang *et al.* [63] implemented a feature selection step first, and later formulated a binary classification problem to predict the congestion based on a predetermined threshold value. However, the threshold value is chosen universally (i.e., the same threshold for all upstream links for a particular incident) which may not be accurate since prediction errors may arise by different speed limitations or mismatching of capacities in different links. Moreover, Wang *et al.* [65] applied a Naive Bayes classifier model

to determine the probability of congestion and incidents in road networks. However, they proposed a binary classifier which cannot predict the exact queue length.

With the emergence of deep learning architectures, several studies are exploring the deep neural networks of late to capture the spatiotemporal dynamics of the road network for traffic prediction. For example, Haiyang *et al.* [15] introduced the spatiotemporal recurrent convolutional networks combining convolutional neural networks (CNN) and long short-term memory (LSTM) neural networks in order to predict traffic speed for different horizons. Min *et al.* [66] introduced a stacked LSTM neural network considering both spatial and temporal correlations to predict traffic speeds. Nevertheless, they only analyzed the correlation between two adjacent links, whereas we consider the spatial interaction of all upstream links from the entire network. Yisheng *et al.* [67] built a stacked auto-encoder model for traffic flow prediction. Besides, Mohammadhane *et al.* [16] also performed traffic flow and speed prediction using decentralized deep learning-based methods. However, these studies did not deal with the incidents-induced congestion in particular. Therefore, the incidents features have not been considered in their analyses. Last but not the least, Honglei *et al.* [17] built an LSTM network for predicting the accident risk citywide. However, their work has certain limitations, such as they have not considered any traffic data (speed, flow or density), which is of utmost importance for analyzing the adverse effect of traffic incidents. Secondly, their model performs the prediction on a coarse level since the spatial and temporal resolution of their data-set is very low (the temporal resolution is 1 hour compared to 5 minutes in our study, and the spatial resolution is 1000 meters in comparison with 100 meters in our study). Moreover, since these types of incidents are non-recurrent and unplanned, this thesis aims to address the problem of minimizing the severity of congestion after the incidents have already happened. Therefore, we

try to forecast the congestion propagation in the network which would help the drivers to avoid the traffic jam and reach the destination with minimal loss of time.

Next, we summarize the key points of the existing studies in Table 2.2.

Table 2.2: Summary of the previous studies on predicting the impact of incidents.

Literature	Methodology used	Research gap
Long <i>et al.</i> [54]	Cell transmission model	1) They did not consider real-time traffic data, 2) spatial transferability is compromised.
Liu <i>et al.</i> [11]	Shock wave model	1) They did not consider real-time traffic data, 2) spatial transferability is compromised.
Kong <i>et al.</i> [56]	Particle Swarm Optimization	They analyzed floating car data, where the credibility of the data depends on other influences like accuracy of map etc.
Sheu <i>et al.</i> [61]	Nonlinear stochastic model	1) They considered the incidents in the intersections only, 2) blockage of more than one lane was not studied.
Yang <i>et al.</i> [63]	Feature selection prior to classification	The same standard was used for all links with different capacity, speed limitations, etc.
Shahabi <i>et al.</i> [13]	Lasso-Granger model	1) They considered only traffic speed data, 2) they did not provide numerical results of their prediction.
Miller <i>et al.</i> [62]	Classification model	1) They did not consider online streaming traffic data, 2) they considered only one upstream-downstream link pair.
Yuye <i>et al.</i> [39]	Regression methods e.g., neural network, CART, etc.	1) Speed has been considered as a categorical feature only, 2) prediction does not get updated with elapsing time.
Min <i>et al.</i> [66]	Stacked LSTM network	They analyzed the correlation between two neighboring links only.
Yisheng <i>et al.</i> [67]	Stacked auto-encoder network	They did not consider incident features.
Mohammadhani <i>et al.</i> [16]	Decentralized deep learning model	They did not deal with incident-induced congestion.
Honglei <i>et al.</i> [17]	LSTM network	1) The resolution of their data is very coarse, 2) they predicted the chance of incidents occurrence, not the after-effect of the incidents.

2.4 Effectiveness of VMS Messages

For optimal utilization of the road network capacity and efficient traffic management during the incidents, the Land Transport Authority (LTA) of Singapore adopts Intelligent Transportation System (ITS), which provides an integrated solution for communication, control, and information processing in transportation. In earlier studies, Borrough *et al.* [68] and Lee *et al.* [69] found that the Variable Message Signs (VMS technology) can potentially reduce the number of secondary crashes. Dos *et al.* [70] also reported that

combining VMS and variable speed limits techniques could possibly reduce rear-end collisions. Several other studies evaluated the impact of the VMS displays either by conducting a survey or through field observations.

First, we will discuss the studies surveying the drivers on the influence of VMS, and highlight their limitations. According to a survey to measure the drivers' intent response to VMS messages along the freeways in Missouri [22], 94% of the investigated drivers answered that they followed the instructions and suggestions of the VMS messages. Wang *et al.* [21] also found that over 70% of the surveyed drivers claimed to be influenced by VMS message information. Moreover, Ran *et al.* [20] set a questionnaire for the drivers in Wisconsin to observe the drivers' response, and obtained that about 70% of the drivers would change their route recommended by the VMS messages. However, all these surveys were conducted by the paper-and-pencil method, which highly depends on the willingness of the drivers to participate in the survey. Shirazi *et al.* [71] conducted a different kind of survey by arranging phone conversations with the drivers in Los Angeles, and concluded that around 70% of the interviewed drivers would divert to an alternative route if the messages provide enough information. However, this experiment may also be biased by the false positive responses from the drivers.

On the other hand, several studies carried out field observations to understand the impact of VMS. Kiron *et al.* [23] conducted a research on the impact of VMS messages in London using three stages of questionnaires, and in the last step, they observed the activities of the drivers during two real-time incidents. They noticed that the percentage of drivers who responded in favor of changing their routes in the first two stages was five times the percentage of drivers who actually changed their routes in the last stage. Similarly, Taisir *et al.* [25] observed in their field study on a major arterial of Saudi Arabia that only 5.9% of the drivers actually followed the instructions on VMS, which is 7% of the total number of drivers who claimed to

abide by the VMS. Therefore, the field studies provided more accurate and unbiased results compared to the surveys.

However, the size of data-set is an important factor in the field study. Since field studies are difficult and sometimes expensive to arrange and control, therefore most of these studies do not have a comprehensive data-set. For example, a field study in Oslo shows that there were approximately 20% of the cars which changed their direction as suggested by the VMS messages [24] [72]. However, they collected the data from two VMS sites and for two evenings only, which may not reflect the seasonal, temporal or spatial variations accurately. Taisir *et al.* [25] also reported the results based on one VMS display only, since there was no other VMS installed in the city where the research was conducted. Moreover, they focused on evening peak hours only in their work. Therefore, the size of the analyzed data-sets was too small to come to any conclusion.

In this thesis, we have adopted a data-driven approach since we have access to the historical data-sets of traffic incidents from the expressways of Singapore along with the VMS information. Therefore, this analysis is not localized to any particular area of the city. Moreover, we have not derived the results based on any survey or personal interaction. Therefore, our analysis is free from the response bias.

2.5 Effect of Rainfall on Traffic

In the past, several studies have dealt with the influence of various weather attributes, such as temperature [73], different kinds of precipitations [26], wind speed and direction [74], snowfall [75], and others [76] on the accidents or crash rate. These factors reduce the visibility on the roads resulting in an overall slowdown of traffic and sometimes causing mishaps. Similarly, the adverse effect of rainfall also has been explored in several studies [77].

For example, Chung *et al.* [78] analyzed the variation in traffic flow data due to rainfall in the freeways of Korea. They found that the non-recurrent congestion existed in the network for 1.6 million vehicle-hours due to rainfall. In the following, we discuss the studies related to the effect of rainfall on traffic and also highlight their limitations which we try to address in this thesis.

Since most of the studies in this area of research are data-driven, the comprehensiveness of the data-set is a critical factor. Mashros *et al.* [79] [80] analyzed the correlation of rainfall with both traffic flow and speed data from Malaysia, which is a tropical country like Singapore. They considered daylight off-peak hour traffic data in one study [79], whereas the night-time traffic is considered in another study [80]. However, their analysis excludes a large subset of rainfall instances since they did not consider the peak hour data. The knowledge of the combined effect of rainfall and peak hour congestion might be beneficial to the traffic management authorities. On the other hand, Lu *et al.* [81] worked with Singapore data; however, they did not analyze the effect of rainfall for different types of roads or expressways separately.

Moreover, the resolution and quality of the traffic and rainfall data are also crucial. Leong *et al.* [29] explored the effect of rainfall on traffic speed in Singapore. However, the resolution of their speed data is coarse, since the values are discretized in four speed-bands, whereas the speed values used in our analysis are divided into ten speed-bands. In another study, Jaroszweski *et al.* [27] analyzed the data-set collected from two major cities in UK, named Manchester and Greater London, to determine the effectiveness of weather radar approach in collecting the rainfall data. In their analysis, the radar approach proved to be more efficient and reliable over the traditional meteorological station-based approach. Therefore, we have also used historical weather radar data in our study.

Although the previously-discussed studies investigated the reduction in traffic speed or flow due to rainfall, none of them have analyzed whether the rate of accidents or crashes increases during rainfall or not. Therefore, we now discuss the limitations of the studies where the correlation between rainfall and traffic incidents has been analyzed.

McGuire *et al.* [28] conducted an experiment with the daily and monthly rainfall and the accidents data from Perth, and stated that there is a relative increase in road accidents when there is an increased rainfall. This study uses rain data collected over a 10 year period; however, it did not consider factors like the improvement in transportation technology or improvements of road condition and safety infrastructure with time. Besides, Eisenberg *et al.* [26] investigated the relationship between precipitation and traffic crashes in different states of US, and observed a strong positive correlation between the rainfall and accidents on a daily basis. However, none of these studies have compared the rate of incidents during rainfall with the incident rate after rainfall, whereas in our work, we compare the frequencies of the incidents obtained in dry weather, during rainfall, and after rainfall. Furthermore, we have analyzed and explained the variation of the frequencies of different types of incidents for different expressways separately.

In the next chapters, we analyze the historical traffic data-sets, develop the algorithms, and build the prediction models to alleviate the adverse effect of non-recurring road incidents on the expressways of Singapore.

Chapter 3

Prediction of Incident Duration

The uncertainty in forecasting the impact of traffic incidents arises due to the challenges associated with predicting the duration of the events. The duration of these incidents turns out to be a significant factor in determining their impact, which in turn, depends on several other factors such as day, time and location of the incident, the number of total and affected lanes, type of the incident, etc. Furthermore, we leverage traffic data (speed and flow) with these features to compute the predicted duration.

The overall duration of a traffic incident can be divided into the following different components: (1) reporting time (r_t): the time taken to detect, verify and report the incident after its occurrence, (2) response time (s_t): the time taken by the response team to arrive at the spot after reporting of the incident, (3) clearance time (c_t): the time required by the team to clear the affected area, and (4) recovery time (v_t): the time taken by the traffic condition to restore back to normal [43]. Since the response time and clearance time mostly depend on the timely actions of the response team, it is quite interesting to predict the span of these two stages from the perspective of the traffic management authorities [19]. Nonetheless, the prediction of the entire incident duration is more useful to the drivers since the impact of the incident exists in the road network all over the four stages [12]. Therefore, considering the duration from the very beginning of the incident to its end is highly beneficial for driver advisory systems so that they can provide more robust guidance to the drivers based on the predictions. Hence, the total incident duration T considered in this thesis is the sum of these four

stages [82]:

$$T = r_t + s_t + c_t + v_t. \quad (3.1)$$

In this chapter, we have built a dynamic incident duration prediction model which is adaptive to the availability of features. At first, we have described the data-set in detail. In the following section, we have discussed the method of computing the effective incident duration using the traffic data. Moreover, we have also illustrated the prediction methods and the performance metric. In the subsequent section, we have demonstrated a comparative analysis of the reported and effective duration of the incidents followed by the prediction performance of different regression methods for both reported duration as well as effective duration. Next, we have analyzed the methods and obtained results concerning the Bayesian prediction of the duration of incidents. Finally, the last section provides the concluding remarks on this topic.

The works described in this chapter are published in the papers [83], [84], and [85].

3.1 Description of the Data-set

In this section, we describe the data-set which consists of the historical records of incidents and traffic data from the expressways of Singapore. The entire data-set is provided by the Land Transport Authority (LTA) of Singapore.

3.1.1 The Expressways of Singapore

There are 10 expressways in the entire road network of Singapore, each of them comprising 180 – 220 road segments. The expressways are shown in Fig. 3.1 along with their directions. In total, there are 2156 expressway links with an average length of 100 meter.

Figure 3.1: The expressways of Singapore island.

We show the histogram of the length of all road-segments or links from the expressways of Singapore in Fig. 3.2, and find that the maximum length

Figure 3.2: Histogram of length of all the links from the expressways of Singapore.

is 202 meter. This high-resolution partition of road network allows us to avoid issues of multi-modal speed distributions within an individual link [86]. The individual links may have two to five adjacent lanes depending on their locations.

3.1.2 Incidents Data

There were 11,278 incidents recorded on the expressways throughout six months (Aug 2016 - Jan 2017). Moreover, we have also considered 1,745 incidents collected from 197 entrance/exit ramps of the expressways. We have a variety of features in our data, such as spatial features (road-segment or link id, latitude & longitude, the expressway and direction), temporal features (the time instants when the incident started and ended), incident features (type of incident), and geographical features (the status of the adjacent lanes including shoulder lane). In Singapore, the lanes are numbered from right to left as lane 1, 2, 3, etc.

At first, we construct a feature matrix using this data where the features are either categorical or numerical. Among them, the categorical variables are nominal because no ordinal relation exists between different labels of the features. Therefore, if the labels were replaced by different integers with a natural ordering, it might lead to poor performance of the model. Hence, we have converted the categorical features (such as weekday/weekend, the direction, etc.) into binary ones using one-hot assignment method. The structure of the feature matrix is shown in Table 3.1.

Table 3.1: Features extracted from the incidents data.

Attribute	Feature	Feature type
Type of Day (d)	weekday/weekend	Categorical
Day of the week (w)	Monday, Tuesday, Wednesday, etc.	Categorical
Time of the day (m)	peak-hour/off-peak	Categorical
Expressway (e)	PIE, AYE, ECP, etc.	Categorical
Direction along the expressway (r)	eastward, westward, northward, southward	Categorical
Condition of shoulder (h)	not affected, affected	Categorical
Total number of lanes (n)	1, 2, 3, 4, 5	Ordinal
Number of affected lanes (a)	0, 1, 2	Ordinal
Type of affected lane (l)	1st, 2nd, 3rd, etc. (from extreme right)	Categorical
Type of incident (y)	accident, breakdown, obstruction, etc.	Categorical

3.1.3 Traffic Data

The traffic data consist of traffic speed and flow values from the expressways (including the ramps) of Singapore. The values are recorded at 5-minute interval in each of the 2156 links. The speed value, thus recorded, represents the average speed of all vehicles traversing the link during the 5-minute interval. On the other hand, the flow value indicates the total number of vehicles that pass through the link in this 5 minutes span. Although the relative distribution of different types of vehicles such as trucks, buses, etc. may influence the duration of an incident, we do not consider it as a separate feature. This is because the proposed models implicitly take those distributions into account. For instance, if a particular expressway is expected to experience a change in the speed flow pattern caused by massive truck movement during a particular time of the day, the models will try to learn the impact from the historical training set. To this end, the models are re-trained periodically to calibrate for the changes in traffic composition. In case the composition changes abruptly (say due to an unforeseen circumstance), the performance of the models will naturally degrade. Although micro-simulation models may consider these factors explicitly, any simulation model will also require re-calibration for an abrupt change, making such models non-suitable for a real-time application.

The average speed values are indicated by ten discrete speed-bands. While the first nine bands represent the speeds up to 90 kmph (each spanning 10 kmph), the 10th band extends over the values higher than 90 kmph. Conversely, the traffic flow data are continuous-valued. The statistical summary of the traffic data is depicted in Table 3.2.

Next, we show the variations of traffic speed and flow in seven days of the week in Fig. 3.3 and Fig. 3.4 respectively. Since the traffic data have been recorded at 5 min interval, the x-axis in both graphs represents the time instants at 5 min interval starting from Monday. The y-axes in Fig. 3.3 and

Table 3.2: Statistics of the traffic data.

Traffic Data	Values
Minimum speed	0 kmph
Maximum speed	100 kmph
Mean speed	81.8 kmph
Median of the speeds	90 kmph
Mode of the speeds	100 kmph
Minimum flow	1 veh/hr
Maximum flow	9960 veh/hr
Mean traffic flow	2154.6 veh/hr
Median of the traffic flows	1653 veh/hr
Standard deviation of the traffic flows	1869.4 veh/hr

Fig. 3.4 indicate mean traffic speed and traffic flow respectively, averaged over all expressways links. Moreover, we have computed the weekly speed or flow by considering the average of all weeks in the entire six months. For example, the mean speed value of Monday illustrated in Fig. 3.3 indicates the speed averaged over all links and all Mondays. We observe that both

Figure 3.3: Variation of average speed on different days of a week.

Fig. 3.3 and Fig. 3.4 have a periodic pattern. Let us explain the periodicity in more detail.

Figure 3.4: Variation of average flow on different days of a week.

In Fig. 3.3, the speed attains the maximum at night (00:00-05:00) for each day of the week. This is because the roads are usually empty at that time. Although for other times of the day, the pattern is similar and repetitive for weekdays (Monday to Friday), the speed-variation is different on weekends (Saturday and Sunday). For weekdays, in the morning peak hour (07:00-10:00) the speed attains a minimum because the roads are congested at that time. At noon (12:00-15:00) the speed increases a bit. However, in the evening peak hour (17:00-19:00) speed reaches the minimum again. Finally, it increases after the evening peak hour until late at night. This pattern in the variation of speed repeats from Monday to Friday. On the other hand, some of the offices, especially customer cares, are open half day on Saturdays, hence there is a small dip in the speed profile of Saturday. However, the congestion is much less on this day of the week compared to weekday peak hours. Usually, the speed varies in the same range from morning to evening, and there is no specific peak hour on Saturdays, as can be seen in Fig. 3.3. Last but not the least, Sunday is considered to be a holiday for almost every office in Singapore. Therefore, unlike weekdays there are no specific peak hours or off-peak hours to be defined on Sundays. However,

people tend to go out on Sundays for visiting different places, particularly in the evenings, which may result in small-scale congestion. Nevertheless, the extent of variation in speed is much less on Sundays compared to other days of the week.

Next, we explain the daily variation of the average traffic flow. As can be seen in Fig. 3.4, the flow attains a minimum at night (00:00-05:00) every day irrespective of whether it is a weekday or a weekend, since very few cars run on the road during those hours. In the morning peak hour (07:00-10:00) of the weekdays, the flow reaches a maximum since people rush to their offices at these hours. At noon, the flow drops a bit on weekdays; however, it again increases and attains the maximum during the evening peak-hour (17:00-19:00) because the roads are overcrowded with cars at that time. On weekends, i.e., Saturday and Sunday, the flow is same for almost the entire day (08:00-11:00) since there are no separate peak hours or off-peak hours on the holidays. Moreover, the average flow of weekends (2500-3000 veh/hr) is the same as that of noon hours on the weekdays.

Overall, we observe the similar periodic nature in both Fig. 3.3 and Fig. 3.4 except the fact that the flow graph is a mirror image of the speed graph with respect to the x-axis. In normal traffic condition, when the flow is low, the average traffic speed is high because the number of cars is much below the capacity. Hence, the cars can travel in almost free flow speed. The traffic is usually in this state during the off-peak hours, especially at midnight or at noon. On the other hand, during peak-hours the flow, i.e., the number of vehicles on the road is high; hence they move in a lower speed. Thus, traffic speed and flow are correlated with each other.

3.2 Methodology

In this section, we describe the approach to compute the effective incident duration using the traffic data. Moreover, we also explain the prediction methods and the performance metric used in this work.

3.2.1 Approach to Compute the Effective Duration

The effective duration of an incident signifies the time span for which the congestion existed in the network because of the incident. In this subsection, we explain the steps of computing the effective duration of the incidents using the traffic speed and flow data from the neighboring links. For this purpose, we assume that the real-time traffic data are accessible from the database of Land Transport Authority of Singapore directly, or perhaps through their website, which provides live updates of the traffic conditions on the Singapore road network [87].

It is essential to consider both speed and flow data as indicators of traffic congestion. From the fundamental speed-flow relationship [88], if both the speed and flow is lower than usual, the link is clearly congested. Consequently, considering two different traffic variables helps to avoid false alarms raised due to sensor noise. Furthermore, rules based on a single traffic variable do not generalize well to diverse city scale networks. For example, the speed limit of the arterial roads is usually lower than that of expressways. Therefore, the speed will drop less during incidents at arterial roads compared to expressways. Hence, the change in flow is a better indicator of congestion for the incidents in arterial roads. Thus, considering both speed and flow allows us to design more robust decision rules for detecting congestion.

Step 1: Let us assume that according to the report, the start and end times of the incident i which occurred at link ℓ are $T_{\text{rep_start}}$ and $T_{\text{rep_end}}$,

respectively. Therefore, the reported duration of the incident is $T_{\text{rep.start}} - T_{\text{rep.end}}$. Since the traffic data are recorded at 5 minute interval, the entire duration is divided in discrete time instants, and each instant is referred to as t_j , where $j \in \{0, 1, 2, \dots, \text{final}\}$. The reported start time t_0 and end time t_{final} are defined by:

$$t_0 = \left\lfloor \frac{T_{\text{rep.start}}}{5} \right\rfloor * 5, t_{\text{final}} = \left\lceil \frac{T_{\text{rep.end}}}{5} \right\rceil * 5. \quad (3.2)$$

Furthermore, $t_1, t_2, t_3, \dots$ indicate 5, 10, 15 ... minutes after the start time.

Step 2: From traffic data, we obtain the traffic speed values $s(u_\ell, t_j)$ and $s(d_\ell, t_j)$ for each time instant t_j , where u_ℓ and d_ℓ are the upstream and downstream links of ℓ respectively. The downstream link is considered for comparison with the upstream link in order to ensure that the traffic slowdown is caused due to the incident only. Moreover, we fetch the traffic flow values $f(\text{inci}_\ell, t_j)$ and $f(\text{non}_\ell, t_j)$ of link ℓ for each time instant t_j , where $f(\text{inci}_\ell, t_j)$ implies the flow value on the day of incident, and $f(\text{non}_\ell, t_j)$ indicates the average flow of the non-incident same day of other weeks for the entire six months. For example, if a particular incident happened on a Monday, we compute the average flow of all other Mondays of the six months except the day of incident to compare it with the flow of the incident-affected Monday. However, unlike speed, the flow of the upstream and downstream links are not compared because, in practice, the average flow in the downstream link cannot exceed that of the upstream link, unless there is an entrance to the expressway in between those two links. Moreover, even if there is an entrance, it is likely to be congested because of the incident. Besides, the maximum capacities of the upstream and downstream links might differ from each other.

Next, we obtain the values of $s(u_\ell, t_j)$, $s(d_\ell, t_j)$, $f(\text{inci}_\ell, t_j)$, and $f(\text{non}_\ell, t_j)$ for each time instant t_j , where $j \in \{-12, -11, \dots, 0, 1, 2, \dots, L-1, L, L+$

$1, \dots, L + 12\}$. According to the notation, $t_{-1}, t_{-2}, \dots$ indicate 5, 10, ... minutes respectively before the reported start time, and $t_{L+1}, t_{L+2}, \dots$ correspond to 5, 10, ... minutes respectively after the reported end time of the incident. Therefore, for computing the effective duration we consider the traffic speed and flow values for the entire duration from 60 minutes before the reported start time to 60 minutes after the reported end time. We take a margin of 2 hours into account because the LTA may be notified late about the incidents (early start time) or the impact on the traffic may not immediately disappear as soon as the incident ends (late end time).

Step 3: Next, we compute the differences in speed $d_{s(\ell, t_j)}$ and flow $d_{f(\ell, t_j)}$, where $d_{s(\ell, t_j)}$ and $d_{f(\ell, t_j)}$ are defined by:

$$d_{s(\ell, t_j)} = s(u_\ell, t_j) - s(d_\ell, t_j) \text{ and } d_{f(\ell, t_j)} = f(inci_\ell, t_j) - f(non_\ell, t_j). \quad (3.3)$$

Step 4: The effective start time $T_{\text{eff_start}}$ is defined by:

$$T_{\text{eff_start}} = (T_{\text{rep_start}} + (t_j^* - t_0)) \ni t_j^* = \underset{t_j}{\operatorname{argmin}} \{t_j | (d_{s(\ell, t_j)} < 0, f(inci_\ell, t_j) < 0.8 * f(non_\ell, t_j))\}, \quad (3.4)$$

i.e., the time instant when the speed in the upstream link becomes less than that of downstream link and the average flow on the day of incident drops to less than 80% of the average flow of non-incident days is considered to be the effective start time ($T_{\text{eff_start}}$) because the congestion starts to grow in the upstream direction at this instant.

Now, the critical question is why we choose 80% to be the threshold ratio of the flow on incident day and the flow of non-incident day. For this purpose, we determine the ratio of $f(inci_\ell, t_j)$ and $f(non_\ell, t_j)$ at each time instant t_j for different incidents (see Fig. 3.5). We observe that the ratio of 0.77 is at the 75th percentile. Therefore, we choose the nearest round figure

Figure 3.5: Box plot of the ratios of traffic flow on the day of incident to that of non-incident days.

0.8 (80%) to be the threshold ratio of the flow data.

Step 5: Similarly, the effective end time $T_{\text{eff_end}}$ is defined by:

$$T_{\text{eff_end}} = (T_{\text{rep_end}} + (t_j^* - t_0)) \ni t_j^* = \underset{t_j}{\operatorname{argmin}} \{t_j | (t_j > T_{\text{eff_start}}, d_s(\ell, t_j) > 0, f(\text{inci}_\ell, t_j) > f(\text{non}_\ell, t_j))\}, \quad (3.5)$$

i.e., the time instant when the speed in the upstream link becomes greater than that of downstream link and the average flow of the day of incident is comparable to that of non-incident days is assumed to be the effective end time ($T_{\text{eff_end}}$). The traffic is supposed to go back to normal at this instant.

Step 6: Therefore, the reported incident duration is $T_{\text{rep_start}} - T_{\text{rep_end}}$, whereas the effective duration is $T_{\text{eff_start}} - T_{\text{eff_end}}$.

3.2.2 Prediction Method and Performance Metric

In this subsection, we explain the steps for predicting the incident duration. In Singapore, the Land Transport Authority (LTA) gets notifications about the incidents from various sources such as traffic sensors, traffic cameras, police or motorists, and takes necessary response actions such as generat-

ing incident records, deploying quick response incident management teams and updating real-time traffic information on electronic signboards, website, mobile app, and radio [89].

Now for each incident i , we extract the spatial, temporal, and geographical features, such as type of day $d(i)$, day of week $w(i)$, time of the day $m(i)$, expressway $e(i)$, direction $r(i)$, total number of lanes $n(i)$, shoulder affected or not $h(i)$, number of lanes affected $a(i)$, type of affected lane $l(i)$, and type of the incident $y(i)$. Moreover, since the duration of the congestion depends heavily on the traffic conditions of the feeding links, we incorporate the real-time traffic data as well for prediction purpose. The fact that the speed values are categorical, whereas the flow values are continuous, does not affect the prediction because we assume the average speed and average flow as independent input features. The speed and flow values $s(l, t_j)$ and $f(l, t_j)$ are recorded during the interval $(t_j - \delta_t, t_j)$, where the sampling interval δ_t is 5 minutes.

However, the features may not be available at the same time. Moreover, the values of the features may vary with elapsing time. Therefore, we construct different feature subsets based on the availability of the features. We demonstrate the subsets of the features in Fig. 3.6. The first subset contains the most generic features, which are usually available immediately after the incident happens. Hence, this subset of features is termed as basic set denoted by $\mathcal{B}(i, t_j)$. Some of the features in the basic set, such as traffic flow or speed values are updated at each instant. The basic set can be expressed mathematically by:

$$\begin{aligned} \mathcal{B}(i, t_j) = & (d(i), w(i), m(i), e(i), r(i), y(i), s(l, t_j), s(l, t_j - \delta_t), s(l, t_j - 2\delta_t), \dots \\ & s(l, t_j - z\delta_t), f(l, t_j), f(l, t_j - \delta_t), f(l, t_j - 2\delta_t), \dots f(l, t_j - z\delta_t)), \end{aligned} \quad (3.6)$$

Figure 3.6: Different sets of features.

and

$$\mathcal{B}(i, t_{j+1}) = a.\mathcal{B}(i, t_j). \quad (3.7)$$

Here $z\delta_t$ represents the horizon of the past speed and flow values starting from the time instant when the incident started, and a is the state transition vector. Therefore, the size of the feature vector increases with time.

Moreover, there are some optional feature subsets depending on how the information about the lanes are released by LTA. Therefore, we train additional regression models which can incorporate these optional features if the required information is available. This optional feature set (union of the optional feature subsets) is denoted by $\mathcal{X}(i, t_j)$. Although the total number of lanes remains constant, the condition of the shoulder, the number of affected lanes, and type of affected lanes may change with time. As suggested by existing studies and our data, it can take 5 – 10 minutes (1 – 2 prediction steps for the proposed model in this work) to provide fine-grained information about the location of the incident [42]. Let us consider the following

example. Suppose an accident happens on an expressway. One way in which an alert would be generated is if one of the drivers calls an ambulance, which will also alert the traffic management authority. At this point, the position of the accident might only be triangulated to the name of the road and nearby exit or landmark. Depending upon the resolution, different sections of a road may have different lanes and may or may not have a shoulder lane. In this situation, the proposed model will make a very generalized prediction based on the type of road, time of the day, etc. After a few minutes, the transportation authority might localize the spot using CCTV cameras and hence, provide a more specific location. Consequently, the information about the number of lanes and shoulder lane can be inferred. Further, the team reaches on-site and may provide (or even update information) about the number of affected lanes. In case CCTV camera is not available, the system would have to wait for an on-site resource to update the ground conditions. The optional set can be written mathematically as:

$$\mathcal{X}(i, t_j) = (n(i), h(i, t_j), a(i, t_j), l(i, t_j)), \quad (3.8)$$

and

$$\mathcal{X}(i, t_{j+1}) = b.\mathcal{X}(i, t_j). \quad (3.9)$$

Here, b is the state transition vector. The proposed regression model performs the prediction using the basic set (i.e., the first feature subset as shown in Fig. 3.4), when $\mathcal{X}(i, t_j) = 0$. However, if the model is aware of the total number of adjacent lanes and the condition of the shoulder lane while the current status of other lanes is still unknown to the model, the basic set and the optional feature set 1 (i.e., the second feature subset in Fig. 3.4) is considered for predicting the remaining duration. Similarly, if the prediction model has information about the closure of all other lanes but the shoulder lane, it performs the prediction with the basic set and the optional feature

set 2 (i.e., the third subset as mentioned in Fig. 3.4).

Finally, the incident duration prediction model takes the complete feature set (the combination of basic set and all optional sets in Fig. 3.4) into account, when all of these features are available. The entire feature vector is denoted by $\mathcal{F}(i, t_j)$. Therefore, we can rewrite it as:

$$\mathcal{F}(i, t_j) = (\mathcal{B}(i, t_j), \mathcal{X}(i, t_j)), \quad (3.10)$$

i.e.,

$$\mathcal{F}(i, t_j) = (a.\mathcal{B}(i, t_{j-1}), b.\mathcal{X}(i, t_{j-1})). \quad (3.11)$$

The primary objective of this work is to find the relationship function Φ between the feature set $\mathcal{F}(i, t_j)$ and the remaining incident duration $T(i, t_j)$ at the t_j -th instant:

$$T(i, t_j) = \Phi(\mathcal{F}(i, t_j)). \quad (3.12)$$

In this way, we build separate regression models using training data for all of these feature subsets at each 10 minute elapse from the starting point of the incidents. Using these models, we predict the duration after 5 minutes, 15 minutes, 25 minutes, etc. until the incident ends in real-time.

Since traffic incidents can be naturally grouped into multiple clusters through common latent similarities among them, we first cluster the incidents into different groups and then train separate models for each group. Therefore, the proposed incident duration prediction model in this study incorporates clustering of incidents followed by applying the regression methods. We show the training and testing steps of the proposed model in Algorithm 1.

In this work, we apply various regression methods, such as traditional ma-

Algorithm 1 Incident Duration Prediction Algorithm

Training step:

- 1: **for** $t = T_{\text{eff_start}} : T_{\text{eff_end}}$ by 10 min **do**
- 2: Choose appropriate feature-set based on availability (from four sets of Fig. 3.6)
- 3: **for** $p = 1 : 4$ **do**
- 4: Cluster the incidents based on features of the p -th set (K-means or GMM clustering)
- 5: Build regression model for each cluster
- 6: **end for**
- 7: **end for**

Testing step:

- 8: **while** the incident ends **do**
 - 9: Find which feature-set is available
 - 10: Choose nearest cluster based on Euclidean distance
 - 11: Predict the duration using the appropriate regression model built by that cluster
 - 12: **end while**
-

chine learning methods like Classification And Regression Tree (CART) [90], Multi-Layer Perceptron (MLP) [91], Treebagger [92], Support Vector Regression (SVR) [93], etc. as well as more recent algorithms like Adaptive Fuzzy Neural Network [46], Gaussian Mixture Regression (GMR) [94], etc. for predicting the incident duration. To compare their performances, the Mean Absolute Percentage Error (MAPE) values are computed for all these regression methods:

$$\text{MAPE} = \frac{100}{N} \cdot \sum_{i=1}^N \left| \frac{e_i}{q_i} \right|, \quad (3.13)$$

where N is the total number of incidents, and e_i is the difference between the actual and predicted duration q_i and $\hat{q}_i$ respectively:

$$e_i = q_i - \hat{q}_i. \quad (3.14)$$

Next, we consider an example of a potential real-world scenario. We show the flow of events in Fig. 3.7 with time when an incident happens.

Let us assume that the traffic is normal at first at around 5:00 pm in an expressway. At 5:05 pm, a vehicle breakdown occurs and blocks the road. Therefore, traffic starts to slow down. The predictive model detects the change in the traffic data and speculates that an incident has happened. Although the incident reports are not available yet (since it takes some time to report the incidents to the traffic management authority), the regression model performs the first prediction using the information it obtains from the traffic data. Meanwhile, the incident is reported approximately at 5:15 pm (10 minutes after the incident happened). The essential features are disseminated after the incident has been reported, and therefore the database (i.e., the location etc.) is updated according to the report. Next, the model performs the prediction again at 5:20 pm. Further, the details about the closure of the lanes are reported at 5:30 pm. Therefore, as all features are available by this time, the prediction gets more accurate. In the meantime, the response team reaches the location and clears the damaged vehicle from the road at 5:40 pm. However, traffic usually takes some time to go back to normal after the incident has been cleared. At 5:50 pm, the traffic conditions are recovered although the queue of the cars still exists. Finally, at 6:00 pm, the model finds the traffic data to be back to normal again and hence, stops the prediction.

3.3 Results

In this section, we illustrate a comparative analysis of the reported and effective duration of the incidents. Moreover, we compare the prediction performances of different regression methods.

Figure 3.7: A real-life scenario demonstrating how our algorithm works.

3.3.1 Comparison of Effective and Reported Duration of the Incidents

As reported duration is obtained from the incident reports, whereas effective duration is computed using the traffic data, it is necessary to estimate if they are significantly different or not. However, there is a limitation in the approach to determine the effective duration of the incidents. The reported incident duration is a continuous variable, whereas the resolution of the traffic data is 5 minutes. To this end, we consider the reported duration to be the baseline, and we determine the change in the start and end time of the incidents separately using the traffic data. Therefore, the difference in the reported and effective duration is always a multiple of 5.

At first, we show the scatter diagram of the reported duration and effective duration in Fig. 3.8. The correlation coefficient of the reported and effective duration is 0.89. We observe in Fig. 3.8 that the effective duration is greater than the reported duration for a large number of incidents (53.75% of all incidents). However, the effective duration can be less than the reported duration as well, though the percentage is small (13.01%). For

Figure 3.8: Scatter diagram of effective duration (in minute) vs. reported duration (in minute).

the other incidents, the reported duration and effective duration are same. However, there are some outliers in the graph (the absolute difference of reported and effective duration is more than 60 minutes for 1.5% incidents). We discard these incidents from this analysis.

To further analyze the differences in start time and end time separately, let us assume that the difference between effective and reported start time is Δt_1 , and the difference between effective and reported end time is Δt_2 . The cumulative distribution of the incidents with Δt_1 and Δt_2 is shown in Fig. 3.9. Δt_1 is positive if time is needed to detect, verify and report the occurrence of an incident. Consequently, effective start time is before the reported start time for those incidents. Conversely, Δt_1 is negative when the effective start time is later than reported start time (i.e., traffic is normal although there is an incident). It may happen when the number of cars is much less than the capacity of the road at the time of the incident. Furthermore, Δt_2 is positive when there exists a time-gap between the clearance of the road and recovery of the traffic. Therefore, in these cases, the incident is reported to be ended although the traffic is not normal yet. By contrast, Δt_2 is negative when the effective end time is before the reported end time

Figure 3.9: Cumulative distribution of incidents with Δt_1 and Δt_2 .

(i.e., traffic goes back to normal before the incident is reported to end). It happens because sometimes incident vehicles are moved away from traffic lanes to road shoulder; hence traffic can resume to normal, even though the incident is not yet over. Another reason could be that traffic flow is way below the capacity by the time the incident ends; hence there is no congestion, and traffic can flow normally.

In Fig. 3.9, the steps in the positive side of Δt_1 and Δt_2 are steeper, which indicates that Δt_1 and Δt_2 are positive for a larger percentage of incidents. It also supports the fact that the effective duration is larger compared to the reported duration for the majority of incidents. Moreover, the cumulative frequency at $x = 0$ of Δt_1 is larger compared to that of Δt_2 , which means that the reported start time overlaps with the effective one for many incidents, whereas the end times do not.

3.3.2 Prediction Performance of Different Regression Methods

In this subsection, we consider several traditional as well as recent methods, such as Classification And Regression Tree (CART) [95], Multi-Layer Per-

ceptron (MLP) [91], Treebagger [92], Support Vector Regression (SVR) [93], Adaptive Fuzzy Neural Network [46], and Gaussian Mixture Regression (GMR) [94] to model the relationship between various traffic factors and the incident duration.

For the first four regression methods, we divide the training data points into different clusters using K -means clustering algorithm [96] and build a regression model for each of them. To determine the optimum number of clusters, we analyze the variation of intra-cluster distance with the number of clusters K . The value of K where the largest drop occurs in the intra-cluster distance value is considered to be the optimum number of clusters. In the next step, each testing data point is assigned to its nearest cluster, and a predicted value of the remaining duration is obtained by applying the model of that nearest cluster. The second step is repeated for all incidents in the test data-sets. In this study, we apply the three-fold cross-validation to choose the training and test data-sets. Therefore, all the steps are iterated for each of the three training and test data-sets.

We choose the optimal parameters for each method through 10-fold cross-validation. An ensemble of five trees for Treebagger and the MLP architecture with three hidden layers produce optimal results. Moreover, the SVR method with radial basis function as kernel provides the best result. For the ANFIS method, the Fuzzy c-means clustering (FCM) [97] method is used in the clustering step. The number of clusters, the maximum number of iterations, and the minimum improvement in objective function between two consecutive iterations are set to 3, 200, and 10^{-5} , respectively. Besides, for the Gaussian Mixture Regression method, we apply the Gaussian Mixture model [98] instead of K -means clustering prior to regression, where the number of clusters is set to 2.

For comparison purpose, we mention the results for the one-time prediction of the reported duration obtained by these methods in Table 3.3.

Table 3.3: MAPE values for one-time prediction of the incidents reported duration.

CART	Treebagger	MLP [39]	SVR	ANFIS [48]	GMR [99]
73.1	55.84	66.3	63.2	55.7	59.36

We find in Table 3.3 that the Treebagger and ANFIS methods perform almost equivalently, and these methods outperform others. However, since the ANFIS method is computationally expensive compared to other methods, we do not prefer to use it further in our study. Since the Treebagger method assigns weights to the available features itself, we do not preset the weights ourselves, and in the next sections, we consider the results obtained by the Treebagger method. For instance, we mention the assigned weights to the features by our model for predicting the reported duration of all the incidents together in Table 3.1. We observe from Table 3.4 that the status

Table 3.4: The assigned weights to the features by the Treebagger method for predicting the reported duration of all the incidents together.

Weekday	Weekend	Day of week	Peak-hour	Off-peak	Express way	Direction	Shoulder lane	Total no. of lanes	Lane 1 or 2 affected	Other Lanes	Type of incident	Speed data	Flow data
0.26	0.09	0.1	0.33	0.15	0.31	0.2	0.68	0.38	0.5	0.17	0.5	0.34	0.6

of the shoulder lane (affected or not), which main lane is affected, the type of incident, and the flow data are the most important features in predicting the duration.

3.3.3 Overall Prediction of Effective and Reported Duration with Different Feature Sets

In this subsection, we evaluate the prediction performances of the regression models built on different feature sets according to their availability. We obtain the results by these regression models for both reported duration as well as effective duration prediction.

For comparison purposes, we provide the results only for the basic feature set and considering all features together. We compare the results obtained by different regression models in Table 3.5 and Table 3.6 for predicting the effective duration and reported duration respectively. The errors are obtained by averaging over all incidents.

Table 3.5: The overall MAPE values (in percentage) obtained by the Tree-bagger model using basic feature set and all features in predicting reported duration.

Features	5 min	15 min	25 min	35 min	45 min	65 min	85 min	105 min	125 min	155 min
Basic	61.2	59.8	55.7	52.3	50.1	46.28	44.47	40.76	38.9	34.41
All	55.84	52.3	49.68	47.7	44.03	41.76	40.9	36.1	33.6	30.02

Table 3.6: The overall MAPE values (in percentage) obtained by the Tree-bagger model using basic feature set and all features in predicting effective duration.

Features	5 min	15 min	25 min	35 min	45 min	65 min	85 min	105 min	125 min	155 min
Basic	68.24	66.55	63.46	60	55.95	50.27	46.62	42.15	38.7	33.06
All	61	58.3	54.62	53.16	48.76	44.67	39.92	35.87	31.69	27.58

Table 3.5 and Table 3.6 show that the error values improve when we have all features compared to the basic feature set. At the beginning of prediction, the difference in MAPE values obtained by basic feature set and by all features is 5.36% for reported duration and 7.24% for effective duration prediction. However, these percentages are 4.39% and 5.48% respectively, at the end of the prediction. In the previous subsection, Table 3.1 shows that the status of the shoulder lane (affected or not) and the type of affected lane have a significant role in predicting the incident duration. Therefore, in general, prediction improves by 5% – 10% if all features are considered instead of the basic feature set only.

3.3.4 Prediction of Reported Duration for Different Classes of Incidents

In this subsection, we analyze the performance of the prediction model in forecasting the reported duration at different instants. At first, the histogram of the reported duration of the incidents is shown in Fig. 3.10. The mean, median, and mode of the reported incident duration are 50.05 minutes, 29 minutes, and 6 minutes, respectively. Next, we categorize the incidents

Figure 3.10: Histogram of reported duration of the incidents.

based on their total duration for comparing the error values. The MAPE values obtained by our Treebagger model using all features are mentioned for different categories of incidents in Table 3.7. The rows represent the classes of the incidents based on the total reported duration, and the columns represent the elapsed time. We observe in Table 3.7 that the MAPE values are very high for short-duration incidents (5 – 25 minute). Hence, the prediction is not very reliable for these incidents. However, for the incidents in the middle range (46 – 125 minute), the MAPE values are 30% – 47% at first, which reduces to approximately 20% – 38% at the end of prediction. Consequently, we achieve a better prediction for longer duration. This is because the number of features corresponding to the traffic data increases

Table 3.7: Variation of MAPE values (in percentage) with elapsed time since the incidents start for reported duration prediction.

	5 min	15 min	25 min	35 min	45 min	55 min	65 min	85 min	105 min	125 min	155 min
5-15 min	98.24	–	–	–	–	–	–	–	–	–	–
16-25 min	87.84	93.7	–	–	–	–	–	–	–	–	–
26-35 min	66.20	70.58	64.98	–	–	–	–	–	–	–	–
36-45 min	56.68	54.66	51.02	48.32	–	–	–	–	–	–	–
46-55 min	47.51	43.65	38.45	33.93	37.94	–	–	–	–	–	–
56-65 min	39.23	36.22	30.78	27.2	29.94	35.62	–	–	–	–	–
66-85 min	33.37	32.35	24.18	22.61	20.23	21.02	24.97	–	–	–	–
86-105 min	29.4	25.86	21.07	21.87	20.44	18.93	16.07	21.24	–	–	–
106-125 min	23.21	24.66	21.74	19.64	17.72	15.16	14.29	18.14	23.02	–	–
126-155 min	43.15	38.36	37.64	34.36	31.72	28.10	25.67	21.08	20.34	23.36	–
156-200 min	52.57	49.15	47.01	44.63	42.67	38.84	36.60	32.77	30.06	28.11	25.02
Rest	75.32	69.36	61.64	58.4	60.22	57.55	58.82	46.37	40.21	50.45	49.63

with elapsing time; hence, the prediction of remaining duration improves significantly as time elapses.

3.3.5 Prediction of Effective Duration for Different Classes of Incidents

In this subsection, we study the performance of our proposed model in predicting the effective duration of the incidents. We report the results for the prediction performed by the Treebagger model only. We have already explained the method of computing the effective duration of the incidents in subsection 3.2.1. The histogram of the effective duration is shown in Fig. 3.11. The mean, median, and mode of the incident duration are 60.75 minutes, 46 minutes, and 6 minutes, respectively. Similarly as in the previous Section, the MAPE values obtained by the regression model taking all features into account are mentioned in Table 3.8. The rows indicate different classes of incidents based on total effective duration, and the columns represent elapsed time. Table 3.8 shows that the error values are in general a bit higher for effective duration. In fact, the difference becomes smaller for longer duration incidents since effective duration is computed using traffic

Figure 3.11: Histogram of effective duration of the incidents.

Table 3.8: Variation of MAPE values (in percentage) with elapsed time since the incidents start for effective duration prediction.

	5 min	15 min	25 min	35 min	45 min	55 min	65 min	85 min	105 min	125 min	155 min
5-15 min	100.9	–	–	–	–	–	–	–	–	–	–
16-25 min	94.6	96.9	–	–	–	–	–	–	–	–	–
26-35 min	75.52	81.6	79.31	–	–	–	–	–	–	–	–
36-45 min	50.96	57.54	50.15	47.65	–	–	–	–	–	–	–
46-55 min	42.54	39.34	34.6	31.26	32.71	–	–	–	–	–	–
56-65 min	38.09	32.33	26.9	29.86	30.62	29.6	–	–	–	–	–
66-85 min	33.7	32.11	24.33	20.21	17.27	17	20.04	–	–	–	–
86-105 min	25.23	20.02	20.88	17.95	16.62	16.32	14.29	20.53	–	–	–
106-125 min	24.36	23.1	20.03	15.9	14.52	15.2	13.6	17.73	21.78	–	–
126-155 min	41.22	38.97	36.39	31.9	30.87	28	26.73	22.01	19.35	15.68	–
156-200 min	52.23	49.33	47.4	43.04	41.77	38.01	36.65	32.48	28.72	27.13	22.58
Rest	76	70.14	60.8	60.3	64.3	60.8	59.1	47.3	40.6	51.26	50

data, and more features corresponding to the traffic data can be incorporated with elapsing time. Therefore, the performance of the incident duration prediction model for forecasting the effective duration is better for longer duration incidents (> 85 minutes). Overall similar pattern of the results is achieved as discussed in the subsection 3.3.4.

3.3.6 Prediction of Reported Duration for the Ramp Incidents

In this subsection, we analyze the performance of our prediction model for the incidents that occurred alongside different entrance/exit ramp locations. These incidents lasted for an average of 63 minutes with 50% of incidents lasting for about 36 minutes or less. At first, we analyze the temporal trend in the performance of the model across all ramps. Table 3.9 shows the prediction errors in terms of MAPE values by considering the reported duration of the incidents. At the start of the incident, the mean error is 71.93%, which reduces to 54.46% after 35 minutes (25% improvement) and 45.26% after 65 minutes (35% improvement).

Table 3.9: The overall MAPE values (in percentage) obtained by the Tree-bagger model using all features in predicting reported duration of the ramp incidents.

5 min	15 min	25 min	35 min	45 min	65 min	85 min	105 min	125 min	155 min
71.93	67.41	64.74	54.46	50.25	45.26	42.13	40.92	40.24	36.17

Table 3.9 shows the average performance of the model for ramps aggregated over various kinds of incidents. In Table 3.10, we mention the forecasting errors for incidents with different duration (rows of the table). The table also shows how the accuracy changes with elapsed time (columns of the table). For ramps, we notice similar temporal trends like expressways (see Table 3.7). As with expressways, the prediction accuracy improves as time progresses.

Since Singapore has a vast heterogeneous urban network, it is natural to assume that the prediction performance of the model will not remain the same for different ramps at different locations. To analyze these trends, the ramps are grouped based on the expressways they serve. Moreover, Table 3.11 shows the variations in the prediction performance for incidents

Table 3.10: Variation of MAPE values (in percentage) with elapsed time for ramp incidents.

	5 min	15 min	25 min	35 min	45 min	55 min	65 min	85 min	105 min	125 min	155 min
5-15 min	113	–	–	–	–	–	–	–	–	–	–
16-25 min	99.4	94.4	–	–	–	–	–	–	–	–	–
26-35 min	82.32	80.2	77	–	–	–	–	–	–	–	–
36-45 min	75.72	69.19	67.25	70.38	–	–	–	–	–	–	–
46-55 min	66.43	63.68	53.77	56.40	50.33	–	–	–	–	–	–
56-65 min	59.81	54.13	48.72	44.68	46.36	47.50	–	–	–	–	–
66-85 min	51.91	47.12	41.22	39.92	35.25	33.44	33.14	–	–	–	–
86-105 min	46.23	39.72	35.18	31.63	29.5	26.4	25.55	27.62	–	–	–
106-125 min	42.98	36.83	33.50	28.73	25.05	23.5	22.95	21.55	24.67	–	–
126-155 min	50.03	43.27	37.72	35.32	31.41	29.49	27.86	24.93	23.02	21.07	–
156-200 min	62.89	56.33	53.2	49.5	45.28	41.75	38.12	36.9	33.77	29.1	26.3
Rest	80.99	75.59	79.53	72.62	68.06	61.91	56.5	51.58	47.18	45.28	45.17

that occurred on ramps located at different expressways. For comparison purpose, the prediction performance is also shown for the mainlines of the expressways connected to the ramps. Table 3.11 also includes the median duration of the incidents along different locations. We observe that the median duration of the ramp incidents on KPE, MCE, and SLE are the least. These expressways are comparatively short in length. Moreover, SLE is located far from the center of the city (the busiest area of Singapore), and a significant part of MCE comprises an underground tunnel (3.5 km out of 5 km). Therefore, the ramps of these expressways may not be much incident-prone. The error values are also lower for these ramps. However, since our model performs better for the incidents in the middle range compared to the low-duration ones, the error value is higher for MCE ramps compared to those of KPE and SLE (the median duration of MCE ramp incidents is 5.5 minutes, whereas it is 10–15 minutes for KPE and SLE). On the other hand, PIE is the longest and busiest expressway in Singapore. Besides, although BKE is far from the center of the city, it connects two countries, Malaysia and Singapore. Therefore, the median duration of the ramp incidents on PIE and BKE is the highest, which leads to a significant prediction error.

However, the median duration, as well as the MAPE values, are almost in the same range for mainline incidents of different expressways.

Table 3.11: The median duration and the MAPE values (in percentage) for the incidents on ramps and mainlines of different expressways.

	Expressways	AYE	BKE	CTE	ECP	KJE	KPE	MCE	PIE	SLE	TPE
Median duration (in minutes)	Mainlines	27	24	19	25	27	22	18	20	19	25
	Ramps	37	47	33.5	23	28	11	5.5	42	15	33
MAPE (in percentage)	Mainlines	60.92	55.68	52.01	58.82	50.17	46.44	42.91	54.54	52.49	49.68
	Ramps	71.62	88.28	74.12	63.6	67.93	49.55	55.5	88.37	53.19	74.31

3.3.7 Comparison of Our Results with Existing Literature

In this subsection, we compare the results obtained in this study to the existing literature. Araghi *et al.* [100] provided a comparative analysis of k-NN and Hazard-based Models in their work. The MAPE values obtained by the two methods were 41.1% and 43.7% respectively. We obtain the MAPE values 55.84% and 61% at first averaged over all incidents for reported and effective duration respectively, which improve to 30.02% and 27.58% after 155 minutes. The proposed prediction model in this study performs better for the incidents with duration larger than 55 minutes (See Table 3.7 and Table 3.8). On the other hand, Li *et al.* [35] classified the incidents based on the duration and determined the error values for different classes of incidents similar to this work. The MAPE value for short duration incidents (5 – 15 minutes) in their prediction was 184%, whereas we obtain the value as 100.9% (effective duration prediction). For long duration incidents (greater than 120 minutes), they obtained 74% MAPE in prediction whereas our error values are much lower as can be seen in Table 3.7 and Table 3.8 for different categories of incidents. In another work of Li *et al.* [36], the MAPE

value averaged over all incidents is 94.7%, whereas we obtain the MAPE value of 61% (effective duration). Khattak *et al.* [18] developed an online incident management tool named iMiT which can predict the incident duration as well as identify the occurrence of the secondary incident. They found that the error values are higher for the extreme cases (incidents in the highest and lowest duration range). This study also shows the similar behavior of the proposed regression model. In recent years, Lin *et al.* [10] achieved better prediction accuracy using the M5P-HBDM model. The MAPE value obtained by this model was 33.15% for all incidents. Qing *et al.* [43] evaluated the error values of five different regression models for comparing the prediction performance. The hybrid tree-based quantile regression method performs the best (MAPE value 49.1%). We obtain similar results for the incidents with duration greater than 35 minutes (See Table 3.7 and Table 3.8). Furthermore, Pereira *et al.* [42] performed the sequential prediction of incident duration. They also considered the successive release of features and therefore, predicted the duration for different feature-sets. However, they applied the text analysis approach for this purpose. Their model could generate reliable predictions after 15 min which gradually reduces the mean absolute percentage error from 100% to 40% with elapsed time. In our work, the overall MAPE value varies over time from 61% to 27.58% considering all incidents together. In conclusion, we achieve competitive or better results for predicting traffic incidents duration compared to the state-of-the-art. The results obtained in the existing studies are summarized in Table 3.12.

3.4 Bayesian Prediction of the Incident Duration

Although the data-driven regression methods can predict the duration of the incidents with reasonable precision. However, the predicted values ob-

Table 3.12: Comparison of our results with other studies.

Literature	MAPE values
Araghi <i>et al.</i> [100]	KNN: 41.1%, HBDM: 43.7%
Li <i>et al.</i> [35]	5 – 15 min: 184%, >120 min: 74%, overall: 56%
Ruimin <i>et al.</i> [36]	2 – 15 min: 185.7%, >15 min: 45.4%, overall: 94.7%
Khattak <i>et al.</i> [18]	5 – 15 min: 329%, >120 min: 80%, overall: 214%
Valenti <i>et al.</i> [40]	ANN: 44%, SVR: 36%, KNN: 36%
Qing <i>et al.</i> [43]	KNN: 59.2%, CART: 57.1%, Quantile Regression: 49.1%
Pereira <i>et al.</i> [42]	MAPE varies over time from 100% to 40%
Wei <i>et al.</i> [49]	MAPE in the range of 35% to 45%
Our work	5 – 15 min: 100.9%, 16 – 35 min: 75% – 96%, 36 – 200 min: 20% – 50%, > 200 min: varies over time from 76% to 50%, overall MAPE varies over time from 61% to 27.58%

tained by these methods are subject to uncertainty because the prediction performance varies with different test conditions. Hence, it is important to provide some measure of confidence associated with the forecast duration of the incidents. Such measures can prove to be highly useful in planning a real-time response. To address this issue, we apply the probabilistic methods, such as Bayesian Support Vector Regression (BSVR) [101] and Gaussian Process (GP) [102]. These methods can estimate the variance of prediction errors (denoted as error bars) as the measurement of uncertainty along with the predicted duration of incidents. Moreover, we analyze the sensitivity and specificity for different error tolerance limit to evaluate the detection performance of these methods.

3.4.1 Variation of the Error-bars with Prediction Errors

In this subsection, we investigate the correspondence of the error bars with the predicted incident duration. The error bars represent a measure of con-

confidence associated with the prediction made by the model. A large error bar implies that the model is not confident about that particular forecast and vice versa. For this purpose, we refer to the distribution of the duration of incidents as shown in Fig. 3.10, which shows that the number of incidents with long duration (> 125 minutes) is comparatively small.

Next, we group the incidents into different categories according to their duration, such as 0 – 20 minutes, 20 – 40 minutes, and so on. We calculate the average of the error bars (in minutes) obtained by BSVR and GP for each group and plot them in Fig. 3.12.

Figure 3.12: Average of the error bars (in minutes) associated with different lengths of incidents (in minutes) obtained by BSVR and GP.

Now, Fig. 3.12 shows that the average error bar increases with the incident duration. Therefore, the data shown in Fig. 3.10 and Fig. 3.12 seem to suggest that the regression models are less confident for incidents with longer duration since these incidents are relatively rare, and therefore the methods have less training data for predicting such events. Consequently, on average, the error bars (i.e., confidence intervals) are large for those incidents.

3.4.2 Sensitivity and Specificity Analysis for BSVR and GP

In this subsection, we evaluate the performances of BSVR and GP by analyzing specificity-sensitivity profile. To this end, we consider different tolerance values τ_d of absolute prediction errors, for example $\tau_d = \{2\sigma, 3\sigma\}$; where

σ is the standard deviation of the prediction errors. The prediction errors which are greater than the tolerance limit τ_d are assumed to be high and vice versa. Our objective is to anticipate those big errors with prior knowledge of the error bars. If the magnitude of error bar is higher than a pre-specified threshold, then the system expects that the prediction performed is highly unreliable. This detector threshold is represented by γ_d , where γ_d is the mean of error bars.

There are four possible outcomes: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). The two parameters sensitivity and specificity are defined as follows:

$$\text{Sensitivity} = \frac{\text{number of true positives (TP)}}{\text{number of positive events (TP+FN)}}, \text{ and} \quad (3.15)$$

$$\text{Specificity} = \frac{\text{number of true negatives (TN)}}{\text{number of negative events (TN+FP)}}. \quad (3.16)$$

The only constraint is to keep the False Positive rate (F.P.R.) low ($\leq 30\%$), where

$$\text{F.P.R.} = 1 - \text{Specificity}. \quad (3.17)$$

This particular value of F.P.R. is chosen for the sake of definiteness. The operator can set the F.P.R. during operation accordingly.

Next, the specificity-sensitivity profiles obtained by BSVR and GP are shown in (Fig. 3.13). Our goal is to check if we can obtain high sensitivity with our constraint. The blue line is termed as the no-discrimination line, which represents the performance of a detector that acts as a random outcome generator. It is used as a benchmark in our analysis.

In Fig. 3.13, BSVR can detect around 67% instances of errors for the tolerance level of 3σ , and with this level of sensitivity, around 25% – 30%

Figure 3.13: Specificity-sensitivity profile for the incidents obtained by BSVR and GP.

false alarms are reported (i.e., specificity 70% – 75%). On the other hand, GP detects 70% – 80% instances of prediction error for this much tolerance level and specificity. However, the sensitivity degrades for GP in case of tighter error tolerance.

Finally, we show the locations of training data points and the incidents having large prediction error (true positive and false negative instances) obtained by BSVR on the map of Singapore in Fig. 3.14. We observe that for

Figure 3.14: Location of training data and incidents with large prediction error obtained by BSVR.

the incidents in the vicinity of historical incidents, the regression models are more confident since more training data are available. Therefore, the BSVR

or GP predictor does not anticipate a large prediction error (false negative). By contrast, for an incident that took place far away from historical incidents, the regression model is less confident, and the error bar is large. These incidents do not strongly resemble the training examples. Hence, the system can infer correctly that these incidents will have high prediction error (true positive).

3.5 Conclusion

In this thesis, we have proposed a data-driven approach to forecast the duration of traffic incidents. We have considered the duration reported by the authorities in addition to the effective duration, calculated from the traffic speed and flow data. The proposed incident duration prediction model can work with incomplete real-time traffic information and also dynamically updates the forecasts when new data become available. To this end, we consider the traffic data and incidents record from the expressways of Singapore. We have built the regression models for several combinations of feature sets and performed the prediction at different time instants till the end of the incidents. We find that for the incidents with duration in the range of 36 – 200 minutes, the mean absolute percentage error in predicting the effective as well as reported duration varies in the range of 20% – 50%. Moreover, for the longer duration incidents (greater than 200 minutes), in the beginning, the proposed model has a mean error of 76%, which reduces to 57.55% after 55 minutes (25% improvement) and 40.6% after 105 minutes (46.58% improvement). Overall, we achieve 55.84% prediction error for reported duration and 61% error for effective duration prediction averaged over all the incidents, which improve to 30.02% and 27.58% respectively, with elapsed time. In general, our regression model makes a reliable prediction for all incidents except the lowest duration range. Therefore, the results

obtained by our model are competitive with existing literature.

Chapter 4

Prediction of Queue Length

Overpopulation of cars due to the continuous growth of traffic demand is one of the most crucial challenges faced by expanding cities. As an adverse effect, the number of traffic incidents is rising in the metropolitan areas across the world. Today Intelligent Transportation Systems (ITS) are used in many applications such as incidents duration prediction, modeling, congestion avoidance, etc. to minimize the impact of incidents. These systems collect real-time traffic data with a high temporal resolution from various sources to provide timely information to the drivers about the network state [4] [3]. Although traffic applications usually rely upon information about the current state of a road network [103], ITS can perform tasks more efficiently, by analyzing the predicted future traffic condition alongside current state. When quantifying and predicting the impact of traffic incidents on traffic network performance, there are many traffic variables such as average link speed, flow, etc. which are affected by traffic congestion caused by the incidents and hence, all these variables can be plausible indicators of the congestion. Nevertheless, if the model performs the forecast about average speed or flow of a particular link, the drivers may not be able to interpret the predictions accurately. This is because there is no such generalized rule about these traffic variables for diverse city scale networks. For example, the speed limit of the arterial roads is usually lower than that of expressways. Therefore, the speed will drop less during incidents at arterial roads compared to expressways. Since the real-time traffic data are not accessible to the motorists, they may find it hard to assess the impact of the

incidents precisely from the predicted values of speed or flow. Consequently, the predictions are subject to the interpretation of the individual driver. As such, we consider another traffic variable named queue-length or length of congestion, which is much easily interpretable from the drivers' perspective since the drivers are generally aware of the approximate distance between two given locations or at least they can obtain the information from Google Maps. Therefore, they can estimate how far they are located from the location of the congestion and hence, they can make the impromptu decision. Hence, we quantify the impact of traffic incidents in terms of queue-length in this thesis. We combine the spatial, temporal, and geographical features of the incidents along with real-time traffic data to predict the queue-length, which enables the drivers to choose their route accordingly.

In this chapter, we have developed a dynamic queue length prediction model which performs multi-step prediction to incorporate changing future traffic conditions. In the next section, we have described the data-set. After that, we have explained the steps to determine the queue-lengths at different instants for the historically recorded incidents in the next section. These queue-lengths are the target variables in the prediction stage. Moreover, we have also developed the experimental setups for various types of prediction models in this section. In the subsequent section, we have presented a comparative analysis of the reported and estimated queue-length of the incidents. Besides, we have compared the prediction performances of different types of models. Finally, the last section provides concluding remarks.

The methods and results of this Chapter are explained in [104] and [105].

4.1 Description of the Data

The data-set used in this study is provided by the Land Transport Authority (LTA) of Singapore, which consists of the traffic speed and flow data as well

as a list of traffic incidents that occurred in Aug 2016 - Jan 2017.

The traffic flow rate of a link is defined as the number of vehicles crossing the link per unit time. In Singapore, traffic flow data are recorded by the sensors installed at the end of each road segment. Therefore, the readings that the sensors capture represent the total number of vehicles leaving the road link at every 5 minutes interval, and the unit is vehicles per hour. On the other hand, traffic speed is defined as the average speed of the vehicles traversing a link in kilometers per hour. The expressways in Singapore typically have a speed limit of 90 – 100 kmph. The sensors record the speed values in the individual links in terms of ten discrete speed-bands, each of them spanning 10 kmph. Therefore, it attains a minimum value of 0 and a maximum value of 10.

Moreover, this data-set contains the detailed information of 11,230 incidents that happened on all the expressways of Singapore throughout the time frame from August 2016 to January 2017. The incidents have the following attributes: (1) a unique serial number termed as incident ID, (2) the immediate upstream link ID and coordinates of the incident location, (3) the expressway and its direction along which the incident happened, (4) the start and end time of the incident, (5) the details about closure of adjacent shoulder lane and main carriageway lanes, and (6) the type of incident (vehicle breakdown, accident, etc.). Among them, the categorical features are converted to binary ones using one-hot assignment method, whereas the numerical features are binarized from decimal numbers. Thus, we construct a feature matrix comprising both categorical and numerical features. Besides, there is an additional feature named queue-length in the data where LTA has reported the maximum congestion length during the incidents. However, the length of congestion is a time-varying quantity, and measuring the queue-length for each individual incident requires a more rigorous approach. Therefore, the queue-length has been reported only for 1209 incidents of the

data-set.

There are 10 expressways in the road network of Singapore, each of them comprising 180 – 220 road segments. The expressways are shown in Fig. 4.1 along with their directions. In total, there are 2156 expressway links with an average length of 100 meter. The individual links may have two to five

Figure 4.1: The expressways of Singapore island.

adjacent lanes depending on their locations.

4.2 Methodology

In this section, we describe the approach to compute the queue lengths using the traffic data. Moreover, we develop the prediction models and explain the performance metric used in this study.

4.2.1 Estimation of Queue Length from the Traffic Data

There is no universally accepted definition of an incident's queue-length [106]. In our analysis, we define the queue-length or congestion length

of an incident as the longitudinal distance where some delays are experienced as a consequence of the incident. Therefore, we assume a link or road segment to be affected by an incident if the average speed of the vehicles falls much below the free flow speed, and traffic flow drops abruptly in that link after the incident. In this subsection, we discuss our assumptions regarding the traffic data, and we set the criteria to identify the congested links. Based on those assumptions, we determine the length of the queues during the incidents.

Step 1: In the first step, we describe the experimental set-up for determining the queue-length associated with the incidents.

Let us first assume that an incident is reported to occur at link ℓ for the duration of $T_{\text{rep_start}} - T_{\text{rep_end}}$, where the length of ℓ can vary from 20 meters to 200 meters. Since the traffic data are recorded at 5 minutes interval, we compute the queue-length at every 5 minutes. Therefore, we approximate the start and end time of the incident to the nearest multiple of 5, as given by:

$$t_0 = \left\lfloor \frac{T_{\text{rep_start}}}{5} \right\rfloor * 5, t_L = \left\lceil \frac{T_{\text{rep_end}}}{5} \right\rceil * 5. \quad (4.1)$$

Next, we have to determine the maximum number of upstream links to be taken into consideration for computing the queue-lengths. For that purpose, we list the lengths of the expressways of Singapore in Table 4.1. We observe from the historical records of incidents that the maximum queue-length can grow up to 14.5 km which indicates that in some cases the congestion can affect the entire length of an expressway. Therefore, to avoid any loss of information, we study all upstream links from the incident location to the extreme end of that expressway whether they were congested or not.

Step 2: Since traffic incidents are non-recurrent phenomena unlike the regular peak-hour congestion, we compare the traffic data recorded at the individual link on the day of the incident with that of non-incident days to understand the impact of the incidents. In this step, we discuss which

Table 4.1: Length of the Expressways in Singapore [2].

Expressways	Length
AYE	26.5 km
BKE	10 km
CTE	15.8 km
ECP	20 km
KPE	12 km
KJE	8 km
MCE	5 km
PIE	42.5 km
SLE	10.8 km
TPE	14 km

metrics we choose for comparing the speed data and flow data of different days.

We refer to the consecutive upstream links of ℓ by ℓ_i , where $i \in \{1, 2, 3, \dots\}$ and each instant by t_j at five minutes interval, where $j \in \{0, 1, 2, \dots, L\}$. From traffic data-set, we obtain the traffic speed $s_{\text{inc}}(\ell_i, t_j)$ and flow value $f_{\text{inc}}(\ell_i, t_j)$ of the day of incident for each time instant t_j at link ℓ_i . On the other hand, we denote the average speed and flow value of the non-incident days by $s_{\text{ninc}}(\ell_i, t_j)$ and $f_{\text{ninc}}(\ell_i, t_j)$ respectively, which are calculated from the traffic data of the same day but other weeks when no incident happened. We pick two different measures of central tendency for traffic speed and flow, respectively.

1) Since the flow data are continuous and can attain any value, the traffic flow values are skewed and asymmetrical. Therefore, we compute the median of traffic flow of the non-incident days and the percentage deviation of $f_{\text{inc}}(\ell_i, t_j)$ about this median.

Let us assume that the traffic flow in link ℓ_i at the time instant t_j on the non-incident days are $f_{\text{ninc}}^{w_1}(\ell_i, t_j), \dots, f_{\text{ninc}}^{w_p}(\ell_i, t_j)$, considering there are p other

weeks in the entire six months. The median, i.e., 50th percentile of these flow values is given by:

$$f_{\text{ninc}}(\ell_i, t_j) = \text{median} (f_{\text{ninc}}^{w_1}(\ell_i, t_j), f_{\text{ninc}}^{w_2}(\ell_i, t_j), \dots, f_{\text{ninc}}^{w_p}(\ell_i, t_j)), \quad (4.2)$$

and the deviation about the median can be expressed by:

$$d_{f(\ell_i, t_j)} = \frac{(f_{\text{inc}}(\ell_i, t_j) - f_{\text{ninc}}(\ell_i, t_j))}{f_{\text{ninc}}(\ell_i, t_j)}. \quad (4.3)$$

2) Since the speed data obtained from the LTA are banded ranging from 1 – 10, the values are not much skewed. Therefore, we compute the mean of traffic speed of the non-incident days as the measure of central tendency and calculate the deviation of $s_{\text{inc}}(\ell_i, t_j)$ about this mean.

Let us assume that the traffic speed in link ℓ_i at the time instant t_j on the non-incident days are $s_{\text{ninc}}^{w_1}(\ell_i, t_j), \dots, s_{\text{ninc}}^{w_p}(\ell_i, t_j)$, considering there are p other weeks in the entire six months. The mean of these speed-band values is:

$$s_{\text{ninc}}(\ell_i, t_j) = \frac{s_{\text{ninc}}^{w_1}(\ell_i, t_j) + \dots + s_{\text{ninc}}^{w_p}(\ell_i, t_j)}{p}, \quad (4.4)$$

and the mean deviation can be expressed by:

$$d_{s(\ell_i, t_j)} = \frac{(s_{\text{inc}}(\ell_i, t_j) - s_{\text{ninc}}(\ell_i, t_j))}{s_{\text{ninc}}(\ell_i, t_j)}. \quad (4.5)$$

Thus, we obtain the values of $d_{s(\ell_i, t_j)}$ and $d_{f(\ell_i, t_j)}$ for each individual link ℓ_i at each time instant t_j , where $i \in \{1, 2, 3, \dots\}$ and $j \in \{0, 1, 2, \dots, L-1, L\}$.

Step 3: Next, we aim to determine from the speed-flow profiles of the individual links if they were congested or not because of the incident. Moreover, if a link was congested, we have to find out how long the traffic slow-down existed in that link. To this end, we develop the Queue-Length Estimation (QLE) algorithm (Algorithm 2) which describes how we define a

link to be congested and consequently, we can determine the queue-length at each instant for an individual incident.

We now explain Algorithm 1 in the rest of this step and the following step. First, we assume that if the link ℓ_i is congested, there should be an abrupt and significant drop in both traffic speed and flow, which indicates the start of congestion in that particular link. Since traffic data are very random by nature, the drop should be substantial to ensure that the variation does not come from the randomness of the data-set, rather it is the consequence of the incident. In order to verify the condition, we evaluate the differences of the speed-deviations $d_{s(\ell_i, t_{j+1})}$ and $d_{s(\ell_i, t_j)}$, and the flow-deviations $d_{f(\ell_i, t_{j+1})}$ and $d_{f(\ell_i, t_j)}$ at each value of j , where $j \in \{0, 1, 2, \dots, L-1\}$. Moreover, we compute the time instant t_j when these differences attain the minimum (or, negative maximum). Mathematically, if we denote the differences by $\Delta_{s(\ell_i, t_j)}$ and $\Delta_{f(\ell_i, t_j)}$ respectively, we can write them as:

$$\begin{aligned}\Delta_{s(\ell_i, t_j)} &= d_{s(\ell_i, t_{j+1})} - d_{s(\ell_i, t_j)}, \quad \text{and} \\ \Delta_{f(\ell_i, t_j)} &= d_{f(\ell_i, t_{j+1})} - d_{f(\ell_i, t_j)}.\end{aligned}\tag{4.6}$$

If the minimum values of $\Delta_{s(\ell_i, t_j)}$ and $\Delta_{f(\ell_i, t_j)}$ are $m_{1_{s(\ell_i)}}$ and $m_{1_{f(\ell_i)}}$ respectively, we want to find the time instants $t_{\min_{s(\ell_i)}}$ and $t_{\min_{f(\ell_i)}}$, which are as follows:

$$\begin{aligned}t_{\min_{s(\ell_i)}} &= t_j : \Delta_{s(\ell_i, t_j)} = m_{1_{s(\ell_i)}}, \quad \text{and} \\ t_{\min_{f(\ell_i)}} &= t_j : \Delta_{f(\ell_i, t_j)} = m_{1_{f(\ell_i)}}.\end{aligned}\tag{4.7}$$

However, to satisfy the condition of being congested, $m_{1_{s(\ell_i)}}$ and $m_{1_{f(\ell_i)}}$ should attain large negative values. How large should the negative values be in order to ensure that the drop is due to the congestion and not any random traffic variation? For this purpose, we first sort the values of $\Delta_{s(\ell_i, t_j)}$ and $\Delta_{f(\ell_i, t_j)}$ separately, obtained at different t_j . We assume that if the drop in the speed and flow are due to the randomness of the data-set, there should not be any specific pattern in the profiles, i.e., the randomness of

Algorithm 2 Queue-Length Estimation (QLE) Algorithm

```

1: for each link  $\ell_i$  do
2:   for  $j = 1: L - 1$  do
3:     Compute  $\Delta_{s(\ell_i, t_j)} = d_{s(\ell_i, t_{j+1})} - d_{s(\ell_i, t_j, 1)}$ 
4:     Compute  $\Delta_{f(\ell_i, t_j)} = d_{f(\ell_i, t_{j+1})} - d_{f(\ell_i, t_j)}$ 
5:   end for
6:    $m_{1_{s(\ell_i)}} \leftarrow \min(\Delta_{s(\ell_i, t)}, 1)$  /*where  $\min(S, n)$  indicates the  $n^{th}$  smallest
   element of  $S$ .*/
7:    $m_{2_{s(\ell_i)}} \leftarrow \min(\Delta_{s(\ell_i, t)}, 2)$ 
8:    $m_{1_{f(\ell_i)}} \leftarrow \min(\Delta_{f(\ell_i, t)}, 1)$ 
9:    $m_{2_{f(\ell_i)}} \leftarrow \min(\Delta_{f(\ell_i, t)}, 2)$ 
10:  if  $m_{1_{s(\ell_i)}} < 0$  and  $m_{1_{f(\ell_i)}} < 0$  then
11:    for  $j = 1: L$  do
12:      if  $\Delta_{s(\ell_i, t_j)} = m_{1_{s(\ell_i)}}$  then
13:         $t_{\min_{s(\ell_i)}} \leftarrow t_j$ 
14:      end if
15:      if  $\Delta_{f(\ell_i, t_j)} = m_{1_{f(\ell_i)}}$  then
16:         $t_{\min_{f(\ell_i)}} \leftarrow t_j$ 
17:      end if
18:    end for
19:     $T_{\text{start}}(\ell_i) \leftarrow \min(t_{\min_{s(\ell_i)}}, t_{\min_{f(\ell_i)}})$ 
20:    if  $t_j > T_{\text{start}}(\ell_i)$  and  $d_{s(\ell_i, t_j)} > 0$  and  $d_{f(\ell_i, t_j)} > 0$  then
21:       $T_{\text{end}}(\ell_i) = t_j$ 
22:    end if
23:    Compute  $\delta_{s(\ell_i)} = m_{2_{s(\ell_i)}} - m_{1_{s(\ell_i)}}$ 
24:    Compute  $\delta_{f(\ell_i)} = m_{2_{f(\ell_i)}} - m_{1_{f(\ell_i)}}$ 
25:  end if
26: end for
27:  $P_{10_s} \leftarrow \text{PCTL}_{10\%}(\delta_s)$ 
28:  $P_{10_f} \leftarrow \text{PCTL}_{10\%}(\delta_f)$ 
29: for each link  $\ell_i$  do
30:   if  $\delta_{s(\ell_i)} > P_{10_s}$  and  $\delta_{f(\ell_i)} > P_{10_f}$  then
31:     for  $j = 1: L$  do
32:       if  $t_j \geq T_{\text{start}}$  and  $t_j \leq T_{\text{end}}$  then
33:          $QL(t_j) \leftarrow QL(t_j) + \ell_i$ 
34:       end if
35:     end for
36:   end if
37: end for

```

the traffic data would cause a haphazard variation in the speed and flow as opposed to an abrupt and sharp dip (initiation of congestion) followed by a sharp rise (dissipation of the congestion) in the profiles. Let us consider an example to explain it. We show the speed-difference graphs of two different links (upstream link 1 and link 20 according to their location) in Fig. 4.2 for a particular incident. We observe for link 1 that the speed-difference

Figure 4.2: Variation of speed-difference in two different upstream links for a particular incident.

falls sharply after 20 minutes, and there is no other such sharp dip in the entire graph. Therefore, we assume that the congestion started in link 1 after 20 minutes. On the other hand, for link 20 we cannot find any such abrupt change in the entire graph. The variations in the speed-differences are almost in the same range for the entire period. Therefore, we can conclude that link 20 was not congested, and the variations in link 20 are due to the randomness of the traffic data, as can be seen in Fig. 4.2. In this context, we try to obtain a more generalized mathematical rule which is satisfied by link 1 but not by link 20 in the previous example. To this end, we compare the 1st minimum and the 2nd minimum of $\Delta_{s(\ell_i, t_j)}$ and $\Delta_{f(\ell_i, t_j)}$ individually for each link ℓ_i . If we observe that the 1st minimum is significantly smaller

than the 2nd minimum in both cases, we can conclude that the speed and flow of the link ℓ_i dropped because of congestion. If we refer to the previous example, we observe in the first graph of Fig. 4.2 that $\Delta_{s(\ell_1, t_4)}$ (i.e., $d_{s(\ell_1, t_4)} - d_{s(\ell_1, t_5)} = -0.57$) is the first minimum, which is significantly smaller than the 2nd minimum $\Delta_{s(\ell_1, t_2)}$ (i.e., $d_{s(\ell_1, t_2)} - d_{s(\ell_1, t_3)} = -0.12$). On the other hand, for link 20 (second graph) the 1st minimum $\Delta_{s(\ell_{20}, t_6)}$ ($= -0.285$) and 2nd minimum $\Delta_{s(\ell_{20}, t_0)}$ ($= -0.195$) are close to each other. Therefore, we compute the difference of the 2nd minimum and the 1st minimum of $\Delta_{s(\ell_i, t_j)}$ and $\Delta_{f(\ell_i, t_j)}$ separately, for the individual upstream link ℓ_i . Let us assume that the differences are $\delta_{s(\ell_i)}$ and $\delta_{f(\ell_i)}$, for each link ℓ_i . Next, we choose the 10th percentile (i.e. the value below which 10% of the observations can be found) of the differences $\delta_{s(\ell_1)}, \delta_{s(\ell_2)}, \delta_{s(\ell_3)}, \dots$ and $\delta_{f(\ell_1)}, \delta_{f(\ell_2)}, \delta_{f(\ell_3)}, \dots$ as the respective minimum cutoff values for speed and flow. These cutoffs are selected by trial and error method. Since we have the reported queue-lengths available for 1,209 incidents, we compute the correlation coefficient of the reported and estimated queue-lengths for different cutoffs. We plot the values of the coefficients with different cutoff values in Fig. 4.3 and choose the best one as the optimum cutoff (10th percentile).

Therefore, the link ℓ_i for which both $\delta_{s(\ell_i)}$ and $\delta_{f(\ell_i)}$ are above the respective cutoff values is assumed to be congested. If either one of them or both are below the corresponding cutoff, we consider the link to be unaffected by the incident. Thus, we can determine if a particular link ℓ_i was congested or not because of the incident.

Ideally, $t_{\min_s(\ell_i)}$ should be equal to $t_{\min_f(\ell_i)}$, and this is the first threshold point (denoted by $T_{\text{start}}(\ell_i)$) when the congestion started to grow in that particular link ℓ_i . However, in reality these two time instants might not be same always. Therefore, we define $T_{\text{start}}(\ell_i)$ as:

$$T_{\text{start}}(\ell_i) = \min(t_{\min_s(\ell_i)}, t_{\min_f(\ell_i)}). \quad (4.8)$$

Figure 4.3: Variation of correlation coefficient of the reported and estimated queue-lengths for different cutoff values.

Thus, we examine each upstream link ℓ_i if it satisfies the above-mentioned condition and if it does, we determine the first threshold point $T_{\text{start}}(\ell_i)$ of link ℓ_i .

In the similar way, we determine the time instant when both traffic speed and flow deviation $d_{s(\ell_i, t_j)}$ and $d_{f(\ell_i, t_j)}$ at link ℓ_i are close to zero, i.e., both speed and flow of the day of the incident are approximately same as non-incident days. We can write it as:

$$T_{\text{end}}(\ell_i) = t_j : t_j > T_{\text{start}}(\ell_i), d_{s(\ell_i, t_j)} \geq 0, d_{f(\ell_i, t_j)} \geq 0. \quad (4.9)$$

Therefore, the link ℓ_i was congested for the duration of $T_{\text{start}}(\ell_i)$ to $T_{\text{end}}(\ell_i)$.

Step 4: The last step is to compute the queue-length at each time instant. In the previous steps, we can determine which links were congested at each instant t_j . Since we have the length of an individual link ℓ_i , we add up the lengths of the congested links to obtain the queue-length at each time instant t_j .

Let us assume that the links congested at a particular instant t_j are $\ell_{c_1}, \ell_{c_2}, \dots, \ell_{c_k}$, where $\{\ell_{c_1}, \ell_{c_2}, \dots, \ell_{c_k}\} \subseteq \{\ell_1, \ell_2, \ell_3, \dots\}$. Therefore, the queue-length at t_j can be expressed by:

$$Q(t_j) = \sum_{n=1}^k \ell_{c_n}. \quad (4.10)$$

Thus, we compute the queue-length or length of congestion at an interval of 5 minutes during the entire span of the incidents.

4.2.2 Experimental Setup and Model Development for Prediction

In order to perform the prediction of queue-length, we develop different models and compare their performances in this subsection. At first, we apply the traditional regression methods such as Multi-Layer Perceptron (MLP) [91], Treebagger [92], and Support Vector Regression (SVR) [93] to build individual model. Next, we propose a hybrid classification-regression model, where we use the traditional classification and regression methods in the model. Last but not the least, we build a deep learning model using LSTM and GRU network individually for queue-length prediction. In this subsection, we describe the experimental setup of each of these three types of models.

4.2.2.1 Traditional Regression Model

For the traditional regression model, we first cluster the incidents into different groups and then train different model for each individual group. For this purpose, the training data points are divided into different clusters using K -means clustering algorithm [96]. To determine the optimum number of clusters, we analyze the variation of intra-cluster distance with the number

of clusters K . The value of K where the largest drop occurs in the intra-cluster distance value is considered to be the optimum number of clusters. In the next step, each testing data point is assigned to its nearest cluster, and thus the queue-length of the particular incident is forecast by applying the model of that nearest cluster. The second step is repeated for all incidents in the test data-sets. In this study, we apply the three-fold cross-validation to choose the training and test data-sets. Therefore, all the steps are iterated for each of the three training and test data-sets. In this way, we build separate regression models using training data at each 10 minute elapse from the starting point of the incidents. Using these models, the queue-length is predicted after 10 minutes, 20 minutes, 30 minutes, etc. until the incidents end in real-time. The training and testing steps of the proposed queue-length prediction model are shown in Algorithm 3.

Algorithm 3 Traditional Regression Model for Queue-length Prediction

Training step:

- 1: **for** $t = T_{\text{start}} : T_{\text{end}}$ by 10 min **do**
- 2: Cluster the incidents based on the features (K-means clustering)
- 3: Build regression model for each cluster
- 4: **end for**

Testing step:

- 5: **while** the incident ends **do**
 - 6: Choose nearest cluster based on Euclidean distance
 - 7: Predict the queue-length using the regression model built by that cluster
 - 8: **end while**
-

In this study, we apply the well-known traditional machine learning methods, such as Multi-Layer Perceptron (MLP) [91], Treebagger [92], and Support Vector Regression (SVR) [93] for predicting the queue-length of the incidents. We select the optimal parameters for each method through 10-fold cross-validation. We use an ensemble of seven trees for the Treebagger model and five hidden layers for the MLP network. Besides, the radial basis

function is used as the kernel for the SVR model.

4.2.2.2 Cascaded Classification-Regression Model

Next, we introduce a hybrid classification-regression model. At first, the model acts as a binary classifier. If the queue length of an incident is predicted to be higher than a predetermined threshold value, we assume the congestion to be impactful. Therefore, in the second step, the model performs regression analysis to predict the queue length of these incidents for fine-tuning. On the other hand, if the predicted queue length is less than the threshold value, we ignore that incident. We show the flowchart of the proposed model in Fig. 4.4.

Figure 4.4: Flow-chart of the cascaded classification-regression model.

For classification purpose, we employ three methods, such as Classification And Regression Tree (CART) [90], Support Vector Machine [59], and Treebagger [107]. In the next step, we apply the same regression methods as the traditional regression model (refer to the section 4.2.2.1). The training

and test data-sets are selected by 3-fold cross-validation.

4.2.2.3 Deep Learning Model

Next, we describe the architecture of the deep learning model. At first, we introduce the two deep learning methods used in this study.

1. Long Short-Term Memory Network (LSTM): A Recurrent Neural Network (RNN) is one type of artificial neural network which can save and retrieve its memory with the feedback loops [108]. However, RNN utilizes only the immediate previous state for predicting the current state, i.e., it can handle only short-term memory, whereas sometimes it is important for the model to learn for a longer period, such as for time-series data. Here lies the advantage of Long Short-Term Memory Network since it is capable of preserving the long-term dependencies as well [109] [110].

The block diagram of an LSTM unit is shown in Fig. 4.5 [1]. An LSTM unit has three major components: 1) The sigmoid layer selectively memorizes the previous outputs, i.e., it receives the input X_t and h_{t-1} and chooses which part of the memory it should forget and thus, it enables the unit to discard unnecessary information. 2) Next, the LSTM unit saves some information from the current input X_t in the memory. A tanh layer combines the current input with the output from the last unit h_{t-1} and computes a vector containing all possible outputs. This is multiplied with the output of the sigmoid layer to update the memory c_{t-1} and obtain the new cell state c_t . 3) The final part of the unit is a combination of tanh and sigmoid function which generates the output of the unit from the previous output h_{t-1} , current input X_t , and the current cell state c_t [111]. Fig. 4.6 shows the unrolled structure of the LSTM units. The same network is trained by the inputs at different time-steps, and each stage passes

Figure 4.5: The block diagram of an LSTM unit [1].

the memory to its successor.

Figure 4.6: The visualization of LSTM units.

2. Gated Recurrent Unit (GRU): Gated Recurrent Unit is a variant of Recurrent Neural Network which can store the long-term memory like LSTM, although the structures of these two networks are different. A GRU unit does not have any forget gate; instead, it comprises an update gate and a reset gate [112]. Therefore, GRU reveals the

entire memory for predicting the present state, unlike LSTM. Since the network of GRU is simpler compared to LSTM, the number of trainable parameters is very less and hence, the time complexity of GRU is low [113].

Next, we show the architecture of the prediction model using LSTM network in Fig. 4.7. Our feature set consists of two types of features, tem-

Figure 4.7: Block diagram of the queue-length prediction model using the LSTM network.

poral (speed, flow, etc.) and static (expressway, direction, etc.). Since the LSTM network has an explicit capability to learn the temporal pattern of the data-set, we feed the time-dependent inputs only to the LSTM layers of the model. On the other hand, the static features are directly fed in the fully connected layers (dense layers). The hidden layers of the LSTM network comprise two LSTM and four dense layers sequentially. The output of the last LSTM layer together with the static inputs are connected to the first dense layer. The last one is the output layer, which gives the predicted

queue-length. To avoid overfitting, we add three dropout layers in different stages with a dropout rate of 40%, 20%, and 10%, respectively. The first dropout layer is in between the last LSTM and the first dense layer, whereas the other two dropout layers are added between the fully connected layers. We use Rectified Linear Units (RELU) as the activation function of the dense layers. We build the GRU network by replacing the LSTM layers with GRU layers.

Figure 4.8: The three dimensions of the input data for the LSTM network.

The input to the LSTM (or, GRU) layers must be three-dimensional as shown in Fig. 4.8. The dimensions are 1) Samples - The number of samples in each batch, which can vary from one batch to another. In a particular batch, each incident is one sample in our work. 2) Time-Steps - The time-steps represent how many previous instants are considered for each sample in a particular batch. It should be the same for all samples within a single batch; however, there is no such constraint between different batches. As the resolution of our traffic data is five minutes, and the queue-length is forecast at each ten minutes interval, the number of previous time

steps since the start of the incidents are 2 for 10 minute prediction (0 min and 5 min), 4 for 20 minute prediction (0 min, 5 min, 10 min, and 15 min), 6 for 30 minute prediction (0 min, 5 min, 10 min, 15 min, 20 min, and 25 min), and so on. 3) Features - The features are time-dependent attributes. The number of features should be the same for each sample of all batches. We construct 32 features considering different combinations of the speed-flow data from the neighboring links. To explain these 32 features, we refer to the notations and definitions described in the subsection 4.2.1. For each upstream link ℓ_i at each time-instant t_j , we take the traffic speed $s_{\text{inc}}(\ell_i, t_j)$, traffic flow $f_{\text{inc}}(\ell_i, t_j)$, speed-difference $d_{s(\ell_i, t_j)}$, and flow-difference $d_{f(\ell_i, t_j)}$ of the day of incident into account. Moreover, since the number of upstream neighboring links is not the same for each incident whereas the number of features should be fixed, we do not consider each upstream link as an individual feature. Instead, we construct the features as the weighted combination of the upstream links. For example, the feature corresponding to the traffic speed values can be represented by:

$$\mathcal{F}_{s_{\text{inc}}} = \sum_i w_{\ell_i} \cdot s_{\text{inc}}(\ell_i, t_j), \quad (4.11)$$

where w_{ℓ_i} is the weight of the upstream link ℓ_i . Now, we choose two inverse-distance weighting functions so that the weights are inversely proportional to the distance of the upstream links from the incident location:

$$w_{\ell_i} = \frac{1}{\text{dist}(\ell, \ell_i)^p}, \quad (4.12)$$

and

$$w_{\ell_i} = e^{-q \cdot \text{dist}(\ell, \ell_i)}, \quad (4.13)$$

where $p \in \{0.05, 0.1, 0.2, 0.4, 0.8\}$, and $q \in \{0.02, 0.05, 0.08\}$. Thus, we construct eight features (considering five values of p and three values of q)

for each attribute with different weightage to the upstream links. Since we have four attributes in total ($s_{inc}(\ell_i, t_j)$, $f_{inc}(\ell_i, t_j)$, $d_{s(\ell_i, t_j)}$, and $d_{f(\ell_i, t_j)}$), the total number of features is 32 for each sample at each time-step. Thus, we reshape our spatiotemporal features as a three-dimensional tensor. Since the influence of the incident spreads both spatially and temporally, we consider the temporal variation in the second dimension of the input data (time-steps) and spatial variation in the third dimension (features). Thus, we feed the LSTM layers with different batches of three-dimensional input data (as described above), where each batch corresponds to different elapsed time. With increasing elapsed time, the number of previous time-instants (i.e., size of the second dimension) increases, whereas the sample size (i.e., size of the first dimension) decreases because we stop the prediction for the incidents which have already ended. Therefore, the first two dimensions are non-identical for different batches.

In the first LSTM layer of the prediction model, an output is transmitted to the subsequent layer at each time-step ($h_0, h_1, h_2, \dots, h_t$ as shown in Fig. 4.6). However, in the next LSTM layer, only the final output is transferred to the fully connected layer (only h_t in Fig. 4.6). Therefore, the second LSTM layer converts the temporal inputs into static outputs and hence, they can be combined with other static features in the succeeding layers. Since the static features are time-independent, we feed them simply as feature arrays to the fully connected layers where the time-steps are not required. The hyper-parameters used in the training step are mentioned in Table 4.2.

The difference of the traditional or cascaded model with the deep learning model is that we input all features together for the first two types of models, whereas for deep learning networks the temporal and static features are fed separately in two different stages. Moreover, we build independent regression model at every ten minutes elapse for the traditional and cascaded model,

Table 4.2: The hyper-parameters used in the training step for LSTM and GRU network.

Parameter	Value
Batch size	150
Optimizer	‘adam’
Loss function	mean squared error
Activation function	‘relu’
Training epochs	optimized on training set
Learning rate	optimized on training set

whereas for the deep learning architecture a single model is trained with different batches of data together, and the prediction is performed using the same model at different instants.

4.2.3 Evaluation Metric

To assess the performance of different methods, we choose the Mean Absolute Percentage Error (MAPE) as our evaluation metric, which is defined by:

$$\text{MAPE} = \frac{100}{N} \cdot \sum_{i=1}^N \left| \frac{e_i}{q_i} \right|, \quad (4.14)$$

where N is the total number of incidents, and e_i is the difference between the actual and predicted queue-length q_i and $\hat{q}_i$ respectively:

$$e_i = q_i - \hat{q}_i. \quad (4.15)$$

4.3 Results

In this section, we illustrate a comparative analysis of the reported and estimated queue-length of the incidents. Moreover, we also compare the prediction performances of different regression methods.

4.3.1 Comparison of the Reported and Estimated Queue-length of the Incidents

In this subsection, we provide a comparative analysis of the reported queue-lengths available from LTA and our estimated queue-lengths. However, measuring queue-length in real-time for every single incident is a challenging task, and it incurs quite a large amount of resources. Therefore, the reported queue-length is available for only 10.76% of the total number of incidents from the data-set. In the following, we show the histograms of both reported and estimated maximum queue-lengths.

Figure 4.9: The histograms and fitted distributions of the reported and estimated queue-lengths.

In this analysis, we fit different distributions to the histograms and find that the log-logistic distribution fits them the best. Therefore, we show the histograms fitted with log-logistic curves in Fig. 4.9 for reported and estimated queue-lengths separately. The first histogram is constructed by

1,209 incidents, whereas the second histogram represents the queue-lengths of 11,230 incidents. The mean, median, and mode values of reported queue-lengths are 2.37 km, 2 km, and 2 km respectively, whereas the values for estimated queue-lengths are 1.5 km, 1.14 km, and 915 m respectively. Although the histograms follow the same type of distribution as can be seen in Fig. 3.10, the statistical measures are much larger for reported queue-lengths. This is also reflected in Fig. 3.10 since the peak of the first histogram is a bit right-shifted compared to the second histogram. In practice, LTA usually reports the queue-lengths for the incidents which cause heavy congestion and significant traffic disruption on the expressways. Hence, the queue-length has not been reported for many incidents where the length of congestion was short, typically less than 1000 meters. Consequently, the mean, median, and mode values of the reported queue-lengths are higher. We show the scatter plot of the available reported queue-lengths and the corresponding estimated queue-lengths in Fig. 4.10. The correlation coefficient of the

Figure 4.10: Scatter diagram of estimated maximum queue-length (in meter) vs. reported maximum queue-length (in meter) for 1209 incidents.

reported and estimated queue-length is 0.917. Therefore, the reported val-

ues of maximum queue-length do not differ much from the values estimated from the speed-flow data.

4.3.2 Performance Evaluation of Different Types of Models

In this subsection, we evaluate the performances of different queue-length prediction models. All experiments are performed by a PC (CPU: Intel(R) Core(TM) i7-4770 CPU @3.40 GHz, 8 GB RAM).

4.3.2.1 Traditional Regression Model

At first, we compare the MAPE values obtained by the traditional regression methods (described in section 4.2.2.1). The errors are computed by averaging over all incidents at 10 minutes interval using these methods individually, and we mention the results in Table 4.3.

Table 4.3 shows that among the traditional machine learning methods

Table 4.3: Variation of MAPE values (in percentage) with elapsed time obtained by traditional regression methods in predicting the queue-length of the incidents.

Methods	10 min	20 min	30 min	40 min	50 min	60 min	80 min	100 min	120 min
Treebagger	128.83	122.87	114.56	108.81	99.83	98.42	94.55	102.6	105.84
MLP	105.04	103.74	99.29	93.15	86.81	85.24	86.36	88.97	90.67
SVR	93.06	90	86.63	82.03	83.88	72.66	76.53	81.88	83.27

SVR performs the best. Therefore, for the cascaded classification-regression model, only SVR method is used in the regression step.

4.3.2.2 Cascaded Classification-Regression Model

Next, we analyze the performance of the hybrid model (described in section 4.2.2.2) for different classification methods. We vary the value of the threshold α as 250 m, 500 m, and 1000 m, and investigate the variation in the

errors accordingly. We have already mentioned the results achieved solely by regression model without classifying the incidents before the regression step (i.e., $\alpha = 0$) in Table 4.3. Therefore, we show the MAPE values obtained by the cascaded model for nonzero threshold values only in Table 4.4.

Table 4.4: Variation of MAPE values (in percentage) with elapsed time obtained by cascaded classification-regression model in predicting the queue-length of the incidents.

		10 min	20 min	30 min	40 min	50 min	60 min	80 min	100 min	120 min
CART-SVR	$\alpha = 250$ m	91.2	89.7	85.93	81.4	76.1	70.38	68.19	72.9	76.23
	$\alpha = 500$ m	85.6	82.2	79.37	76.48	70.13	62.5	64.21	67.23	69.2
	$\alpha = 1000$ m	76.42	74.18	71.53	68.3	63.1	58.4	55.13	61.8	60.13
SVM-SVR	$\alpha = 250$ m	86.6	83.9	79.23	75.46	70.3	67.2	66.47	68	72.1
	$\alpha = 500$ m	80.34	78.21	74.7	71.6	68.4	63.42	61.85	62.1	66.49
	$\alpha = 1000$ m	70.2	68.3	66.26	63.5	60.18	57.3	53.1	59.1	62.1
Treebagger-SVR	$\alpha = 250$ m	84.3	80.17	77.44	74.32	67.1	62.6	64.7	68.2	70.89
	$\alpha = 500$ m	78.5	75.23	71.6	65.48	63.12	61.5	57.34	59.7	63.2
	$\alpha = 1000$ m	68.4	65.78	63.12	59.25	58.8	55.2	54.32	57.7	59.3

We observe in Table 4.4 that the values of the errors decrease with increase in the threshold. However, with increasing α the precision of the model is compromised because we discard those incidents for which the queue length is predicted to be less than α . Therefore, for higher α we fail to predict the exact queue length of a larger proportion of incidents. Hence, there is a trade-off between prediction accuracy and the range of precise operation of the model.

Overall, the cascaded model of Treebagger in the classification stage, and SVR in the regression stage performs the best.

4.3.2.3 Deep Learning Model

The deep learning models (described in the section 4.2.2.3) are built using Keras framework [114] with Tensorflow backend [115]. The results obtained by the two deep learning algorithms LSTM and GRU are mentioned in

Table 4.5. Since the number of trainable parameters is less for GRU due to

Table 4.5: Variation of MAPE values (in percentage) with elapsed time obtained by the deep learning methods in predicting the queue-length of the incidents.

Methods	10 min	20 min	30 min	40 min	50 min	60 min	80 min	100 min	120 min
LSTM	73.7	62.58	53.54	46.16	43.68	45.6	49.9	56.46	53.03
GRU	78.4	68.24	57.37	55.36	53.65	52.34	58.71	61.77	62.52

the simpler network structure, LSTM performs slightly better on an average.

4.3.2.4 Overall Analysis of Different Models

Although the cascaded regression model has performed better than the traditional regression model, the former one has certain limitations. While performing the prediction using cascaded model, a certain percentage of incidents gets discarded in the classification stage. Consequently, the accuracy of the cascaded model largely depends on the accuracy of the classification stage. Therefore, we opt to build a model which can perform the prediction reliably without discarding any incident irrespective of the length of the queue. From Table 4.3, Table 4.4, and Table 4.5, we find that the deep learning model outperforms other models significantly. Therefore, in the next subsection, we present the detailed results obtained by the deep learning model only.

Moreover, we observe in the previous section that the error values improve with elapsing time for all the models. Since we can incorporate more features corresponding to the traffic speed and flow data with elapsing time, there is a significant improvement in prediction error. However, the number of samples drastically decreases as time elapses since many incidents get cleared with the advancement of time and the duration of all the incidents is not equal (for example, 1,000 incidents having a duration longer than 120 minutes compared to 10,919 incidents longer than 10 minutes).

Consequently, the size of the available training data is small and hence, the prediction errors deteriorate, especially after 60 minutes.

4.3.3 Prediction of Queue-length for Different Categories of Incidents Using LSTM Model

In this subsection, we determine whether there is a relation between the variation of MAPE values and the duration of the incidents. To this end, we divide the incidents into different classes based on their duration, such as 11 – 20 minutes, 21 – 30 minutes, and so on. Next, we compare the MAPE values obtained for different classes of incidents by the LSTM neural network in Table 4.6. The rows represent the classes, and the columns indicate the elapsed time. We report the error values for each particular class at an interval of 10 minutes till the end of the shortest incident of that class. For example, the lengths of the shortest incidents in the first three classes are 11 minutes, 21 minutes, and 31 minutes, respectively. Therefore, we mention the errors for these classes until 10 minute, 20 minute, and 30 minute, respectively. Table 4.6 shows that the error values are significantly

Table 4.6: Variation of MAPE values (in percentage) with elapsed time obtained by the LSTM network for different categories of incidents based on their duration.

	10 min	20 min	30 min	40 min	50 min	60 min	80 min	100 min	120 min
11-20 min	101.71	–	–	–	–	–	–	–	–
21-30 min	93.7	88.61	–	–	–	–	–	–	–
31-40 min	75.64	64.13	62.98	–	–	–	–	–	–
41-50 min	81.04	69.34	58.68	52.1	–	–	–	–	–
51-60 min	70.54	57.6	51.21	56.56	45.94	–	–	–	–
61-80 min	73.5	61.45	51.35	44.06	48.26	45.83	–	–	–
81-100 min	67.37	57.3	41.54	42.12	53.3	49.93	45.92	–	–
101-120 min	69.42	57.07	52.65	46.93	43.31	41.35	52.43	58.47	–
Rest	75.47	66.2	59.76	45.68	33.86	39.36	48.65	47.3	53.03

high (above 90%) for the first two categories of incidents (lower duration).

On the other hand, for rest of the incidents, the errors are in the range of 70% – 80% at first, which improve to 45% – 60% at the end of prediction. Therefore, the errors improve significantly with elapsing time for incidents with the duration longer than half an hour. Since we consider a larger set of features from traffic data, the LSTM network performs better as time elapses. However, since the number of samples in the last few categories is comparatively low, the performance of the LSTM method degrades after 60 minutes.

Moreover, we observe at the beginning of prediction (after 10 minutes elapsed) that the errors are higher for the first two classes of incidents, although the number of features at a particular instant is same for all classes. This is because the impact of these incidents lasted for less than half an hour in total, which includes both the progression and dissipation phase of the queue. In the context of queuing theory, if the development and dissipation of the queue are assumed as a birth-death process [116], the prediction model has to capture the pattern of the entire birth-death process within such a short period. Since the dynamics of the birth process and death process are different, the model can not forecast the queue-length accurately for the short-duration incidents. On the contrary, for incidents having the duration longer than 30 minutes, the model has sufficient time to learn the birth and death process separately. However, for each class, we observe an unexpected change in the variation of error amidst the switching from birth to death process. For example, in the fifth class (51 – 60 minute), the error at first improves from 70.54% to 51.21% after 30 minutes, followed by an unexpected increase in error at 40 minute. It happens because, for most of the incidents in this class, the queue grows until 30 minutes and reaches the maximum length, followed by subsequent dissipation afterward. Similarly, for the seventh class (81 – 100 minute) the error increases at 50 minute, which indicates the initiation of the death process of the queue. Once the

model learns about the death process from the previous data, the prediction gets more refined in the later instants.

4.4 Conclusion

In this study, we have proposed a dynamic queue-length prediction model to forecast the queue-length of the non-recurring road-incidents from the expressways of Singapore. For this purpose, we have explored the traffic data-sets and incident records obtained from the Land Transport Authority. At first, we have analyzed the speed-flow data to estimate the length of the queue at each instant for the entire period of the incidents. Next, we have built various queue-length prediction models, and among them, the LSTM model outperforms others. The model is trained with the historical data to predict the queue-length of the incidents in real-time, and it performs the prediction in a moving horizon manner until the end of the incidents. For the medium duration incidents (31 – 60 minute), prediction error improves from 70% – 80% to 50% – 60%. On the other hand, for longer duration incidents the performance of the prediction model improves from 70% to 45% approximately. Overall, the model makes a better prediction for the incidents where the impact existed in the network for more than half an hour.

Chapter 5

Effectiveness of VMS Messages

Massive urbanization, growth in population, and economic development lead to a proliferation in traffic incidents and congestion in the roads of the metropolitans. For optimal utilization of the road network capacity and efficient traffic management during the incidents, the Land Transport Authority (LTA) of Singapore adopts Intelligent Transportation System (ITS), which provides an integrated solution for communication, control, and information processing in transportation. The LED road traffic signs, commonly known as VMS messages, notify the drivers about any kind of disruption in traffic, such as accidents, obstacles, roadworks, etc. Like all other metropolitan cities, the VMS displays have been strategically distributed on the expressways of Singapore to disseminate information about the traffic incidents.

In the first section, we have described the data-sets and the details of VMS messages. In the following sections, we have explained the approach to our analysis and presented the results. Finally, the last section provides concluding remarks.

This work has been published in the paper [\[117\]](#).

5.1 Description and Analysis of the Data

In this section, we describe the raw data collected from the Land Transport Authority (LTA) of Singapore. The data-set considered in this study primarily comprises three types of data: (1) historical records of incidents, (2) the details of VMS messages, and (3) traffic data. The data have been

collected from two major expressways in Singapore (PIE and CTE), and for two months (September - October 2016). The expressways are divided into short road segments (of length 120 meter on an average) labeled by unique link IDs.

5.1.1 Incidents Data

In the incidents data, the following attributes are available: (1) an incident ID which is unique to each accident, (2) the link ID where the incident happened with the respective coordinates, (3) the expressway and its direction along which the incident occurred, and (4) the start time and end time along with day and month of the incident. The incidents data studied in this work comprise two types of incidents, i.e., accidents and obstacles. There are overall 588 incidents of these two types, where 90.48% of them are accidents. We show the distribution of the two types of incidents for the two expressways in Fig. 5.1.

Figure 5.1: Distribution of the incidents according to their types and expressways.

5.1.2 Details of VMS Messages

There are in total 70 VMS displays on PIE and CTE in Singapore. The VMS data contain the following entries: (1) a unique VMS ID, (2) the activation time of the message, (3) the corresponding incident ID, (4) the location of the VMS display (i.e., the link ID where it is located), and (5) the information on the VMS signs. There were in total 1891 VMS messages recorded for 588 incidents. Usually, LTA activates most of the messages within a few minutes after the incidents have been reported. Fig. 5.2 shows the histogram of the differences between the incident start time and the first activation time of the VMS. In the x-axis, 0 represents the start time of the incident. We observe that for 96.6% of those 588 incidents, the first VMS messages were activated within 10 minutes after the incident starts. For the other messages, either the incident details were not immediately available, or the incident did not affect traffic at the time of reporting. Therefore, those VMS messages were displayed only when the information about the traffic incidents was obtained, or traffic lanes were closed, such as for incident recovery. Additional VMS messages which are located further away from the incident were displayed later, only when the congestion extended over time.

In addition, the traffic data are available from the nearest upstream links of the exit points on the expressways in between the VMS and incident locations. There are 72 exits on PIE and CTE. Fig. 5.3 shows the histogram of the distances between the VMS displays and their nearest downstream exit points. We observe in Fig. 5.3 that for 56% of the displays, the nearest exit is within 500 meter and in 92% cases, the distance is less than 1 km.

Figure 5.2: Histogram of the differences between the incident start time and the first activation time of the VMS.

Figure 5.3: Histogram of the distances between the VMS display locations and their nearest downstream exits.

5.1.3 Traffic Data

The traffic data comprise link ID, the recording time, and the corresponding speed and flow value of the expressways along with the exit points. The traffic flow and traffic speed values are recorded in each road segment at every five minutes interval. The speed value represents the average speed of all the vehicles that pass through that segment in the 5-minute span. However, the traffic speed data are in the form of speed bands. While the first nine bands represent speeds up to 90 kmph (each spanning 10 kmph),

the 10-th band corresponds to the speed higher than 90 kmph. On the other hand, the flow value indicates the number of cars passing through that road segment in 5 minutes span, and the unit of flow data is vehicles per hour.

5.2 Method of Analysis

In this section, we explain the steps how we evaluate the effectiveness of VMS messages. For this purpose, we show a schematic diagram of the incident and VMS message locations in Fig. 5.4. Let us assume that an

Figure 5.4: A schematic diagram of the road with exits and VMS message locations.

incident happened at time t_{start} on one Monday at link ℓ , and the activation time of the VMS messages $V_1, V_2, \dots, V_n$ is $T_1, T_2, \dots, T_n$ respectively, where $T_j \geq t_{\text{start}}$ for $j = 1, \dots, n$. Moreover, we suppose that the VMS displays are located at the links $\ell_1, \ell_2, \dots, \ell_n$ respectively. Now, we explain the steps of our analysis as shown in Fig. 5.5.

We start our analysis from the time instant $T_{\min}$ when at least one of the n VMS messages has been activated, i.e. $T_{\min} = \min(T_j)$, where $j = 1, \dots, n$.

Figure 5.5: Flow-chart of our approach.

At a particular time instant T , first we select one VMS that was already activated, say V_j and find the upstream expressway links nearest to the exit locations $E_1, E_2, \dots, E_m$ in between the VMS display location ℓ_j and incident location ℓ . Next, we examine using the traffic data if the exits E_k , where $k = 1, \dots, m$ are congested or not. This step is important prior to analyzing the impact of VMS because if the exit is located along a congested stretch of the expressway or the exit ramp itself is congested, there are two possibilities: (1) the cars are stuck in the congestion, hence the drivers may not be able to leave the road through the exit. (2) If the driver somehow manages to escape from the congestion and drives through the exit, still it can not be concluded that the driver changed his direction seeing the VMS, rather he may have changed the route seeing the congestion itself. Therefore, we compute the average speed and flow of the same exit link E_k at time T of non-incident Mondays (as the incident happened on one Monday) and calculate the differences of the traffic data recorded on the day of incident with this average of non-incident days. Let us assume that the traffic speed in link E_k at the time instant T on the day of incident is $s_{E_k, T}$ and on non-incident Mondays are $s_{E_k, T_{M_1}}, \dots, s_{E_k, T_{M_p}}$, assuming there are p Mondays in the two months September - October 2016. Hence, for link E_k at time instant T , the speed difference is given by:

$$d_{s_{E_k, T}} = s_{E_k, T} - \frac{s_{E_k, T_{M_1}} + \dots + s_{E_k, T_{M_p}}}{p}. \quad (5.1)$$

Similarly, we compute the flow difference $d_{f_{E_k, T}}$ for the link E_k at time instant T . Now, we consider the link E_k to be congested if both traffic speed and flow are lower on the day of incident compared to the average of non-incident days, i.e. $d_{s_{E_k, T}} < 0$ & $d_{f_{E_k, T}} < 0$. Thus, we determine for all the exits $E_1, \dots, E_m$ if they are congested or not at the time instant T .

Although the data of non-incident days are varied, we consider the average of non-incident days to be the threshold for comparison purpose to alleviate the effect of recurrent or peak-hour congestion. In this way, we examine the exit links and their adjacent expressway links if they are congested or not. If all the exits are congested, we discard that particular VMS and choose the next active VMS at that instant. Otherwise, we proceed to the next step, i.e., analyzing if the VMS has any effect or not.

For that purpose, we investigate the change in outgoing traffic flow from the expressway to the individual exits. Let us assume that the traffic flow in link E_k at the time instant T on the day of incident is $f_{E_k,T}$ and on non-incident days are $f_{E_k,T_{M_1}}, \dots, f_{E_k,T_{M_p}}$. We compute the median, i.e., 50-th percentile of the flow values of non-incident days and denote it as $\text{med}(f_{E_k,T})$:

$$\text{med}(f_{E_k,T_M}) = \text{median}(f_{E_k,T_{M_1}}, f_{E_k,T_{M_2}}, \dots, f_{E_k,T_{M_p}}). \quad (5.2)$$

Next, the flow difference for link E_k at time instant T is determined as given by:

$$D_{f_{E_k,T}} = f_{E_k,T} - \text{med}(f_{E_k,T_M}). \quad (5.3)$$

Ideally, the average traffic flow in the exit link on the day of incident should exceed that of normal day, i.e., $D_{f_{E_k,T}} > 0$ if there is an effect of VMS. Therefore, we compute the fractional change in traffic flow due to the VMS messages which is denoted by flow change ratio (FCR):

$$FCR = \frac{D_{f_{E_k,T}}}{\text{med}(f_{E_k,T_M})}. \quad (5.4)$$

We consider a VMS to have an impact if FCR is greater than 0 for at least one exit. Hence, we discard those exits where FCR is less than 0 and next, compute the average of the FCR values for all other exits to obtain the final result.

We repeat the same steps at an interval of five minutes until the incident ends. When the end of the incident is reached, we pick another incident and repeat all the steps.

5.3 Results

In this section, we show the results of our analysis, and based on that, we deduce if the VMS system has a significant impact or not on the Singapore road network.

5.3.1 Analysis of the Impact of VMS

At first, we show the variation in average flow change ratio (FCR) with elapsing time in Fig. 5.6 since the activation of VMS. The x-axis in Fig. 5.6 represents the elapsed time in minutes, where $x = 0$ represents the activation time of the messages. The VMS messages have been aligned at $x = 0$ based on their activation time. Therefore, the negative x-axis represents the time before the activation of the messages. The primary objective of this study is to compare the flow change ratio before and after the activation of VMS; therefore, the time axis is shown since 25 minutes before the respective messages were activated.

Fig. 5.6 shows that there exists a sharp positive slope in the FCR graph after $x = 0$. Therefore, we can conclude that overall there is an impact of VMS. Secondly, the value of FCR is not positive immediately after $x = 0$; rather it increases after $x = 10$, which is very obvious because after seeing the VMS message, the drivers take some time to travel to the nearest exit. Last but not the least, the maximum value of the average FCR in the graph is 0.24. Therefore, at a particular time instant, on an average, the traffic flow leaving through the exits may increase by up to 24% compared to normal days. The mean FCR before and after activation of VMS is -0.05 and 0.09 ,

Figure 5.6: The variation of average flow change ratio (FCR) with time averaged over all incidents.

respectively. Therefore, the FCR increases by 14% after activation of VMS.

Next, we compare the results obtained in this study to the existing literature in Table 5.1 and investigate if the impact of VMS in Singapore is comparable to other cities. Table 5.1 shows that most of the studies presented their results based on the participating drivers' responses, where the participation rate is very unlikely to be 100%. Moreover, the participants may respond positively in the surveys whereas, in practice, they are reluctant to follow the messages. On the contrary, our results are free from the response biases. In fact, the previous studies compared the results obtained by the questionnaires and field observations and found that the positive response rate in the survey differs significantly from the actual change in traffic flow [23] [25]. Therefore, although the percentage of positive response is low in the field observations as well as in this study, the results are more accurate.

Table 5.1: Summary of the results obtained by previous studies.

Literature	Method of data collection	Percentage of positive response
Praveen <i>et al.</i> [22]	Motorists' survey in Missouri	94% of the surveyed drivers
Wang <i>et al.</i> [21]	Questionnaire survey in Rhode Island	70% of the participated drivers
Ran <i>et al.</i> [20]	Questionnaire survey in Wisconsin	70% of the participated drivers
Elham <i>et al.</i> [71]	Phone survey in Los Angeles	70% among the called drivers
Kiron <i>et al.</i> [23]	Both questionnaire and field observations in London	Positive response in the survey is 5 times the actual number
Alena <i>et al.</i> [24]	Field study in Oslo	20% of the cars changed direction
Taisir <i>et al.</i> [25]	Both questionnaire and field observations in Saudi Arabia	5.9% driver changed direction, 85% positive response in survey
Our work	Historical data	14% driver changed direction

5.3.2 Comparative Analysis of the Results for Different Categories of Incidents

In this subsection, we present a comparative analysis of our results for different categories of incidents based on their features. First, we plot similar graph in Fig. 5.7 as in Fig. 5.6, however for the incidents of PIE and CTE separately. Fig. 5.7 shows that the value of average FCR is, in general, higher for PIE compared to CTE at any particular time instant. Since PIE is longer than CTE, it is more likely that more VMS messages can be displayed upstream of an incident; therefore, the motorists are better informed. Besides, PIE has more exits; hence there are more alternatives available to the drivers.

Next, we plot the FCR graphs for peak hour and off-peak hour incidents in Fig. 5.8. We observe in Fig. 5.8 that the values of average FCR are higher for off-peak hour incidents compared to that of peak hour incidents. For peak hour incidents the maximum value of average FCR is around 20%, whereas for off-peak hour incidents it is close to 37%. Therefore, the impact is more significant for off-peak hour incidents. This is because in peak hour

Figure 5.7: The variation of average flow change ratio (FCR) with time for the incidents in PIE and CTE.

most of the roads experience heavy traffic, hence motorists may choose not to divert.

Besides, the type of incident is also an important feature. Therefore, the FCR plot is shown with time in Fig. 5.9 for accidents and obstacles separately. In Fig. 5.9, the FCR curve for accidents is quite similar to Fig. 5.6, whereas there is not much variation in the FCR curve for obstacles. Since the obstacles only cause partial closure of the lanes, the overall capacity of the road remains relatively unaffected. Furthermore, the average FCR value is significantly high at the higher duration range for accidents since the average duration of accidents is longer than that of obstacles.

Finally, we compare the mean and median values of the FCR averaged over all exits for different categories of incidents in Table 5.2.

5.4 Conclusion

The primary objective of this study was to explore the impact of VMS messages on the traffic conditions of the expressways in Singapore. To this

Figure 5.8: The variation of average flow change ratio (FCR) with time for the peak hour and off-peak hour incidents.

Table 5.2: Mean and median of FCR averaged over all exits for different categories of incidents.

		Time		Expressway		Type of incident		All together
		Peak hour	Off-peak	PIE	CTE	Accident	Obstacle	
Before VMS is activated	Mean	0.023	-0.13	0.02	-0.15	-0.06	-0.13	-0.056
	Median	0.01	-0.17	-0.01	-0.17	-0.07	-0.17	-0.07
After VMS is activated	Mean	0.068	0.17	0.31	0.02	0.36	-0.014	0.092
	Median	0.028	0.11	0.21	-0.01	0.33	-0.1	0.052

end, we have analyzed the traffic incidents and VMS data from the two most crowded expressways of Singapore. Our results show that on an average, the value of FCR increases from -5.6% to 9.2% with elapsing time. Therefore, the VMS messages can effectively inform the drivers on the roads about the route guidance and significantly improve congestion avoidance.

However, in this work, we have used the traffic flow data for analyzing the impact of VMS, whereas the total number of vehicles would have been a better metric for this purpose. Moreover, there might be other sources to broadcast information about the incidents, like radio channels, the Internet,

Figure 5.9: The variation of average flow change ratio (FCR) with time for accidents and obstacles.

etc. Therefore, understanding the impact of VMS based on historical records is a rather convoluted task. Lastly, since VMS technology is still in its nascent stage, the awareness among drivers and thereby, the effectiveness of these messages as a traffic guidance tool is significantly less than optimal. With growing recognition for the efficacy of VMS technology, we hope to see a significant increase in the impact of VMS on overall traffic conditions in coming years.

Chapter 6

Effect of Rainfall on Traffic

Being situated in the equatorial region, Singapore typically has a tropical climate with plenty of rainfall. On an average, Singapore gets rainfall around 167 days of an entire year. As per the Statistics, the country has an average yearly rainfall of 1956.1 mm in 2016 [118]. In the wet months, the monthly rainfall can go up to 300 mm. Therefore, the weather condition of Singapore may have a measurable impact on the road network. Owing to the poor visibility and decreased frictional coefficient between the vehicles and the wet roads, there is a higher probability of occurrence of an accident during rainfall. Therefore, the drivers are not able to drive at normal speed. Moreover, trees may fall on the roads or catch fire as a result of thunderstorm and lightning, creating an obstacle to the vehicles. In addition, the roads remain wet for a prolonged period even after it stops raining. In fact, there may be a higher risk of a breakdown or crash at that time due to lack of the drivers' carefulness. Therefore, we compare the frequency of incidents during rainfall with the frequency after rainfall. Moreover, we also analyze the variation of traffic parameters, such as average speed and flow for different expressways.

This chapter is organized as follows. At first, we have described the rainfall data-set in detail. We already illustrated the incidents and traffic data-sets in the previous chapters (Section 2.1 and Section 3.1). Therefore, we have presented a brief description of these data-sets here. In the next section, we have computed the frequencies of each type of incidents for different weather conditions. Moreover, we have compared the frequencies of these incidents on different expressways of Singapore. In the following sec-

tion, we have evaluated the effect of rainfall on the average traffic speed of the expressways. Moreover, we have also examined the average traffic flow values for different expressways to determine whether the number of cars on the roads reduces during the rainfall or not. Finally, the last section provides concluding remarks on this study.

6.1 Description of the Data-set

The rainfall data are obtained from the website of the National Environmental Agency (NEA) in Singapore [118]. The data are collected by radar and then published as images in 5 minutes interval. We show a sample rainfall radar map downloaded from the NEA website in Fig. 6.1.

Figure 6.1: Rainfall radar map downloaded from NEA website.

To extract the data from these raw images, we use the Optical Character Recognition (OCR) method. It converts the images into text in ASCII format. At first, the rainfall and road-maps are superimposed to locate the particular links on the rainfall map. Next, if it does not rain, the OCR interprets it as 0. When it rains, the OCR determines the rainfall intensity

according to the color code shown on the NEA website. Moreover, if the OCR is unable to interpret the weather condition, the rainfall values are represented by a negative value.

The rainfall data used in this study are for the same time period as the traffic data (Aug 2016 - Jan 2017). However, the rainfall values are missing for certain intervals. Therefore, we discard the incidents from this analysis which occurred during these intervals. Next, we show the distribution of rain intensity recorded at 5 minutes interval in Fig. 6.1. The missing values are denoted by negative values.

Figure 6.2: Rain intensity at 5 minutes interval averaged over all links.

Since the rainfall data are available non-uniformly for different months (i.e., the data are partially available for a few months), we cannot compare the monthly rainfall intensities. Instead, we plot the daily average rainfall intensity of each month in Fig. 6.3. Due to its geographical location, the climate of Singapore is largely influenced by the Northeast Monsoon which

Figure 6.3: Average daily rainfall intensity recorded in different months.

causes heavy showers, especially in the afternoons [119]. This wet season lasts from December to early January. Therefore, the daily rainfall rate is higher in these months. On the other hand, the afternoon and evening thunderstorms are more common in the months of Oct-Nov caused by the interaction of land and sea breezes [119]. The period of Aug-Sept is comparatively drier; however, occasional rainfall may be caused by the "Sumatra squalls" during this period [119].

Next, we show the percentage of rainfall in different expressways in Fig. 6.4. In general, the western part of Singapore is wetter compared to the

Figure 6.4: The distribution of rainfall in different expressways of Singapore.

eastern side because of the location of Bukit Timah Hill in the middle obstructing the wind. Now, a significant portion of AYE and PIE runs through the western side of the island. Therefore, we can observe in Fig. 6.4 that the percentage of rainfall is the highest in AYE and PIE. On the other hand, the expressways in the east, such as KPE, TPE, etc. have a lower percentage of rainfall. Thus, despite its small size, there is a variation of climate in different parts of Singapore which affects the traffic condition, directly or indirectly.

The traffic speed, flow, and incidents data from the expressways of Singapore are provided by the Land Transport Authority (LTA). Traffic flow is defined by the number of vehicles traversing a reference point per unit time, and its unit is vehicles per hour. On the other hand, the average speed of the vehicles traversing a reference point is denoted by traffic speed, and the unit is kilometers per hour. There are 10 expressways in the road network of Singapore, each of them having 180 – 220 links. In total, there are 2156 expressway links with an average length of 100 meter.

The incidents data contain the detailed information of 11,230 road incidents that happened on all the expressways of Singapore throughout the time frame from August 2016 to January 2017. The incidents have the following attributes: (1) a unique serial number termed as incident ID, (2) the immediate upstream link ID and coordinates of the incident location, (3) the expressway and its direction along which the incident happened, (4) the start and end time of the incident, (5) the details about closure of adjacent shoulder lane and main lanes, and (6) the type of incident (vehicle breakdown, accident, obstacle, roadwork, heavy traffic, and miscellaneous).

6.2 Effect of Rainfall on the Occurrence of Incidents

In this section, we compare the frequencies of occurrence of the incidents for different weather condition. There are six types of incidents, such as vehicle breakdown, accident, heavy traffic, roadwork, obstacle, and miscellaneous. Moreover, the rainfall data are available for 9 expressways in Singapore (excluding MCE, where rainfall data are not available). Therefore, we compute the frequencies of different types of incidents on the individual expressways. However, prior to that, we describe the definitions and formulas in a separate subsection.

6.2.1 Analysis

To obtain the incident frequency during dry weather, rainy weather, and after rain, at first we need to determine the periods of different weather conditions. The time instants when the rainfall intensity is nonzero are accumulated to obtain the total rainy weather period. The after rain period is defined as half an hour after the rainfall stops in a particular place. Therefore, we denote the summation of these post-rainfall periods as after rain. Rest of the period is assumed to have dry weather.

Therefore, the percentage of rainy weather period is defined by:

$$\text{Percentage of rainy weather} = \frac{\text{Total duration of rainy weather}}{\text{Total duration of known weather}} * 100\%. \quad (6.1)$$

In this context, let us assume that according to the rainfall data, an event of rainfall r_i occurred in link ℓ for the duration of $t_{r_i,\ell,\text{start}}$ min to $t_{r_i,\ell,\text{end}}$ min. Therefore, the rainy weather period is $t_{r_i,\ell,\text{start}}$ min to $t_{r_i,\ell,\text{end}}$ min, whereas the after rain period is $t_{r_i,\ell,\text{end}}$ min to $(t_{r_i,\ell,\text{end}} + 30)$ min. Now, there are multiple occurrence of rainfall in the entire six months at different links. Therefore,

the percentage of rainy weather (P_{rain}) can be expressed by:

$$P_{\text{rain}} = \frac{\sum_{\ell} \sum_i (t_{r_{i,\ell},\text{end}} - t_{r_{i,\ell},\text{start}})}{(30 + 31 + 30 + 31 + 31 + 31) * 24 * 60} * 100\%, \quad (6.2)$$

where the denominator is the entire period of 6 months (Aug 2016 - Jan 2017) in minutes.

In the similar way, we can write the percentage of after rain period (P_{after}) as:

$$P_{\text{after}} = \frac{\sum_{\ell} \sum_i (t_{r_{i,\ell},\text{end}} + 30 - t_{r_{i,\ell},\text{end}})}{(30 + 31 + 30 + 31 + 31 + 31) * 24 * 60} * 100\%, \text{ and} \quad (6.3)$$

the percentage of dry weather (P_{dry}) is:

$$P_{\text{dry}} = (100 - P_{\text{rain}} - P_{\text{after}})\%. \quad (6.4)$$

Using these formulas, we obtain that 87.45% of the entire period was dry, rainfall occurred for 8.03% of the total duration, and after rain period existed for 4.52%.

Now, let us assume that an incident $I_{i,\ell,\text{rain}}$ occurs during the rainfall r_i at link ℓ . Therefore, the incident frequency in rainy weather (F_{rain}) can be expressed by:

$$F_{\text{rain}} = \sum_{\ell} \sum_i \frac{I_{i,\ell,\text{rain}}}{(t_{r_{i,\ell},\text{end}} - t_{r_{i,\ell},\text{start}})}. \quad (6.5)$$

If an incident $I_{i,\ell,\text{after}}$ occurs within half an hour after the rainfall r_i stops, we can express the incident frequency after rain (F_{after}) as:

$$F_{\text{after}} = \sum_{\ell} \sum_i \frac{I_{i,\ell,\text{after}}}{(t_{r_{i,\ell},\text{end}} + 30 - t_{r_{i,\ell},\text{end}})}. \quad (6.6)$$

Now, if an incident happens in dry weather, let us assume that $I_{i,\ell,\text{dry}}$ took place in between the end of rainfall r_i and the start of rainfall r_{i+1} at link ℓ . With this assumption, the frequency of incidents in dry weather can be

written as:

$$F_{\text{dry}} = \sum_{\ell} \sum_i \frac{I_{i,\ell,\text{dry}}}{(t_{r_{i+1,\ell,\text{start}}} - t_{r_{i,\ell,\text{end}}})}. \quad (6.7)$$

The unit of incident frequency, thus obtained, is incident/min.

6.2.2 Results

6.2.2.1 Variation of Number of Incidents in Different Weather Conditions

Before analyzing the frequency of incidents, we compare the total number of incidents for different weather condition. In Fig. 6.5 (a), we show the count of each type of incident for dry weather, rainy weather, and after rain period, whereas Fig. 6.5 (b) shows the number of incidents occurred on each expressway in different weather condition. As can be seen in Fig. 6.5,

(a) Different types of incidents.

(b) Incidents along different expressways.

Figure 6.5: Distribution of different categories of incidents in dry weather, rainy weather, and after rain.

since the weather was dry during 87.45% of the entire period, the number of incidents is much higher in dry weather irrespective of the type of incident or expressway.

Fig. 6.5 (a) shows that the vehicle breakdown is the most frequent type

of incident. The second most common one is roadwork because of several road openings, maintenance works, etc. on the expressways. Next come the heavy traffic and accidents, followed by obstacles and miscellaneous at the end. Besides, we can observe in Fig. 6.5 (a) that the ratio of any other type of incidents except accidents (such as, breakdowns, roadworks, etc.) in dry weather and rainy weather is much higher (almost 12 : 1) than the ratio of accidents in dry and rainy weather (around 4 : 1). It indicates that the number of accidents or crashes is relatively high during rainfall.

In Fig. 6.5 (b), PIE is the most incident-prone expressway since it is the longest and busiest expressway of Singapore. On the contrary, KJE runs through the western part of Singapore, which is far from the busy central area of the country. Moreover, KPE comprises the longest underground tunnel in Singapore (8.5 km long tunnel in 12 km expressway). Hence, there is no significant impact of rainfall in KJE and KPE. Therefore, the number of incidents are lower along these expressways.

Next, we categorize the incidents by their types for the individual expressway in different weather condition, separately. Fig. 6.6 shows each category of incidents in the stacked bars. We observe in Fig. 6.6 that the proportions of accidents and heavy traffic are higher in rainy weather compared to dry weather on each expressway. On the contrary, the proportion of roadwork is higher in dry weather. This is because roadworks are usually disrupted during rainfall since rainfall may wash out the constructions. In general, Fig. 6.6 shows a similar trend for different expressways with slight variations.

6.2.2.2 Variation in Frequency of Incidents for Different Weather Conditions

Following the same steps as in section 6.2.2.1, next we determine the frequencies of different categories of incidents for different weather condition.

Figure 6.6: Break down of different types of incidents on each expressway in dry weather, rainy weather, and after rain.

At first, we compare the frequencies of different incident types, such as accidents, breakdowns, etc. in Fig. 6.7 (a) where we observe that the frequencies are the lowest in dry weather for all types of incidents. Moreover, the frequencies are the highest after rainfall for all major types of incidents, which supports our hypothesis that incident frequency is higher after rainfall compared to during rainfall. However, the obstacles are more frequent during rainfall, probably because the obstructions, such as, fallen trees etc. are mainly caused by the thunderstorm which usually happens during the rainfall. Therefore, the obstacles are often cleared by the time the rainfall stops. Fig. 6.7 (b) shows the frequencies of incidents along various expressways averaged over all types of incidents together. The frequencies in dry weather

and rainy weather are almost same for AYE, KPE, and TPE, although it is higher after rain. On the other hand, in few expressways, such as BKE and CTE, the frequencies during rainfall and after rainfall are almost comparable, whereas in dry weather it is lower. As a whole, the frequency of incidents after rainfall is higher than the frequency in dry weather for all expressways except KJE, where the frequencies are comparable to each other in different weather conditions.

(a) Different types of incidents.

(b) Incidents along different expressways.

Figure 6.7: Frequency of different categories of incidents in dry weather, rainy weather, and after rain.

Next, we show the frequency of each type of incident in Fig. 6.8 for different weather condition on various expressways. We will look into each expressway one by one.

On AYE, the accident frequencies are the same in dry and rainy weather. However, the frequency is much higher after rainfall. On the other hand, the frequency of roadwork is higher in dry weather compared to rainy weather. This might be because in general the works on the roads are temporarily stopped during rainfall. For other types of incidents, the frequency is the highest after rainfall followed by the frequency during rainfall, and the frequency in dry weather is the lowest. Overall, the frequency of each type of incident is higher along AYE than any other expressway, except PIE.

Figure 6.8: Frequency of each type of incident in different weather condition on various expressways.

In BKE, the breakdowns and accidents happen during rainfall almost as often as after rainfall. Moreover, the heavy traffic incidents are the most frequent during rainfall, because rainfall causes a reduction in the average traffic speed of the vehicles resulting in congestion. On the other hand, the frequency of roadworks is higher in dry weather compared to rainfall, similar as in AYE.

Along CTE, the frequencies of almost all types of incidents, such as breakdowns, accidents, heavy traffic, and obstacles are same during and after rainfall and higher than the respective frequencies in dry weather. Only the frequency of roadwork is same in dry weather and wet weather.

Next, in ECP, the frequency of each type of incident follows an almost similar trend as in Fig. 6.7 (a).

Along KJE, the frequency of breakdowns is much high in dry weather compared to that in rainy weather. For other types of incidents, the frequencies in dry weather, during rainfall, and after rainfall are comparable. Overall, the frequency of each type of incident is much low along this expressway compared to other expressways.

In KPE, the frequencies of the incidents are the lowest irrespective of its type. Obstacles occur the most during rainfall, similar as in Fig. 6.7 (a). Roadworks take place more in dry weather compared to rainy weather like AYE.

Since PIE is the longest expressway in Singapore connecting east to west and running through the center of Singapore, the frequencies of the incidents are the highest along this expressway (3 – 4 times compared to other expressways). The frequency of each type of incident attains the highest value after rainfall and the lowest value in dry weather.

In SLE, the breakdowns and obstacles occur the most during rainfall, whereas accidents, heavy traffic, and roadworks are more frequent after rainfall.

Lastly, the frequencies of breakdowns and accidents are a bit low in rainy weather along TPE. Therefore, the effect of rainfall is not much significant for this expressway.

Overall, the frequencies of accidents, heavy traffic, and obstacles increase in all the expressways because of rainfall.

6.3 Effect of Rainfall on Traffic Speed and Flow

Rainfall may cause severe traffic congestion on the expressways, even when there is no incident. Therefore, we analyze the available rainfall and traffic speed data to investigate if the average traffic speed of the vehicles reduces during rainfall or not. Moreover, drivers often tend to avoid driving during rainfall, unless there is any time constraint. Therefore, we also compare the traffic flow data during rainfall with that in dry weather to examine if the flow decreases during the rainfall (i.e., the number of cars decreases on the roads) or not. In this section, we analyze the effect of rainfall on average

traffic speed and flow separately. Prior to that, we explain the formulas in a separate subsection.

6.3.1 Analysis

Let us assume that the link ℓ has been reported to have a rainfall at the time instant t on a particular day of the week. Now, from traffic data, we obtain the traffic speed and flow value $s_{rain}(\ell, t)$ and $f_{rain}(\ell, t)$ for the time instant t at link ℓ on the day of rainfall. Moreover, we compute the traffic speed and flow value $s_{dry}(\ell, t)$ and $f_{dry}(\ell, t)$ for link ℓ at the time instant t , where these values imply the average traffic parameters of the non-rainy same day of other weeks from the entire six months. For example, if the rainfall occurred on a Monday, we compute the average speed and flow of all other Mondays of the six months except the days of rainfall to compare them with the speed and flow of the rainy Monday.

Next, we compute the percentage of the difference in speed $d_{s(\ell, t)}$ and the percentage of the difference in flow $d_{f(\ell, t)}$, where $d_{s(\ell, t)}$ and $d_{f(\ell, t)}$ are defined by:

$$d_{s(\ell, t)} = \frac{(s_{dry}(\ell, t) - s_{rain}(\ell, t))}{s_{dry}(\ell, t)} * 100\%, \quad d_{f(\ell, t)} = \frac{(f_{dry}(\ell, t) - f_{rain}(\ell, t))}{f_{dry}(\ell, t)} * 100\%. \quad (6.8)$$

6.3.2 Results

We compute the speed-differences and flow-differences for each link ℓ using the formula (6.8), whenever there is rainfall. Next, we average the speed-differences over the links belonging to a particular expressway. Thus, we obtain the average difference in speed of dry weather and rainy weather for each expressway. Similarly, we also compute the flow-differences for all the expressways. The values, thus obtained, are mentioned in Table 6.1 and Table 6.2, respectively.

Table 6.1: Speed difference of dry weather and rainy weather for an individual expressway.

Expressway	Speed-difference (kmph)	Speed-difference (%)
AYE	7.3	9.79
BKE	8.55	10.45
CTE	8.3	11.5
ECP	8.72	11
KJE	7.2	9.16
KPE	5.35	7.73
PIE	9.1	11.71
SLE	5.31	6.1
TPE	5	5.54
All highways combined	7.88	10.14

We observe in Table 6.1 that the vehicles on the expressways travel at a slower speed during rainy weather condition. The speed-difference is the maximum in PIE (11.71%) and CTE (11.5%), whereas KPE, SLE, and TPE have the lowest speed-difference. This is also reflected in Fig. 6.6, where the frequencies of incidents are lower in these expressways. The mean speed-difference is 10.14% averaged over all expressways which indicates that the traffic slows down because of rainfall irrespective of the expressway.

The average flow-difference in Table 6.2 for all highways combined indicates that the number of cars decreases by 3.88% in rainy weather compared to dry weather. Moreover, we find that the flow-difference is the highest in CTE (6.07%). On the other hand, the flow differences are negative in some expressways like KPE, SLE, and TPE. The last two expressways run through the north side of Singapore, and they connect Malaysia with Singapore. The number of vehicles on these expressways does not vary much due to rainfall since there are different time-constrained rules and regulations, time-specific tariffs, etc. involved with international transportation. However, rainfall causes a slowdown of traffic and hence, the vehicles travel

Table 6.2: Flow difference of dry weather and rainy weather for an individual expressway.

Expressway	Flow-difference (vehicles/hr)	Flow-difference (%)
AYE	74.02	3.06
BKE	32.13	0.49
CTE	105.22	6.07
ECP	78.22	4.15
KJE	41.08	1.73
KPE	-17.38	-1.93
PIE	84.42	1.57
SLE	-91	-9.77
TPE	-33.22	-3.57
All highways combined	52.75	3.88

at a lower speed compared to normal days. As a result, traffic density (the number of cars per unit length) increases leading to an increase in average flow. Therefore, the flow-differences are negative in these expressways. Besides, since KJE comprises the largest underground tunnel in Singapore, its traffic is not affected by rainfall and hence, the traffic flow in rainy weather is almost the same as the flow in dry weather.

6.4 Conclusion

The primary objective of this study was to analyze the effect of rainfall on the road network of Singapore. To this end, we have fused the rainfall data with the incidents and traffic data collected from the expressways of Singapore. We have observed that the frequencies of accidents, breakdowns, and obstacles significantly increase in rainy weather. Sometimes, the incident frequency even increases after rainfall. However, the frequencies of different types of incidents vary across the highways in different weather conditions.

Besides, traffic congestion may also happen because of rainfall even when there is no incident. We have found that the average speed decreases by

10.14% during rainfall compared to dry weather. Moreover, there is a reduction of 3.88% in average traffic flow as well. The effect is more significant on CTE, PIE, ECP, etc., whereas SLE, TPE, and KJE have the least effect of rainfall on traffic.

Chapter 7

Concluding Remarks

According to the Annual Vehicle Statistics published by the Land Transport Authority in 2017, Singapore had a total vehicle population of 961,842 [120]. The traditional transportation solutions are no longer capable of handling this huge population of vehicles in a complex city network like Singapore and meeting the needs of dependability, security, flexibility, and predictability of the commuters. Therefore, Intelligent Transportation Systems aim to provide solutions in different aspects of transportation. In the context of urban transportation networks, the non-recurring road incidents cause approximately 25% of traffic congestion on the arterial roads, and the proportion is even higher for urban expressways. Therefore, the ultimate goal of this work is to help mitigate the effect of the incidents by predicting future traffic conditions and using advanced technologies to make route guidance better.

In this chapter, we present the conclusions about each topic in Section 7.1 and potential ideas for future works in Section 7.2.

7.1 Conclusions

In the previous chapters, we have analyzed the historical traffic data-sets, developed the algorithms, and explained the results obtained by our models on critical aspects of transportation research. In Chapters 3 and 4, we have built dynamic traffic prediction models for forecasting the incident duration and queue-length in real-time. Next, we have analyzed the importance of

VMS technology on the road network of Singapore in Chapter 5. Later in Chapter 6, we have investigated the effect of rainfall on the traffic incidents of Singapore. Finally, this section presents a summary of the key results and the limitations of each topic.

7.1.1 Prediction of Incident Duration and Queue-length

In this study, we have proposed data-driven traffic prediction models for forecasting the duration and spread of congestion due to the non-recurring road incidents, such as accidents, vehicle breakdowns, obstacles, etc., on the expressways of Singapore. For this purpose, we have incorporated the spatiotemporal data-sets of incidents as well as different underlying factors like speed and flow information, affected lanes, etc.

At first, we have verified the reported duration of the historically recorded incidents using traffic data. Next, we have built the prediction model which forecasts the duration of the incidents in a moving horizon manner in real-time. The predictions are performed dynamically at a specific interval until the end of the incidents so that prediction gets refined with elapsing time. Moreover, at each instant, the feature-set can be adjusted based on the availability of the features. We have observed that the Treebagger performs better than other methods. For the incidents with duration in the range of 36 – 200 minutes, the mean absolute percentage error (MAPE) in predicting the duration is in the range of 25% – 55%. Moreover, for the longer duration incidents (greater than 65 minutes), prediction improves significantly with time. For example, the MAPE value varies over time from 76% to 50% for the incidents having a duration greater than 200 minutes. Finally, the overall MAPE value averaged over all incidents improves by 50% with elapsing time.

Besides, we have also determined the spread of congestion for each incident using the traffic speed and flow data of the neighboring upstream links

from the incident location. The lengths of congestion, thus obtained, are used as the target variables for the queue-length prediction model, which incorporates the updated traffic data and various spatiotemporal features as inputs and forecasts the queue-lengths at each instant. In this study, we have trained a Long Short-Term Memory network to perform the prediction in real-time. The experimental results show that at the start of the incident, the proposed model has a mean error of 73.7%, which reduces to 45.6% after one hour of prediction. Overall, the model makes a better prediction for the incidents where the impact existed in the network for more than 30 minutes.

There are few constraints encountered while working on this thesis. The first limitation is that the incidents and traffic data-sets were available only for the expressways. Usually, the traffic parameters, such as speed limit or road capacity are different for arterial roads from the expressways. Therefore, it is essential to analyze the spatio-temporal spread of the incidents occurred on the arterial roads, and compare them with the incidents on the expressways to understand the behavior of the entire network of Singapore. However, the scope of this analysis was limited to the expressways only. Secondly, although the significant traffic variables, such as traffic flow, number of lanes, expressway and its direction, etc. have been considered in this work, the incidents data lack in other information, for example number of involved vehicles, the driver's behaviour, etc. Moreover, unlike incident duration, the queue-length or length of congestion is not readily available from the incident report. Hence, we compute the queue-lengths by mathematical and statistical analysis based on some assumptions. Since traffic data is very random in nature, the mathematically derived queue-lengths may differ from reality and consequently, may affect the prediction. Lastly, the traffic speed-data are not continuous-valued; instead, they are specified by ten discrete speed-bands. These are some limitations concerning the data-set used in our work.

7.1.2 Effectiveness of VMS Technology

In this thesis, we have conducted a small-scale study on the usefulness of VMS technology in route guidance and congestion avoidance. For this purpose, we have collected the data-set for two months from the two busiest expressways of Singapore, viz. PIE and CTE. The results show that the proportion of drivers who have changed their direction seeing the VMS messages has increased by 14%. Moreover, from the temporal trend of average flow change ratio, we have observed that when VMS messages are on, the flow change ratio increases with elapsing time, which indicates that more cars tend to leave the road seeing the VMS messages to avoid the incident. In Singapore, the VMS displays are more effective on PIE because it is the busiest expressway of Singapore carrying a huge number of vehicles every day. The average proportion of drivers leaving this expressway changes from 0.02 to 0.31 after the VMS messages have been displayed. Moreover, the drivers care about the VMS instructions more carefully when an accident takes place because accidents tend to create more severe traffic congestion compared to other types of incidents. Therefore, 42% more drivers change their routes in the occurrence of an accident on the expressways.

However, there is a limitation in this study. Apart from the incidents and traffic data, many other traffic variables, such as the total number of lanes, lane change ratio, human behavior, etc. could be considered to make the analysis more accurate. Besides, it would be very interesting to expand the analysis by incorporating the impact of information dissemination through V2X in future work. Lastly, since VMS technology is still in its elementary stage, the traffic management authorities should take proper initiatives to increase the awareness among the drivers and thereby, make the VMS technology more effective as a traffic guidance tool.

7.1.3 Effect of Rainfall

In this study, we have explored the effect of rainfall on traffic incidents in the expressways of Singapore. At first, we have computed the frequencies of occurrence of the road incidents for different weather conditions. Our analysis shows that the frequency increases during rainfall, and further increases more after rainfall. Moreover, rainfall causes a reduction in the average flow and speed by 10.14% and 3.88%, respectively. In the future, we plan to analyze more comprehensive data-sets in order to obtain more reliable results. Besides, the effect of different kinds of precipitation, such as rainfall, snowfall, etc. in other countries should be analyzed as well to make the experiment more robust.

7.2 Future Work

In this section, we provide suggestions and future recommendations about different aspects of our research.

7.2.1 Enhancing Robustness of the Models

The incidents and traffic data-set used in this thesis is available from the expressways only and does not include arterial roads of Singapore. Therefore, the available data-set is insufficient for understanding the impact of incidents as well as rainfall on the individual areas or districts of Singapore. Besides, in the future, we plan to test our predictive models for other cities as well. While the human mobility patterns, such as peak hour-off peak hour or weekday-weekend etc. have similar effects on traffic of other cities, the weather factors, such as seasonal variation, the effect of precipitation, etc. are much different in the subtropical or temperate zone countries compared to tropical places like Singapore. The underlying causes responsible for road incidents may also vary from one city to another. Therefore, the

proposed models need to be more robust against all such differences in the characteristics of the features. Moreover, in Singapore the variable speed limit control strategy is not implemented yet, therefore in the future, we plan to analyze the data-sets from other cities where such technologies are used for incident management. Furthermore, this model can be extended for predicting the impact of planned events, such as music concerts, sports events, etc.

7.2.2 Implementing the Predictive Models in Real-time

We have performed the present analysis based on the previously recorded historical data-sets. However, our models are designed to predict the incident duration or queue-length using real-time data. The loop detectors can be used to record traffic information, and that information will be gathered from the entire network and transferred to the server. Based on that, the prediction model will forecast the future traffic condition, such as the expected duration of the incident, the estimated queue-length, etc. Thus, the system can be tested in actual operations to benchmark different models properly. Moreover, from the traffic management perspective, the system should be combined with a dynamic routing service so that it enables the driver to choose an alternative route and avoid the congestion in case of an incident. This will lead to more dependable prediction model and route guidance system in the future.

7.2.3 New Algorithmic Approaches

In our work, we have built a dynamic prediction model using LSTM network since LSTM can handle the temporal dynamicity of the traffic congestion better than the traditional machine learning methods. In the similar way,

CNN is able to learn the spatial dynamics of the data better than other networks. Therefore, in future we propose to develop a combination of CNN and LSTM-based network to capture the spatio-temporal variation of the impact of incidents with more accuracy. However, since the deep learning networks require a large amount of data to be trained, we also plan to collect a larger data-set so that our model can be better trained using these algorithms.

Moreover, the incident records usually contain texts and sometimes images. Currently, our proposed prediction models extract features from the incident reports having specific formats. However, integration of the natural language processing algorithms with our prediction models can enhance the flexibility of the models by enabling them to extract the features from the incident reports with unforeseen formats. Therefore, the models will be more suitable for practical implementation.

7.2.4 Future of VMS Technology

While analyzing the impact of VMS in Singapore, we have considered historical data-sets from the expressways only. However, the VMS displays should be installed on the arterial roads as well to make the drivers aware of the incidents. Thus, the congestion can be minimized in the entire network of Singapore. Moreover, since VMS technology is still in its nascent stage, the awareness among drivers and thereby, the effectiveness of these messages as a traffic guidance tool is significantly less than optimal. With growing recognition for the efficacy of VMS technology, we hope to see a significant increase in the impact of VMS on improving overall traffic conditions in coming years.

7.2.5 Improvement of Infrastructure

From the traffic management perspective, the clearance time is a significant part of the entire incident duration. This study seems to suggest that the shoulder lane plays a significant role during the incidents in the expressways of Singapore. If the affected vehicle is small, it should be shifted to the shoulder lane as soon as possible so that the main lanes get cleared, thereby reducing the clearance time. Besides, the traffic management authorities should open an online portal for drivers to upload their car camera videos in real-time which record their speed using Global Positioning System tracking when they suspect the vehicle in front of them is crossing the speed limit. In this way, the reckless drivers can be deterred ensuring the safety of the road for all commuters.

Last but not the least, the city infrastructure should be improved in line with the rise in traffic incidents and hazardous conditions on the roads. The modern IoT devices and technologies ranging from various kinds of sensors to cameras must be employed to monitor the weather and traffic condition and integrated with existing traffic prediction models for higher precision. Moreover, there is a sheer need of a central server or distributed cloud platform to store all these online real-time streaming data. However, security is a crucial issue in any big data technology. Therefore, we have to find cost-effective solutions to maintain the quality and security of the real-time traffic data available in the shared cloud for traffic control, especially incident management applications.

Publications

Journal Papers

1. B. Ghosh, M. T. Asif, J. Dauwels, U. Fastenrath, and H. Guo, “Dynamic prediction of the incident duration using adaptive feature set,” *IEEE Transactions on Intelligent Transportation Systems*, 2018.
2. B. Ghosh, J. Dauwels, and U. Fastenrath, “Estimation and real-time prediction of the incidents queue-length,” *submitted to IEEE Transactions on Intelligent Transportation Systems*, (Oct 2018)
3. B. Ghosh, T. C. Wei, and J. Dauwels, “Does accident frequency increases after rainfall?,” *to be submitted to IEEE Transactions on Intelligent Transportation Systems*.

Conference Papers

1. B. Ghosh, M. T. Asif, J. Dauwels, W. Cai, H. Guo, and U. Fastenrath, “Predicting the duration of non-recurring road incidents by cluster-specific models,” in *Intelligent Transportation Systems (ITSC), 2016 IEEE 19th International Conference on*. IEEE, 2016, pp. 1522–1527.
2. B. Ghosh, M. T. Asif, and J. Dauwels, “Bayesian prediction of the duration of non-recurring road incidents,” in *Region 10 Conference (TENCON), 2016 IEEE*. IEEE, 2016, pp. 87–90.
3. B. Ghosh, J. Dauwels, and U. Fastenrath, “Analysis and prediction of the queue length for non-recurring road incidents,” in *Computational Intelligence (SSCI), 2017 IEEE Symposium Series on*. IEEE, 2017, pp. 1–8.
4. B. Ghosh, Y. Zhu, and U. Fastenrath, “Effectiveness of VMS Messages in Influencing the Motorists Travel Behaviour,” in *Intelligent Transportation Systems (ITSC), 2018 IEEE 21st International Conference*, IEEE 2018, pp. 837–842.

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