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Impact of Points of Interests on Road Traffic Congestion in Developing Countries

by

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Dedicated to my loving parents

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Candidate's Declaration

This is hereby declared that the work titled "Impact of Points of Interests on Road Traffic Congestion in Developing Countries" is the outcome of research carried out by me under the supervision of Dr. Tanzima Hashem, in the Department of Computer Science and Engineering, Bangladesh University of Engineering and Technology, Dhaka 1205. It is also declared that this thesis or any part of it has not been submitted elsewhere for the award of any degree or diploma.

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Abstract

Reducing the road traffic congestion has become an important challenge in recent years; the researchers have focused on identifying causes and remedies for the traffic congestion. However, the impact of the locations and activity time of points of interests (POIs) such as shopping centers, hospitals and schools, on road traffic has not yet been explored. More importantly, in developing countries, POIs are not established in a planned manner and cause traffic congestion. In this thesis, we analyze how POI locations and activities affect the road traffic. Specifically, we first identify the traffic congestion pattern caused by POI activities in our field study in a metropolitan city Dhaka of a developing country and develop a model to quantify the spatio-temporal impact of POI activities on road traffic congestion. In addition, we develop a model to predict the impact of POI activities on road traffic congestion using fuzzy regressions for different POI categories. We categorize POIs based on predictability, regularity, cause (i.e., event or schedule driven) of POI traffic. Our developed models would enable us to select an appropriate location for future POIs, suggest changing of activity time of POIs, and predict a fastest path from a source to a destination based on POI impact on surrounding areas and thereby reduce the traffic congestion. We perform a set of case studies and experiments to show the effectiveness of our quantification and prediction models using real datasets of POI activities and road traffic of Dhaka city.

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Chapter 1

Introduction

Traffic jams in roads have become a major problem in most of the big cities around the world, especially cities (e.g., Dhaka, Delhi, etc.) of the developing countries where road networks are not well planned and traffics on the road are poorly managed [1]. These traffic jams cause huge delays, increased fuel wastage and monetary losses for the commuters in city. A recent study shows that in Dhaka city a commuter on an average spends 2.35 hours daily in the traffic of which 1.30 hours are due to traffic jam [2]. Reducing the road traffic congestion has become an important challenge in recent years; the researchers have focused on identifying the cause and remedies for the traffic congestion. However, the impact of the locations and activity time of points of interests (POIs) such as shopping centers, hospitals and schools, on road traffic has not yet been explored. More importantly, In developing countries, POIs are not established in a planned manner and cause traffic congestion in various forms. In this thesis, we analyze how POI locations and activities affect road traffic; and based on these observations, we develop two models: (i) a model to quantify the impact of POI activities on road traffic congestion, and (ii) a model to predict the impact of POI activities on road traffic congestion.

Several recent research works [1, 3, 4] have proposed different techniques that primarily focus on identifying traffic congestion of vehicles and suggesting alternative paths to avoid traffic congestions. These solutions do not consider one of the main underlying reasons of the traffic jam, i.e., the activity of people around POIs such as schools, hospitals, and shopping centers. In this thesis, we investigate the impact of the locations and activity time of the POIs on road traffic congestion. Each POI has its own type of activities and these activities vary with time. The POI traffic, i.e., the number of people who enter and leave a POI depends on the activity pattern of the POI and is an important factor for road traffic congestion. For example, the shopping centers are more crowded during holidays, before any special events and festivals. Thus, the traffic on the surrounding roads of the shopping centers increases at these times. Educational institute such as schools cause more traffic on road during their opening and closing time. Similarly, the traffic increases during visiting hours of hospitals.

1.1 Motivation

In developing countries, it is common that there are many POIs such as schools and shopping centers, in a single road and the activity period of nearby POIs overlaps (e.g., the closing time of a school and the visiting hours of a hospital). In such a scenario, the road traffic gets accumulated and further increases the traffic congestion.

Our developed models to quantify and predict the impact of POI activity patterns on road traffic congestions would allow us to reduce the traffic congestion in the following ways:

- Identifying the appropriate location for the establishment of POIs in the future. At present while selecting a location for a new POI, only road infrastructure is taken into consideration. This new research direction will show us that the activity patterns of the new POI and existing other POIs in the surrounding area are also important factors for selecting a location for the new POI. Based on POI activity patterns and relevant POI traffic, our proposed model can predict their impact on road traffic congestion. Thus, selection of locations for new POIs based on both road infrastructure and activities of POIs definitely reduce the possibilities of traffic congestions on road.

- Suggesting the change of the activity time of POIs after quantifying their impact on road traffic congestion. For example, if there are an educational institute (e.g., school) and a hospital on the same road and the closing time of the educational institute and the visiting hours of the hospital overlaps, then our method can suggest to change the closing time of the educational institute or the visiting hours of the hospital to avoid the impact of combined POI impact on road traffic.

- Predicting of the fastest path from a source to destination based on the impact of POIs on road traffic in the surrounding area. This will allow us to distribute the traffic among all roads and reduce the congestion. People who do not use POIs on a specific road will not mind to take another road to reach the destination if they can travel faster.

1.2 Challenges and Solutions

A traffic congestion on a road does not always represent that the congestion has been caused by POI activities and POI traffic on that road. A major challenge in quantifying the impact of POI on road traffic congestion is the separation of POI traffic from regular road traffic. We conducted a field study in a metropolitan city, Dhaka of a developing country Bangladesh. During our field study, we identify the traffic congestion pattern caused by POI traffic and develop a model to quantify the spatio-temporal impact of POI traffic on road traffic congestion. We observe that the impact of POI traffic causing road congestion is more pronounced on the adjacent area of the location of a POI, where the affected area gradually spreads or shrinks with time with the increase or decrease of POI traffic, respectively.

In addition, we also observe that POI traffic do not interact with the similar manner for all POI. For some POIs, the relevant traffic and the time period affecting the road is predictable, whereas for some these are not. In developing countries like Bangladesh, there are different types of vehicles such as rickshaws, cycles, bikes, cars, and buses that have different speed but no separate lanes and can stop at any place beside a road. It is a common scenario that rickshaws are waiting for passengers in front of a POI during its active period, occupy the road space and blocks the regular traffic flow. We count all vehicles that come and go to a POI along with the vehicles (including waiting rickshaws) that are parked at the road as its POI traffic. Thus, it is not possible to measure POI traffic in a straightforward way. Further, it is not feasible to implant costly sensors under roads in Dhaka. For our analysis, we rely on manual intervention and video data to measure POI traffic. We perform an initial set of case studies for two POIs, a hospital along with medical diagnostic center and a shopping center, located at two important areas of Dhaka city and validate the effectiveness of our proposed model.

1.2.1 Quantification Model

We develop a method to estimate POI traffic (i.e., the number of vehicles that interact with a POI) on roads. We observe that vehicles in the Dhaka city flow in substreams instead of lanes. Lanes are predefined and lanes for similar vehicles normally have the same width. On the other hand, the number and width of substreams may change dynamically on a road based on traffic pressure, i.e., they are not fixed. We observe that POI traffic does not affect all substreams in a similar way. Based on the substream wise traffic parameters such as the speed change ratio and the time headway [5] and POI traffic, we identify whether activities of a POI have impact on road traffic congestion. Our quantification model assumes that substream wise POI traffic and related measurements such as the length of each substream affected with POI traffic and the width of each substream are available in terms of input parameters. With the help of these parameters, our model quantifies the impact of a POI on a road traffic congestion in terms of the area that has been affected by POI traffic. The calculated area is called *POI Impact Area*. The larger the POI impact area, the higher is the impact of the POI activities to cause a traffic congestion.

1.2.2 Prediction Model

We develop a model to predict the impact of POI activities on road traffic congestions using fuzzy regressions [6]. We use training data sets to develop prediction models and we observe that the developed prediction models differ for different POI categories. We categorize POIs based on predictability, regularity, cause (i.e., event or schedule driven)of POI traffic. Specifically, the training datasets have information related to substream wise POI traffic, speed change ratio, time headway, time and the affected area by POI traffic for a specific POI category. For different combinations of values of parameters in the training datasets, our approach computes sets of fuzzy coefficients required for the prediction model.

The prediction model works in two steps: first identify whether the POI traffic will have impact on the traffic congestion and if yes, then it predicts the impact of POI activities in terms of the POI impact area. The input to the prediction model is the POI category, road structure, POI traffic, speed change ratio, time headway and time. We develop algorithms to select fuzzy coefficients (computed in the training phase) that match in terms of the input parameters of the prediction model and compute the POI impact area to predict the impact of POI activities on road traffic congestion.

1.3 Contributions

In summary, we have the following contributions:

- We present a technique to identify whether activities of a POI have impact on road traffic congestion based on our observations during the field study.
- We develop a model to quantify the impact of POI activities on road traffic congestion in terms of POI impact area.
- We develop a model to predict the impact of POI activities on road traffic congestion using fuzzy regressions.
- We perform a set of case studies and experiments to show the effectiveness of our quantification and prediction models.

1.4 Organization

The thesis is organized as follows. In Chapter 2, we present existing literature related to our approach. In Chapter 3, we present our model to quantify the impact of POI activities on road traffic congestion and in Chapter 4, we present our model to predict the impact of POI activities on road traffic congestion. In Chapter 5, we present our data collection strategies, experiments and analysis to show the effectiveness of our models. Chapter 6 concludes the thesis with future research directions.

Chapter 2

Literature Survey

In recent years, researchers [1, 3, 4, 7] have focused on identifying causes of traffic congestions on roads and developed techniques to suggest alternative paths to avoid traffic congestions. However, none of these existing approaches have considered the impact of POI activities on road traffic congestion. According to [7], traffic congestions can be recurrent, if traffic exceeds road capability, or non-recurrent, if an accident or special event takes place. The research problem that we consider in this thesis falls under non recurrent traffic congestion.

In the early stage, Ahmed and Cook [8] have proposed a statistical model for traffic prediction, which cannot handle uncertain, unstable or rapidly changing traffic condition. Models like as non-linear time series [9], nonparametric regression [10], bayesian networks [11, 12] exist in the literature to predict near future traffic. These models have been developed mainly based on simulation and theoretical analysis and not suitable for real-time traffic data as for certain time (e.g., peak hour), traffic data may not have been matched with time series or regression model. These models also have not addressed the uncertain condition as non-recurrent traffic.

Researchers used the multi-regime model [13, 14] in the early period to predict traffic because of the unscheduled or sudden event. After that the data-driven model [15] has been developed to construct the spatio-temporal interrelation and traffic prediction. Howard et al. [16] have provided multivariate kernel regression models to predict travel time in a road network. Kamarianakis et al. [17] have implemented classical time series approaches for short-term speed prediction in a network of motorways. Du et al. [18] have proposed a travel time prediction algorithm in a small scale simulated network. Finally, Sun et al. [19] have implemented more robust artificial intelligence algorithms for short-term traffic flow prediction in networks. However, none of these prediction models consider the impact of POI traffic on the road traffic congestion, where the POI traffic can be can be regular, predictable or unpredictable and be a cause of road traffic congestion in developing countries. Furthermore, POIs are normally established in an unplanned way in the developing country. This thesis is the first attempt to quantify the impact of POI traffic on road traffic congestions.

In recent years, researchers have focused on short-term travel time prediction because of its importance in traffic data collection technologies such as data Automatic Vehicle Identification systems [16, 20–22], Electronic Toll Collection (ETC.) systems linked to detectors [23, 24], and Global Positioning Systems (GPS) [25–28]. In [29], the authors have introduced a new travel time prediction algorithm that can be extended to use multi-source data. However, there are still several issues that need to be addressed; for example, if and how these data may be associated to a macroscopic view of traffic conditions that is essential for most traffic management strategies. The requirement of using publicly available datasets for larger data coverage [30, 31] has been recently discussed in [28], and the difficulties in fusing data from different sources in travel time prediction have been presented in [26]. The mentioned literatures run experiments in well-developed road structure. Unfortunately, the road structure and POI in the developed country are not similar to ours (e.g., lack of parking facility). In addition, the used technologies in their experiments are expensive and quite difficult to maintain in a developing country.

Short-term traffic forecasting algorithms are always data intensive approaches. Therefore, these processes are highly dependent on the systems and technologies for data collection. Several studies have systematically reviewed data collecting methodologies, in particular collecting section based data such as travel time [32, 33]. In [34], the authors have proposed a model on video based data collection, which is not applicable to our scenario due to our current road structure and lack of these facilities. Recently, the proliferation of wireless communication infra-structures and navigation technologies have enhanced data collection and data coverage. These technologies (i) collect vehicle positions, (ii) infer relevant information concerning vehicular kinematic characteristics and congestion, and (iii) provide congestion information to drivers [35].

There are still several uncertainties that need to be addressed carefully due to the lack of maturity in both technological and modeling aspects. A typical example is how to account for the bias induced by market penetration of such technologies. Oh et al. [36] and Jintanakul et al. [37] reported the difficulty in using probe vehicle technologies because of low market penetration. Herrera et al. [38] suggested that a 23% penetration of cell phones in the driver population is enough to provide accurate traffic measurements. Ma et al. [39] tested different penetration rates of vehicle infrastructure integration technologies for evaluating the effectiveness of travel-time predictions. Recently, in [40], the authors provided a methodology based on fused data from loop detectors and probe vehicles for estimating travel time. Unfortunately, the above technologies are not available to the traffic system (to both vehicle and drivers) of our country.

In [41, 42], the authors predict traffic congestions due to planned events such as concerts, and sports. The technique proposed in [41] does not quantify the impact of such an event on road traffic. In [42], the technique focuses on predicting traffic congestions due to such an event based on historical data. Both of these techniques are different from our considered problem of identifying impact of POI traffic on road networks. Activities on POIs are normally occur in a regular, periodic, predictable or in a unpredictable manner.

With the advancement of technology and cheap availability of sensors, some recent approaches [43–46] use an immense amount of sensors to collect, detect and forecast the impact of traffic anomalies. In [43], the authors use sensor based traffic to enhance the accuracy of traffic prediction model. In [44, 45], the authors predict the spatio-temporal impact of incidents on road traffic. In [47], the authors identify spatio-temporal traffic condition on the basis of varying several environment conditions such as traffic parameters, weather condition, regular or irregular traffic. Again, none of these approaches consider the impact of POI activities on road traffic. Furthermore, in developing countries, it is also not feasible to implant such an enormous amount of sensors on the road to collect traffic data and thus, these approaches are not extensible to quantify the impact of POI traffic on road networks. We depend on manual and video data for collecting and analyzing traffic data in our case studies. Though existing literature [48] have explored video data analysis to retrieve real traffic information, those techniques are not applicable for us as they do not consider POI traffic separately. In [49], the authors use Bing Map information to analyze and predict traffic information on road networks. However, real time traffic data from Bing Map are not available in Bangladesh.

Chapter 3

Quantification Model

In this chapter, we first define and discuss related traffic parameters in Section 3.1, we then present our observations to identify POI impact on road traffic congestion during our field study in Section 3.2 and assumptions in Section 3.3, and finally, we present our model to quantify the impact of POI activities in terms of POI Impact Area on road traffic congestion in Section 3.4.

3.1 Preliminaries

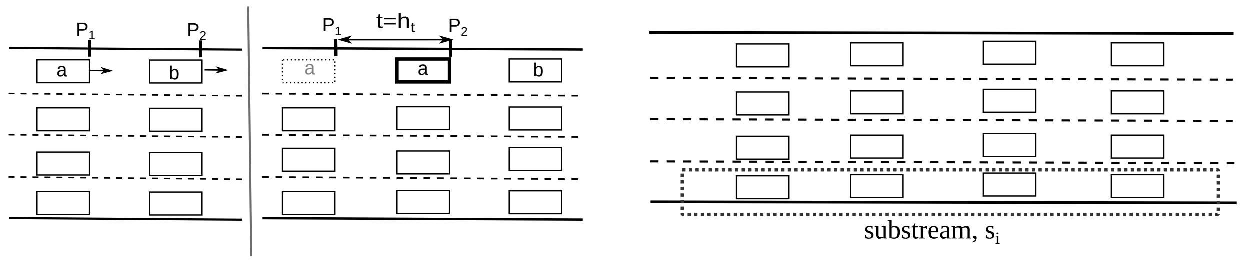
The *speed change ratio* $\Delta v(l, t_2 - t_1)$ of a vehicle at a specific location l (road, lane or substream) and the time period $(t_2 - t_1)$ is defined as the percentage of the decreased ratio of current traffic speed (v_c) compared with maximum allowed speed (v_{ref}) at l and $(t_2 - t_1)$, as shown in Equation (3.1):

$$\Delta v(l, t_2 - t_1) = \frac{v_{ref}(l, t_2 - t_1) - v_c(l, t_2 - t_1)}{v_{ref}(l, t_2 - t_1)} \times 100\% \tag{3.1}$$

In developing countries, maximum allowed speed may not be always mentioned in road networks. In those cases, we consider (v_{ref}) as the historical average speed value at l during $t_2 - t_1$.

We assume that a *traffic congestion* exists at a location l during the time period $(t_2 - t_1)$, if $\Delta v(l, t_2 - t_1)$ falls below a *limit threshold* λ. The values of λ may differ based on road types such as street, road, highways and residential areas.

In addition to the speed change ratio, we use *time headway* and *substream* in our POI impact quantification model. Time headway (h_t) denotes the difference between the time when



(a) Time Headway, h_t (b) Substream, s_i

Figure 3.1: Traffic speed

the front of a vehicle arrives at a point on the highway and the time the front of the next vehicle arrives at the same point (in seconds). In [5], a substream is defined as the vehicles that are traveling at the same speed and form a random series. Figure 3.1(a) and (b) show examples of time headway and a substream s_i, respectively.

3.2 Field Study

Traffic congestion on a road can be caused by POI traffic or regular traffic or both. We conducted a field study to observe the traffic congestion pattern when there is *POI impact* on road traffic congestion. To remind the reader, a traffic congestion exists on a road if the speed change ratio with respect to the maximum allowed speed on that road falls below a threshold λ. During the field study, we considered five popular POIs of different categories: school, diagnostic center, hospital, shopping mall, and mosque. Among these POIs, the school and the mosque are situated at residential areas and other POIs are located at busy roads of Dhaka city. In all cases, we have the following observation: *When a POI is in its effect period then its POI traffic affects its adjacent road lanes more than the furthest lanes.*

Figure 3.2 shows an example scenario of our observation for a POI P. Red and blue arrows represent POI traffic and regular traffic, respectively. In Figure 3.2(a), the POI P is closed and there is no traffic congestion on road. In Figure 3.2(b), P is active, the effect period of P starts as a few POI traffic interact with road. However, still the POI does not have any impact on causing road traffic congestion. In Figure 3.2(c), significant POI traffic joins the road traffic, causes the lane blockage, reduces the width of the remaining part of the road, makes speed change ratio to fall below λ and thus, starts having impact on traffic congestion. In Figure 3.2(d), POI traffic blocks most part of the road, slows down regular traffic flow significantly and POI impact becomes more severe in such a scenario then its previous states.

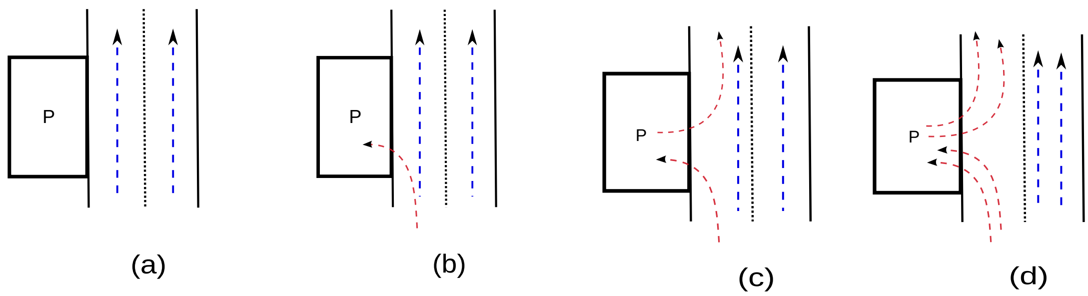
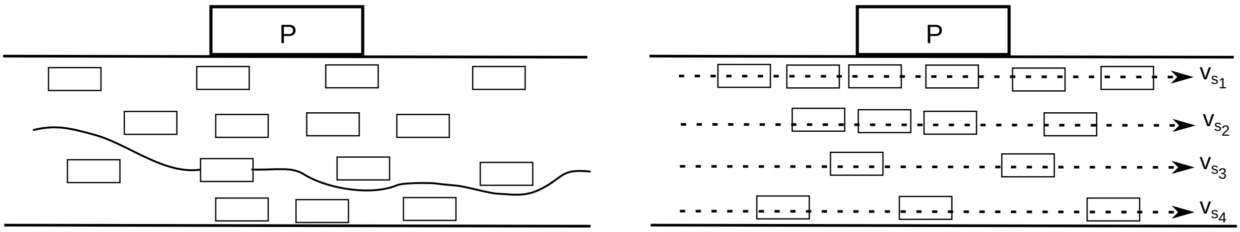


Figure 3.2: POI impact on road traffic at different timestamps

According to our observation, to identify whether POI traffic has caused road traffic congestion we have to consider each substream traffic speed independently instead of road traffic speed as shown in Figure 3.3. If POI has impact on road traffic congestion then the adjacent substreams have less traffic speed compared to farthest substreams, i.e., $(v_{s_1} < v_{s_2} < ...v_{s_4})$, where all substreams are considered on the road at the same side of the POI. We also observe that vehicles also pick up and dropp off people for the POI on the adjacent substreams of the opposite side of the road. Thus, the impact of the POI activity is more pronounced in the farthest substreams of the POI (i.e., the adjacent substreams of the opposite side of the road) than the adjacent substreams of the POI on the opposite side, where all substreams are assumed to be on the road at the opposite side of the POI.

Sometimes, it may happen that a traffic congestion covers the full road due to high POI traffic and the traffic speed of different substreams are similar as they are measured over full road length. Thus, it may not be possible to identify whether a POI has impact on road traffic congestion based on our observation, i.e., considering only substream traffic speed. To address this issue, we consider time headway, which gives a detail view of the traffic state. For example, vehicles that enter, exit or wait besides a POI have a high time headway compared to those which are far away from the POI. Similarly vehicles that pick up or drop off passenger on the road to the opposite side of the POI have high time headway compared to other substreams on the opposite side. In summary, both traffic speed change ratio and time headway of substreams together identify whether a POI has impact on road traffic congestion.



(a) Road traffic speed

(b) Substream speed

Figure 3.3: Traffic speed

3.3 Assumptions

To develop a model to quantify the POI impact, we make the following assumptions:

- We assume that vehicles move in a substream but in reality it might happen that the substreams are not clearly visible. We also assume that every substream has a fixed width though it may vary over the length of a substream.

- We assume a simplified road structure, two way road with a divider in the middle. We do not consider the presence of U turn points or road junctions

- We assume that a POI has entry and exit point on the main road and quantify the impact of the POI on the main road. We do not consider the impact of the POI on the side lanes.

3.4 POI Impact Quantification Model

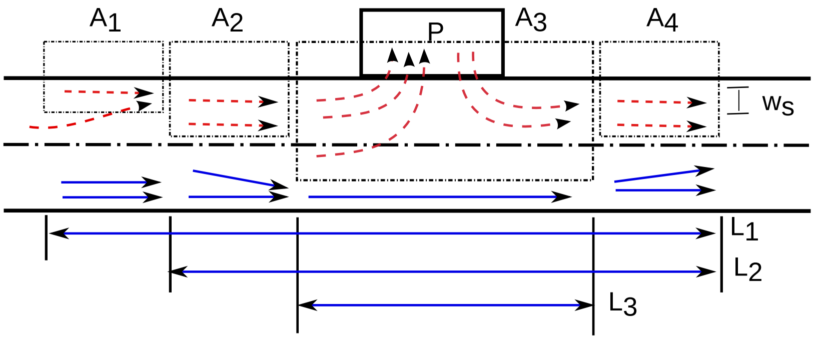


Figure 3.4: POI impact in terms of coverage area

In this section, we quantify the impact of a POI on road traffic congestion. We model the level of POI impact in terms of *POI Impact Area*, i.e, the area where POI traffic has accumulated and caused traffic congestion. To find out the POI Impact Area, we need to compute the number of substreams n and the length l of of each substream, where vehicles related to POI traffic have accumulated and caused road traffic congestion. Note that we have already mentioned in Section 3.2 about how to identify traffic congestion caused by POI traffic using traffic parameters speed change ratio and time headway.

With the upcoming POI traffic, which are queued behind the existing POI traffic, the length l increases and the POI Impact Area expands. Often, there might be a scenario, where each substream may not have traffic congestion of the same length. As an example, we see in Figure 3.4 that POI traffic are more accumulated and congested at entry and exit point of a POI p. Dot lines and solid lines in the figure show POI traffic and road traffic, respectively. We also see that POI traffic are congested in smaller area with the increase of the distance from p. Thus, in the same road different substreams may have traffic congestion of different length.

Let a substream s_i on the road has traffic congestion of length l_i and width w_i. Thus, POI Impact Area of each substream A_i can be expressed as $A_i = l_i \times w_i$ and the total POI Impact

Area A can be expressed as follows:

$$\begin{aligned} A &= \sum_{i=1}^{n} A_i \\ &= l_1 \times w_1 + l_2 \times w_2 + ... + l_n \times w_n \end{aligned} \tag{3.2}$$

It is important to note that outside of the POI Impact Area, a road can have traffic congestion which may have been caused by either POI traffic or road traffic or both. However, with the increase of the POI Impact Area, the remaining space in the road for regular traffic decreases and the probability of the road traffic congestion outside the POI Impact Area increases.

Chapter 4

Prediction Model

In this chapter, we propose a model for the prediction of the impact of POI activities on road traffic congestion using fuzzy linear regression. The values of fuzzy coefficients used in the model differ based on the category of POIs. We use fuzzy regression because the impact of POI on the road traffic congestion can only be estimated, not perfectly measured. We will see that the fuzzy linear regression gives us output as a set of upper, and lower limits, which are good suites for our requirements. Furthermore, the fuzzy regression allows us to predict the POI impact by considering our specified threshold λ. To remind the readers, a traffic congestion occurs when the average speed change ratio of a road falls below λ and the values of λ may differ based on road types such as street, road, highways and residential areas.

We first discuss fuzzy linear logic briefly in Section 4.1, present different categories of POIs in Section 4.2, and then elaborate our model in Section 4.3.

4.1 Preliminaries

In [6, 50], the fuzzy linear regression is stated as follows:

$$\widetilde{y} = \widetilde{A_0} + \widetilde{A_1}x_1 + \widetilde{A_2}x_2 + ... + \widetilde{A_n}x_n \tag{4.1}$$

where, $x = (x_1, x_2, ..., x_n)^t$ is the real input set, $\widetilde{A} = (\widetilde{A_0}, \widetilde{A_1}, \widetilde{A_2}, ..., \widetilde{A_n})^t$ is the fuzzy coefficient set, $\widetilde{y}$ is the fuzzy output and n is the number of parameters. The fuzziness of a fuzzy coefficient is represented with center α and spread c [6, 50, 51], where $\alpha, c \in \mathbb{R}$. A fuzzy coefficient set is characterized using a membership function, i.e., a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The fuzzy coefficient set $\widetilde{A} = (\widetilde{A_0}, \widetilde{A_1}, \widetilde{A_2}, ..., \widetilde{A_n})^t$ is represented using the following membership function:

$$\mu_A(a_j) = \begin{cases} 1 - \frac{|\alpha_j - a_j|}{c_j}, & \alpha_j - c_j \leqslant a_j \leqslant \alpha_j - c_j \\ 0, & otherwise \end{cases} \tag{4.2}$$

The value 0 of $\mu_A(a_j)$ means that a_j is not a member of the fuzzy set; the value 1 means that a_j is a member of the fuzzy set [52]. Any value between 0 and 1 of $\mu_A(a_j)$ at a_j represents the grade of membership of a_j in A.

Tanaka et al. shows in [6] that fuzzy coefficient set $\widetilde{A}$ can be replaced as (α, c). Hence the fuzzy coefficients $\widetilde{A} = (\widetilde{A_0}, \widetilde{A_1}, \widetilde{A_2}, ..., \widetilde{A_n})^t$ can be denoted using the following vector form:

$$\widetilde{A} = (\alpha, c), \alpha = (\alpha_0, \alpha_1, ...\alpha_n)^t, c = (c_0, c_1, ..., c_n)^t$$

Therefore, we can rewrite Equation (4.1) as follows:

$$\widetilde{y} = (\alpha_0, c_0) + (\alpha_1, c_1)x_1 + (\alpha_2, c_2)x_2 + ... + (\alpha_n, c_n)x_n \tag{4.3}$$

To determine the output $\widetilde{y}$ for the fuzzy regression with the minimum fuzziness, we need to find minimized total spread c. The following linear problem [6, 51] is formulated to compute the fuzzy coefficients (center, α and spread, c):

$$min(J) = \sum_{j=0}^{N} \left(\sum_{i=0}^{M} c_j \, |x_{ij}| \right)$$

$$\sum_{j=0}^{N} \alpha_j x_{ij} + (1-h) \sum_{j=0}^{N} c_j \, |x_{ij}| \geqslant y_i$$

$$\sum_{j=0}^{N} \alpha_j x_{ij} - (1-h) \sum_{j=0}^{N} c_j \, |x_{ij}| \leqslant y_i$$

$$c_j \geqslant 0$$

In the above linear problem, $\alpha_j \in \mathbb{R}, j = 0, 1, 2, ..., N, x_{i0} = 1, i = 1, 2, ..., M, 0 \leqslant h \leqslant 1$, N is the number of fuzzy parameters, M is the number of real parameters and J represents the total fuzziness of the fuzzy regression model. The value for h is adjusted such that the linear regression model provides the minimum fuzziness.

In [6], the membership function for a fuzzy output is defined as follows:

$$\mu_Y(y) = \begin{cases} 1 - \frac{|y - x^t\alpha|}{c^t|x|}, & x \neq 0 \\ 1, & x = 0, y = 0 \\ 0, & x = 0, y \neq 0 \end{cases}$$

where $|x| = (|x_1|, ..., |x_n|)^t$. The membership function $\mu_Y(y) = 0$ when $c^t\,|x| \leqslant |y - x^t\alpha|$, which indicates the center of the output is $x^t\alpha$ and the spread (fuzziness) of the output is $c^t\,|x|$.

The fuzzy output y_i is computed as $\widetilde{y_i} = \left(y_i^L, y_i, y_i^U\right)$, where $i = 1, 2, ...M$. The lower bound of $\widetilde{y_i}$ is $y_i^L = \sum_{j=0}^{N} (\alpha_j - c_j)\, x_{ij}$, the center line is $y_i = \sum_{j=0}^{N} \alpha_j x_{ij}$ and the upper bound of $\widetilde{y_i}$ is $y_i^U = \sum_{j=0}^{N} (\alpha_j + c_j)\, x_{ij}$.

4.2 POI Categories

Points of interests (POIs) such as schools, hospitals, banks, shopping centers offer a variety of facilities and services that range from basic needs to entertainment of users. POIs normally involve different number of people depending on their activities and popularity. We categorize POIs based on predictability, regularity, cause (i.e., event or schedule driven) of POI traffic.

We define two related terms to POI traffic are *active time*, and *effect period* of a POI. Generally *active time* of a POI indicates the time period when the POI remains open to serve its people. However, it is observed that during this period of time a POI may not affect road traffic. The POI affects road traffic when people enter or exit the POI. As an example, a school has effect on road traffic when the class time starts or ends. During class time, significantly less number of vehicles carrying people towards or from POIs interact with road traffic. We call the time period when a POI has interaction with road traffic as *effect period.* On the other hand, a shopping center has relatively more interaction with people, people can enter or exit a shopping center at any time. Thus, active time and effect period are same for a shopping center. Effect period is an important criteria to quantify the impact of a POI on road traffic congestion.

A POI has impact on road traffic during its effect period when a significant amount of *POI traffic* occupies the road space, blocks regular traffic flow and causes traffic congestion. POI traffic includes vehicles that enter, exit, park for people related to POIs. The vehicles that travel through the road but do not interact with any POI is considered as *regular traffic*. POI traffic may not remain same during the effect period. For example, for a hospital, patient carrying vehicles may come or leave hospital at any time, but its POI traffic is more significant in the visiting hour of the hospital.

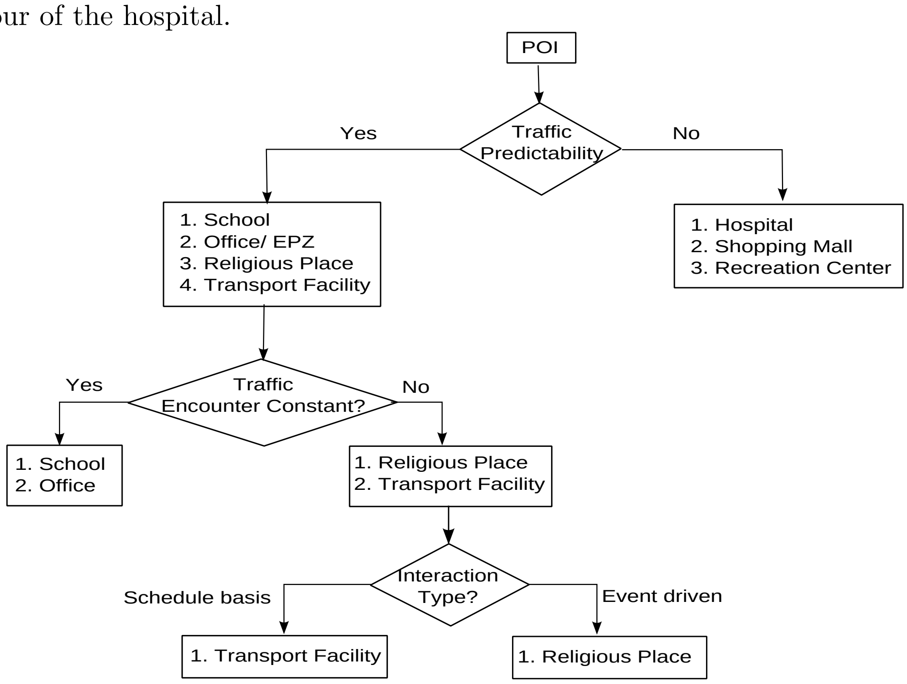


Figure 4.1: POI categorization based on POI traffic

We categorize POIs based on predictability, regularity, cause (i.e., event or schedule driven) of POI traffic (see Figure 4.1). POI traffic may not be always predictable, for example, in a POI like shopping center or hospital, we cannot predict how much POI traffic is involved in a certain period of time. On the other hand, POIs like a school, office, airport or rail station have predictable POI traffic.

For predictable POI traffic, there are two scenarios depending on whether the POI traffic is constant or not. In a school or office, same sets of people interact with the POI in every working day and the POI traffic remains constant. The other category of POIs like a religious place or transport facility such as airport or rail station has predictable but not constant traffic. These POIs can be further categorized based on their event or schedule driven activities. For example, for a religious place its POI traffic can be predicted based on religious events such as Eid or Christmas prayers, whereas in a rail station POI traffic is predicted based on the schedule of arrival or departure of trains.

4.3 Our Model

Given a POI category, estimated POI traffic N_{poi}, substream wise speed change ratio, Δv, and time headway h_t, our model predicts the impact of POI activities on road traffic congestion in terms of POI impact area. The impacted length for each substream s_i is predicted using the fuzzy regression logic as follows:

$$l_i = \widetilde{A_0} + \widetilde{A_1}\Delta v + \widetilde{A_2}h_t + \widetilde{A_3}N_{poi} \tag{4.4}$$

Fuzzy coefficient set can be represented with respect of center, α and spread, c. Therefore, Equation (4.4) can be written as (4.3):

$$l_i = (\alpha_0, c_0) + (\alpha_1, c_1)\Delta v + (\alpha_2, c_2)h_t + (\alpha_3, c_3)N_{poi} \tag{4.5}$$

Our model learns the value of center, α and spread, c from the training datasets and use them in the prediction phase. The computation of the value of center, α and spread, c for a certain time span by solving linear programming problems is discussed in Section 4.3.1. In Section 4.3.2, we discuss our prediction methodology.

Since POI traffic N_{poi} has significant higher value than speed change ratioΔv and time headway h_t, one may argue that applying normalization for N_{poi}, Δv, and h_t would be a better option. However, we do not need normalization as we use the same equation to learn the values of α and c in the training phase, where $\alpha, c \in \mathbb{R}$.

4.3.1 Training phase

Without loss of generality, let us consider an example to solve linear programming problems for computing center, α and spread, c for the the following dataset. Table 4.1 shows traffic data for time duration t_1, t_2, t_3, and t_4.

Table 4.1: Sample input data for a certain time period

impact length, l_i	$l_i^{t_1}$	$l_i^{t_2}$	$l_i^{t_3}$	$l_i^{t_4}$
speed change ratio, Δv_i	$\Delta v_i^{t_1}$	$\Delta v_i^{t_2}$	$\Delta v_i^{t_3}$	$\Delta v_i^{t_4}$
time headway, t_{h_i}	$t_{h_i}^{t_1}$	$t_{h_i}^{t_2}$	$t_{h_i}^{t_3}$	$t_{h_i}^{t_4}$
POI traffic, N_i	$N_i^{t_1}$	$N_i^{t_2}$	$N_i^{t_3}$	$N_i^{t_4}$

We formulate the linear programming problem with our dataset as follows:

$$min \sum_{j=0}^{N} \left(\sum_{i=0}^{M} c_j \left| x_{ij} \right| \right)$$

$$\Rightarrow min \left(c_0 + (\Delta v_i^{t_1} + \Delta v_i^{t_2} + \Delta v_i^{t_3} + \Delta v_i^{t_4})c_1 + (t_{h_i}^{t_1} + t_{h_i}^{t_2} + t_{h_i}^{t_3} + t_{h_i}^{t_4})c_2 + (N_i^{t_1} + N_i^{t_2} + N_i^{t_3} + N_i^{t_4})c_3 \right)$$

with the respect to the constraints:

$$\alpha_0 + \alpha_1 \Delta v_i^{t_1} + \alpha_2 t_{h_i}^{t_1} + \alpha_3 N_{poi}^{t_1} - (1-h) \left(c_0 + c_1 \Delta v_i^{t_1} + c_2 t_{h_i}^{t_1} + c_3 N_{poi}^{t_1} \right) \leqslant l_i^{t_1}$$

$$\alpha_0 + \alpha_1 \Delta v_i^{t_1} + \alpha_2 t_{h_i}^{t_1} + \alpha_3 N_{poi}^{t_1} + (1-h) \left(c_0 + c_1 \Delta v_i^{t_1} + c_2 t_{h_i}^{t_1} + c_3 N_{poi}^{t_1} \right) \geqslant l_i^{t_1}$$

...

...

$$\alpha_0 + \alpha_1 \Delta v_i^{t_4} + \alpha_2 t_{h_i}^{t_4} + \alpha_3 N_{poi}^{t_4} - (1-h) \left(c_0 + c_1 \Delta v_i^{t_4} + c_2 t_{h_i}^{t_4} + c_3 N_{poi}^{t_4} \right) \leqslant l_i^{t_4}$$

$$\alpha_0 + \alpha_1 \Delta v_i^{t_4} + \alpha_2 t_{h_i}^{t_4} + \alpha_3 N_{poi}^{t_4} + (1-h) \left(c_0 + c_1 \Delta v_i^{t_4} + c_2 t_{h_i}^{t_4} + c_3 N_{poi}^{t_4} \right) \geqslant l_i^{t_4}$$

$$c_0 \geqslant 0, \ c_1 \geqslant 0$$

$$c_2 \geqslant 0, \ c_3 \geqslant 0$$

In the above scenario, there are total $12(= 2 * 4 + 4)$ equations and 8 unknown variables. Therefore, we can find $(\alpha_i, c_i)^t$ by solving the above mentioned linear programming problem.

4.3.2 Prediction phase

The prediction of the impact of POI traffic on road traffic congestion works in two steps. First, it identifies whether the POI traffic will have an impact on the traffic congestion and if yes, then it predicts the impact of POI activities in terms of the POI impact area.

4.3.2.1 Impact Identification

We already know from Section 3.2 of Chapter 3 that a traffic congestion does not always represent that there is an impact of POI activity as it can be also caused by regular traffic. Algorithm 1 shows the pseudo-code to determine whether whether POI activity will have an impact on the traffic congestion. The input to the algorithm are POI traffic N_{poi}, a set of substreams $S = \{s_1, s_2, \ldots, s_n\}$ on the considered road, a set of speed change ratios $V = \{\Delta v_1, \Delta v_2, \ldots, \Delta v_n\}$, and a set of time headways $T = \{t_{h_1}, t_{h_2}, \ldots, t_{h_n}\}$, where Δv_i and t_{h_i} represent the speed change ratio and time headway for substream i for $1 \leq i \leq n$. The output of the algorithm is Imp, which is 1 if POI activity has an impact on the traffic congestion, 0 otherwise.

We assume that the algorithm runs when there is a traffic congestion on road, i.e., the average speed change ratio falls below to a threshold λ. First our algorithm checks whether the POI is in its effect period, i.e., $N_{poi} > 0$. If not, then the algorithm returns false. Otherwise the algorithm attempts to identify whether the POI activity has an impact on traffic congestion based on substream wise speed change ratio using Function $IdentifyImpactonSpeed$. The function checks whether (i)the speed change ratio of the adjacent substreams of the POI are more than those of the farthest substreams of the POI, where all substreams are assumed to be on the same side of the POI and (ii)the speed change ratio of the farthest substreams of the POI are more than those of the adjacent substreams of the POI, where all substreams are assumed to be on the opposite side of the POI. If these conditions are true the function returns 1, i.e., the POI activity has an impact on the road traffic. If the conditions are not true because speed change ratios of all substreams are similar then the function returns -1. Otherwise the function returns 0, i.e., the POI activity has no impact on the road traffic.

If the returned value of Function $IdentifyImpactonSpeed$ is 1 or 0, then Algorithm 1 also returns Imp as 1 or 0, respectively. If the returned value is -1, then the algorithm calls Function $IdentifyImpactonTimeHeadway$. The function checks whether (i)the time headway of the adjacent substreams of the POI are higher than those of the farthest substreams of the POI, where all substreams are assumed to be on the same side of the POI and (ii)the time headway of the farthest substreams of the POI are higher than those of the adjacent substreams of the POI, where all substreams are assumed to be on the opposite side of the POI. If these conditions are true the function returns 1, i.e., the POI activity has an impact on the road traffic. Otherwise the function returns 0, i.e., the POI activity has no impact on the road traffic. Algorithm 1 assigns the returned value of the function to Imp and returns Imp.

Algorithm 1: IdentifyImpact(N_{POI}, S, V, T)

Input: N_{POI}, S, V, T

Output: Imp

$Imp \leftarrow 0$
if $N_{POI} > 0$ **then**
  $Flag \leftarrow IdentifyImpactonSpeed(S, V)$
  if $Flag \neq -1$ **then**
    $Imp \leftarrow Flag$
  else
    $Imp \leftarrow IdentifyImpactonTimeHeadway(S, T)$
  end if
end if
return Imp

4.3.2.2 Impact Quantification

From the training phase, we have sets of fuzzy coefficients center, α and spread, c for different categories of POIs for different time periods. If Algorithm 1 returns 1, to predict the impact of a POI activity on road traffic congestion, we first match the category of the POI, time period and its surrounding road structure with the attributes of available POIs for which fuzzy coefficients center, α and spread, c have been computed in the training phase and select the fuzzy coefficients for the POI that closely matches with the considered POI.

Algorithm 2 shows the pseudo-code for predicting the impact of POI activity on traffic congestion in terms of POI impact area A. The key idea of this algorithm is to project the affected length of each substream by the POI activity and then multiply it with the width of the substream, and add to A. A is initialed with 0 (Line 1). Though our prediction model uses Algorithm 1 to determine whether POI activity has an impact on road traffic congestion, but it does not ensure that the POI activity has an impact on every substream of the road. The fuzzy linear regression allows us to determine whether the POI activity has an impact for a certain substream.

After selecting fuzzy coefficients, for each substream s_i, Algorithm 2 determines the upper and lower bound of impact length, l_i^U and l_i^L, respectively, using Function $ComputeImpactbyFLR$ (Line 3). The value for parameter h is set to 0.5 for this purpose. The Algorithm 2 determines the projected impact length l_{i_λ} for substream s_i using Function $ProjectImpactbyFLR$ (Line 4). The value for parameter h is set to λ and c to 0 for this purpose. If the projected length is lower than the lower bound then the POI activity has no impact on the substream s_i. Otherwise the POI activity has an impact and thus added to A after multiplying it with the substream width w_i.

Let us consider an example where the road length is 250 meter. Table 4.2 shows sample data as lower bound, upper bound of the impact length and projected impact length for a single substream s_i. In the first case, for a certain substream s_i the upper bound is 100 meter and the lower bound is 20 meter and our projected impact length is 15 meter. The projected length for this substream falls below the lower bound and thus, the POI activity has no impact on the traffic congestion of this substream. In the second case, the upper bound is 175 meter and

Algorithm 2: ImpactQuantify(S, W)

Input: S, W

Output: A

$A \leftarrow A + l_i \times w_i$

for all substream, $s_i \in S_n$ **do**

  $[l^U, l^L] \leftarrow ComputeImpactbyFLR(s_i, h \leftarrow 0.5, c)$

  $l_{i_\lambda} \leftarrow ProjectImpactbyFLR(s_i, h \leftarrow \lambda, c \leftarrow 0)$

  if $l_{i_\lambda} \geq l^L$ **then**

    $A \leftarrow A + l_{i_\lambda} \times w_i$

  end if

end for

return A

Table 4.2: Sample output data for a single substream

Case study	Case 1	Case 2	Case 3
Upper bound, l_i^U	100	175	250
Lower bound, l_i^L	20	95	200
Projected affected length, l_{i_λ}	15	140	255
Impact	No	Yes	Yes

lower bound is 95 meter. As our projected length is 140 meter, which falls between the upper and lower bound, we can say that there is impact of POI activity on this substream. In third case, the upper bound is 250 meter and the lower bound is 200 meter and the projection is 255 meter, which falls over the upper bound. This also indicates that the POI activity has an impact on the traffic congestion of this substream.

Chapter 5

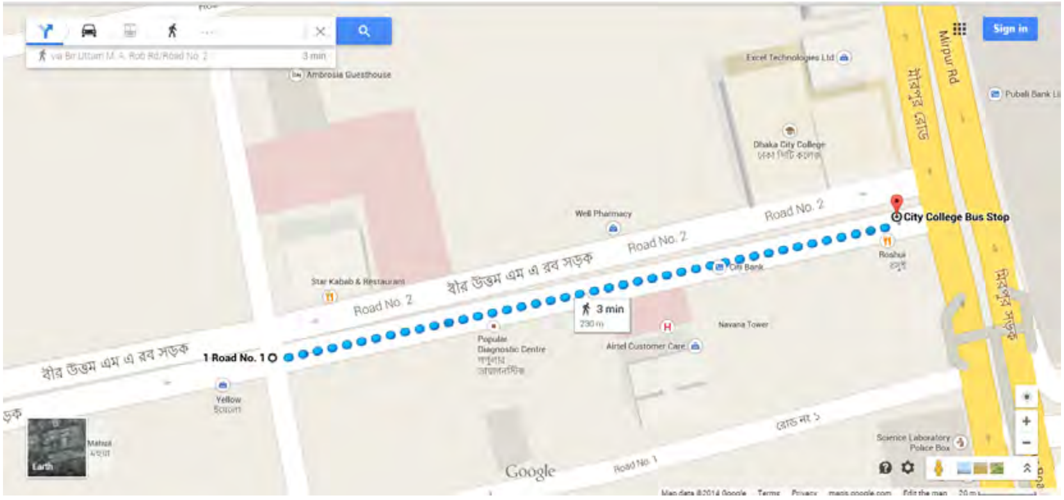
Results and Discussion

In this chapter, we first discuss our data collection strategy in Section 5.1, and then we present our case studies to identify the POI impact on road traffic congestion in Section 5.2, and finally we present experiments and analysis to show the effectiveness of our prediction model in Section 5.3.

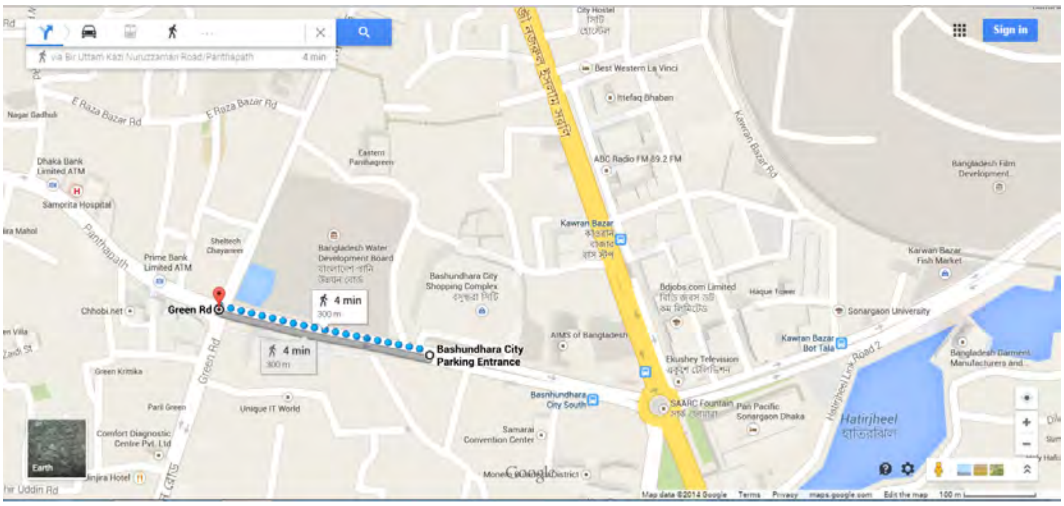
5.1 Data Collection Model and Experiment Setup

In our case study, we select two POIs: Popular Diagnostic Center and Hospital, and Boshundhara City Shopping Mall, located at two main streets of Dhaka city. To measure the impact of these two POIs on the road traffic, we collected traffic data for the span of seven days. In each day, we collected POI traffic (N_{POI}), speed change ratio (Δv), time headway (h), and affected area (A) on hourly basis for the entire active time, 10AM to 10PM, of a POI. For each POI, 3 persons were involved in the data collection, where one person manually counted the POI traffic, one person measured the time headway for all substreams, and the third person operates two video cameras in two directions that are used to measure the speed and affected area parameters.

Figure 5.1 shows the road segments and surrounding road networks of two POIs. Figure 5.1(a) shows the road segment, which is a part of Bir Uttam M. A. Rob road in Dhanmondi-2, in front of Popular hospital and diagnostic center. The figure shows that the corresponding road segment starts from City college bus stop and ends in the junction with Road No. 1. The length of this road segment is 250 meters (approximate). On the other hand, in Figure 5.1(b) we can see the affected road segment for the second POI, Boshundhora City shopping mall. The road segment is a part of Panthopath Road, which starts from Panthopath and Green road junction and ends at SAARC fountain in Kawranbazar. The length of this road segment is 600 meters (approximately half of the entire road segment is highlighted in Figure 5.1(b)).



(a) Popular Hospital



(b) Bashundhora City

Figure 5.1: Nearby road segments of selected POIs

We measured the traffic data for three days (Sunday, Monday and Wednesday) for Boshundhora city shopping mall and diagnostic center and two days (Monday and Wednesday) for for Popular hospital and diagnostic center. Each day we collected the data for the entire active period, from 10am to 10pm, of POIs. We counted POI traffic, and measured speed change, time headway, and affected area for every 15 minutes time span. POI traffic is estimated based on the number of vehicles that interact with the POI, which can occur in two ways: (i) vehicles that come to the POI premise, pick up or drop off passengers and then leave, and (ii) vehicles that park in the surrounding road network. We counted POI traffic per 15 minutes duration. To be specific, we incremented POI traffic by 1 for every vehicle that come and move way in 15 minutes time span. On the other hand, if a vehicle enters the POI premise in one of our 15 minute time slot and leaves in another 15 minutes time slot, POI traffic is incremented by 1 in each of these two time slots. In addition, we counted the parked vehicles in the road network surrounding the POI and added to the POI traffic count. The POI traffic estimation was cross checked with video data for verification.

For the speed change, we measured the time that a vehicle takes to cross the road from the video data. Then we found the current speed by dividing the road length with the measured time. We measured the speed of a vehicle in every substream in 5 minutes interval. For the time headway, we counted the number of vehicles that cross a certain point of a substream in every $60 - 90$ seconds. Then we measured the average time headway by dividing this vehicle count with the corresponding time span. In this way, we measured the average time headway for every substream in the road.

We measured the affected substream length with video cameras. We set the video cameras such that they cover the area of the affected substreams. Then we measured the length from the video data. To measure length, we first counted vehicles and multiplied it with their corresponding length. We also verified it by measuring the length with acute angle of view and corresponding calculation. A summary is provided in Table 5.1.

To gather the video data, we deployed two video cameras on the road divider to cover the whole road segment. We put the cameras in such a way that they covered every section of the road. We used high tripod to cover vertical distance and set of lenses to cover the horizontal

Table 5.1: Traffic parameter measurement

Parameter (Substream wise)	Measurement	Verification
Current speed	Video data	N/A
Affected length	Video data (vehicle count)	Video data (view angle)
POI traffic (overall)	Manual estimation	Video data
Time headway	Manual count	Video data

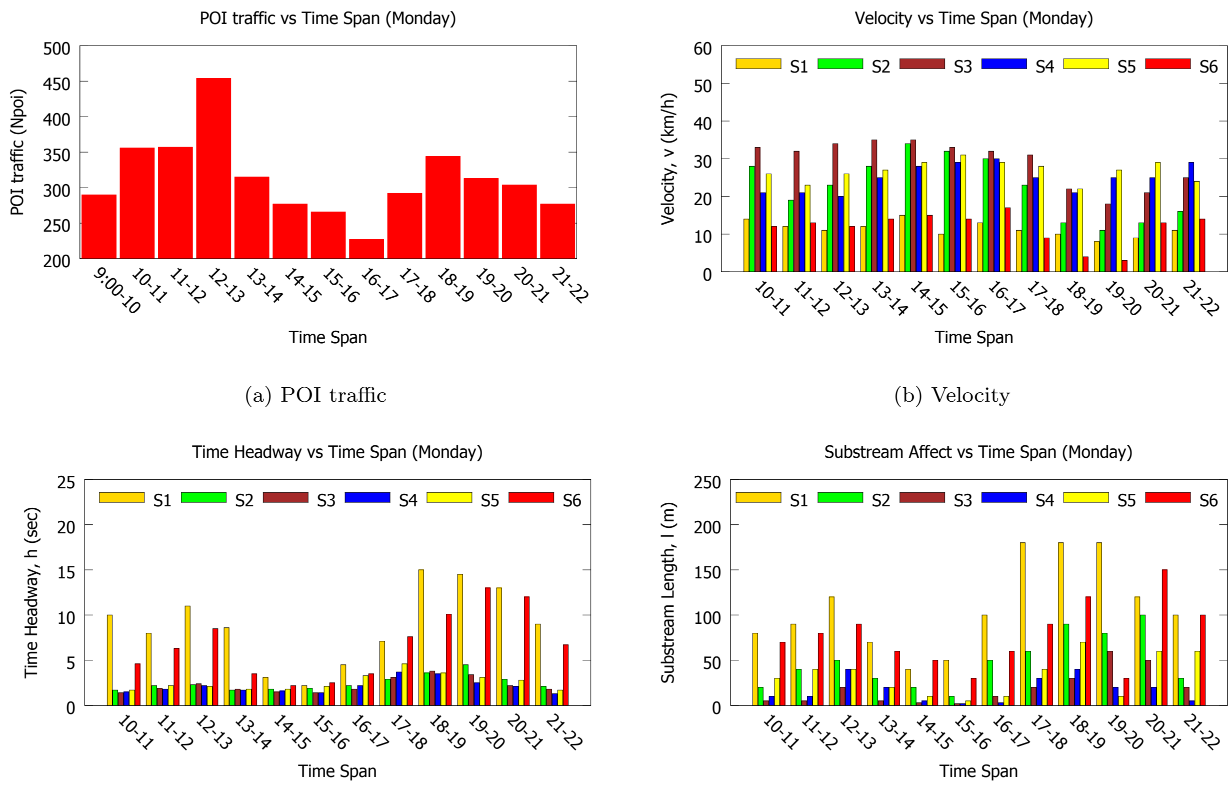
distance. We used additional storage to gather video data. We also set up environment for cameras' battery charging along with few spare batteries. The list of equipment is shown in Table 5.2.

Table 5.2: Video gathering equipments

Item name	Quantity
Video Camera (Model - Canon VIXIA HF-32)	1
Video Camera (Model - Sony Bateria NP-FV 10)	1
Tripod (most vertical length as 8 feet)	2
Regular lens	2
Fish-eyed lens	1
Spared battery	5
SD Memory card (32GB)	3
Portable Hard-disk (2TB)	1
Laptop	1
Multiplug	1

We used a workstation as Apple Macbook Pro with 2.5GHz i5 processor, 8GB ram and 256GB flash storage for our experiments. We used JAVA as our coding language, where IDE is Eclipse Helios version - 4.5.1, JDK version is 1.8, and sqlite-3.3.1 as our model storage. We also used hibernate framework to communicate to the database and Apache's Math jar file to implement the mathematical analysis.

5.2 Case Studies: Impact of POIs on Road Congestion



(a) POI traffic

(b) Velocity

(c) Time headway

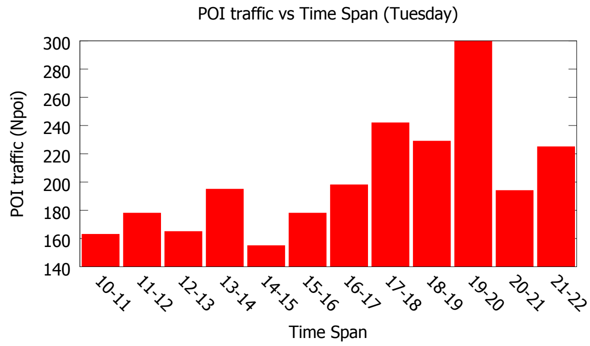
(d) Area

Figure 5.2: Diagnostic Center and Hospital on Monday

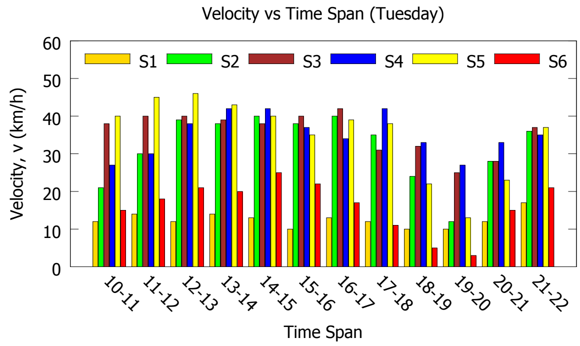
In this section, we show the correlation between POI traffic and road congestion by analyzing seven days of traffic data.

Figure 5.3 shows the POI traffic and its impact on the road traffic for Popular Diagnostic Center and Hospital (located at Road 2, Dhanmondi, Dhaka 1205) on Tuesday from 10AM to 10PM. We can see from Figure 5.3(a) that this POI has the maximum POI traffic between 7PM to 8PM, when most of the patients come to see doctors and get their test done. We also see that there is a significant increase of POI traffic during 5PM-8PM than the rest of the days as doctors see the patients during this period.

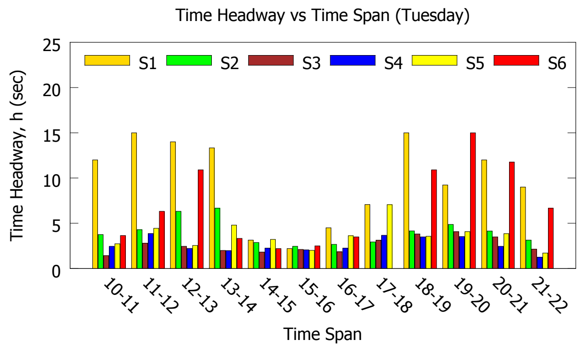
Figure 5.3(b) shows the velocity of 6 substreams (S1-S6, where S1-S3 is on the same side of



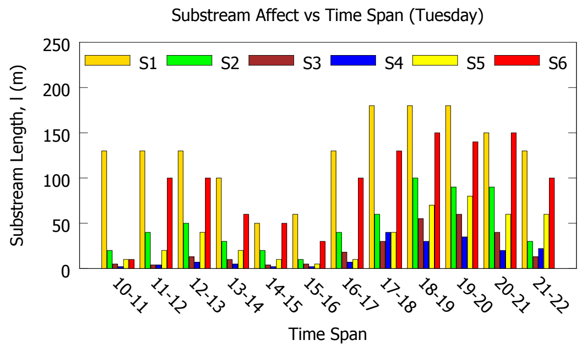
(a) POI traffic



(b) Velocity



(c) Time headway

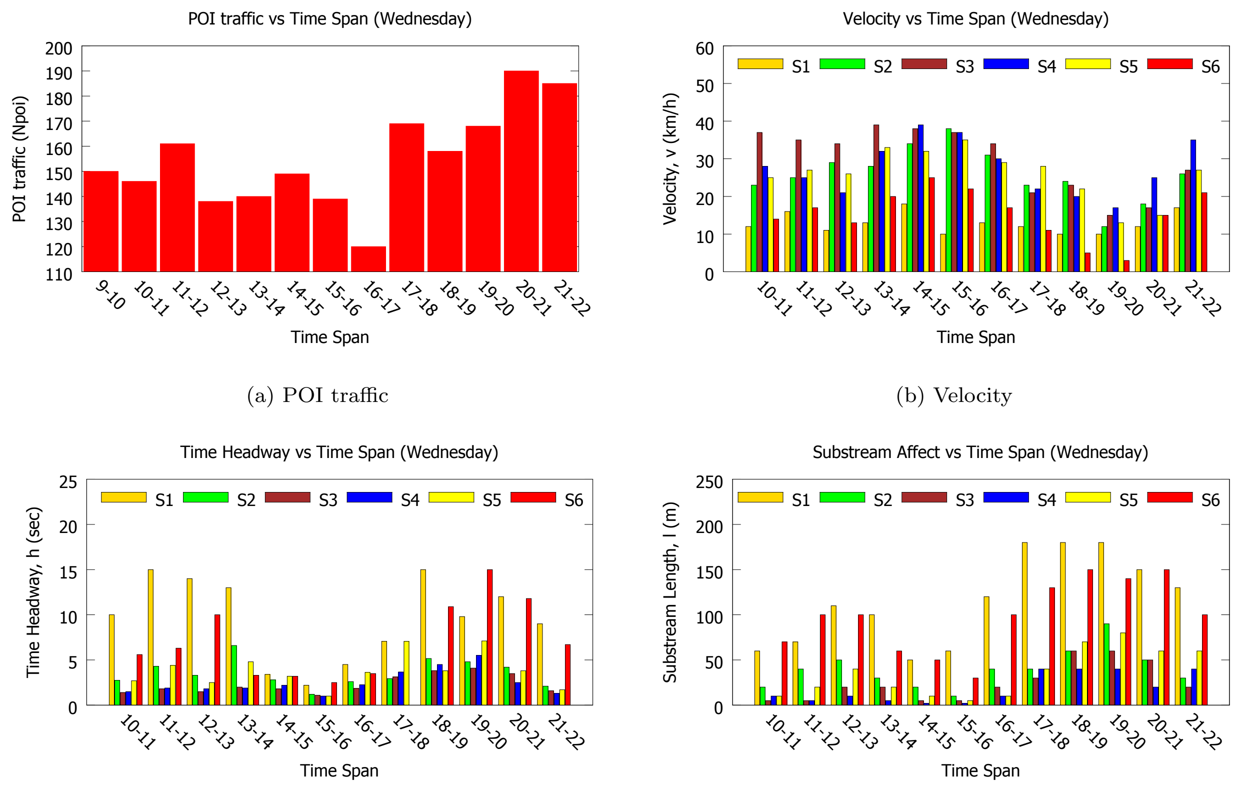


(d) Area

Figure 5.3: Diagnostic Center and Hospital on Tuesday

the POI and S4-S6 is on the opposite side of the POI). We find that substreams S1 and S6 are the most affected substreams by POI traffic, and thus have less speed than other substreams. This is because these two substreams have more POI vehicles stopping with passengers coming at the center or waiting for the passengers leaving the center. Since there is an U-turn for vehicles coming from the other side to enter into the diagnostic center, S4 substream is more affected by the POI traffic than S5. Most importantly, we observe that during peak hours (7PM-8PM), when POI traffic is maximum, the speed of all substreams reduce significantly. Figure shows that, for all substreams the speed decreases by 30% to 40% during 7PM-8M compared to the speed of the corresponding substream on other times of the day.

Figure 5.3(c) shows the average time head-way, the time needed for a vehicle to move forward a car length, of vehicles in each substream for different time-spans of the day. We observe that



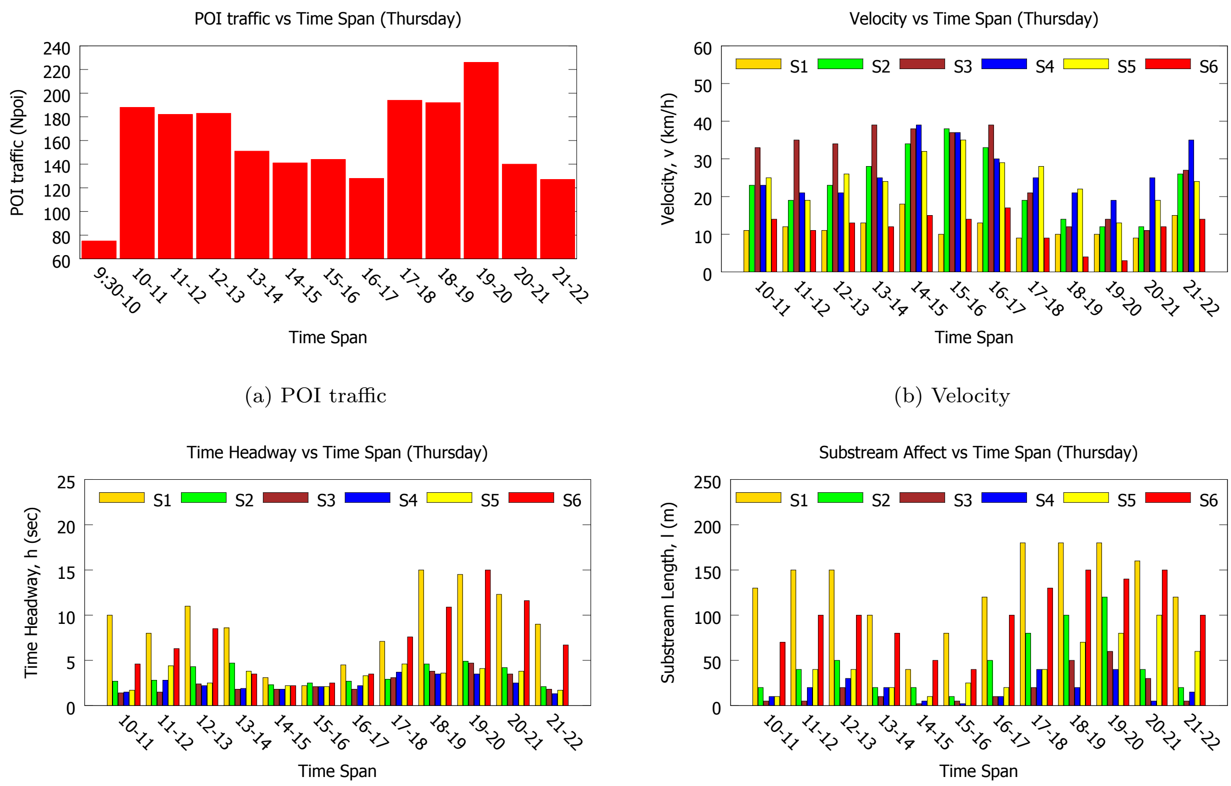
(a) POI traffic (b) Velocity

(c) Time headway (d) Area

Figure 5.4: Diagnostic Center and Hospital on Wednesday

the time head-way significantly increases for the most active period of the POI, i.e., from 7PM to 8PM. The figure also shows that the average time-headway from 5PM to 8PM is much higher than the average time-head way of the other part of the day for all substreams. We also see that the time head-way for substreams 1 and 6 are higher than the other substreams as vehicles carrying hospital passengers stopping at these substreams completely blocks the substream for a long time.

Figure 5.3(d) shows the average affected length in different substreams during different time span of the day. We measure the affected area of a substream by multiplying the length of the substream with the width (e.g., the width of a single sedan car, which is approximately 1.676 meters). Figure shows that the average affected length increases with the increase of the POI traffic, and the affected length is maximum during 5PM-8PM, when the POI traffic is also the



(a) POI traffic

(b) Velocity

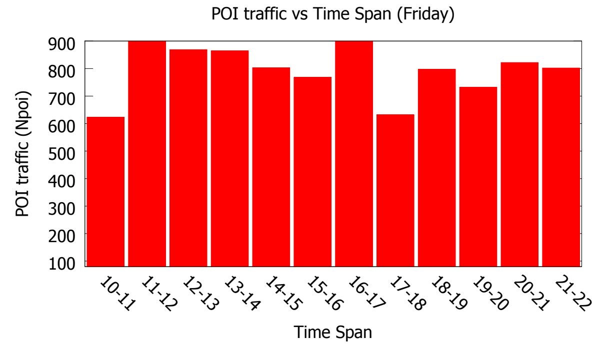
(c) Time headway

(d) Area

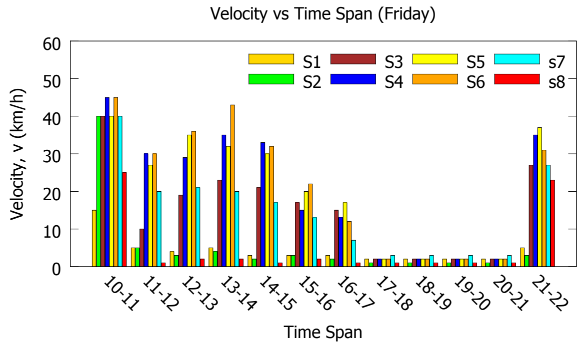
Figure 5.5: Diagnostic Center and Hospital on Thursday

maximum (Figure 5.3(a)).

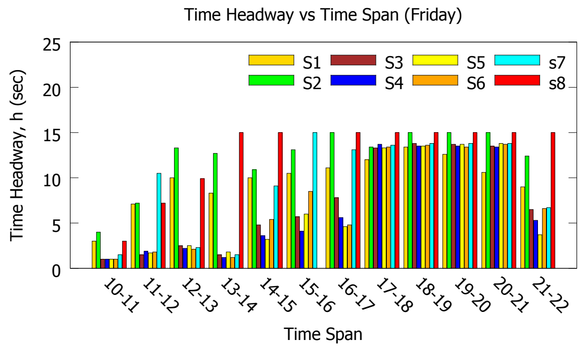
From the above analysis, we see that the POI traffic has significant impact on the road traffic. We have also observed similar behavior of POI impact on road traffic during other weekdays. Figure 5.4, Figure 5.5, and Figure 5.2 show the impact of POI traffic on Wednesday, Thursday, and Monday, respectively. Though Wednesday and Monday show similar traffic patterns to that of Tuesday, POI traffic patterns on Thursday is slightly different than that of the other days. Figure 5.5(a) shows that POI traffic on Thursday between 5PM and 8PM is higher than that of the other days as more patients come to visit doctors on the last day of the week. Figure 5.5(b) shows the velocities of 6 substreams on Thurday. We find that the speed is decreased by approximately 10% to 15% than the other days of the week during the POI active time (5PM-9PM). Similarly, Figure 5.3(c) shows the average time headway and Figure 5.3(d) shows the average substream length, which are higher than the other days of the week.



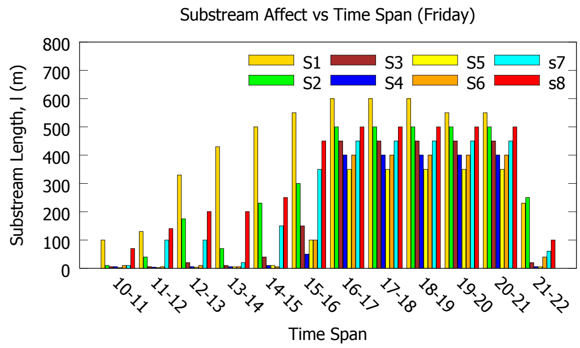
(a) POI traffic



(b) Velocity



(c) Time headway

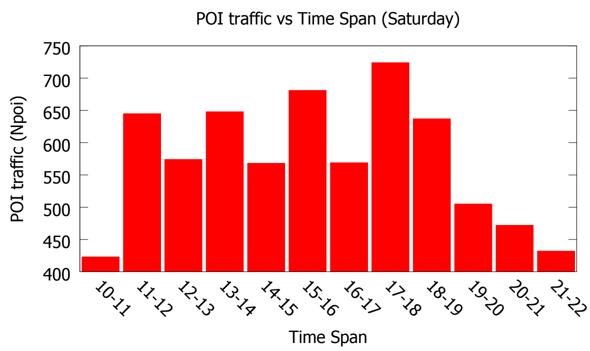


(d) Area

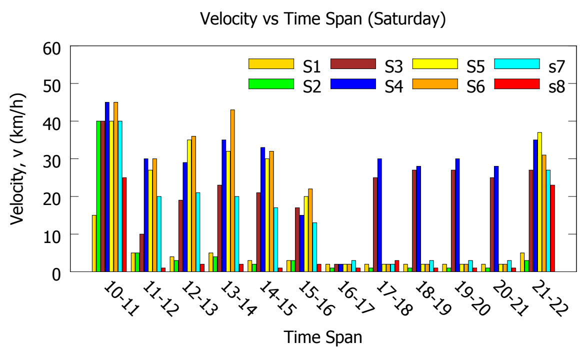
Figure 5.6: Shopping Mall for Friday

Figure 5.6 shows the the POI traffic and its impact on the road traffic for Bashundhora City Shopping Mall (located at Kazi Nazrul Islam Avenue, Kawranbazar, Dhaka-1215) on Friday from 10AM to 10PM. We see from Figure 5.6(a) that the POI attracts maximum traffic during the early active period (11AM-12PM) and in the late active period (4PM-5PM). We observe an interesting traffic behaviour, i.e., right after POI traffic high interaction during 4PM-5PM, the traffic interaction suddenly drops between 5PM and 6PM. This is because a large number of POI traffic during 4PM-5PM causes a huge congestion, which prohibits new vehicle to come into the POI area.

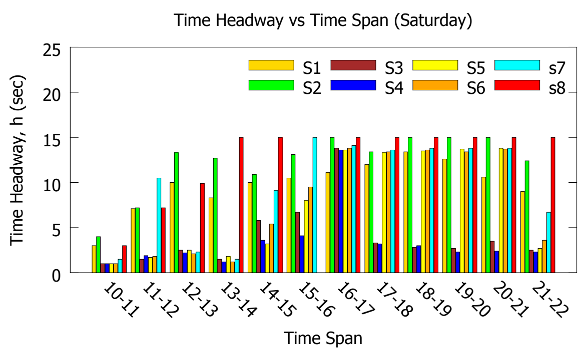
Figure 5.6(b) shows the velocity of 8 substreams (S1-S8, where S1-S4 is on the same side of the POI and S5-S8 is on the opposite side of the POI and substreams are numbered from the



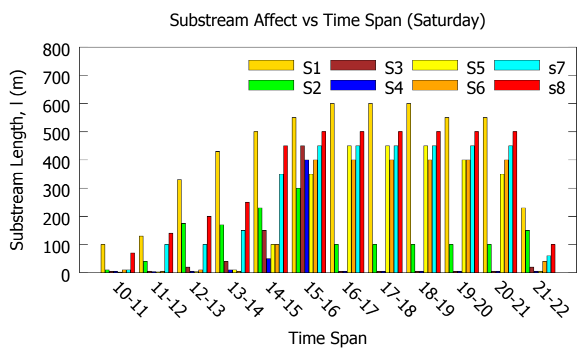
(a) POI traffic



(b) Velocity



(c) Time headway



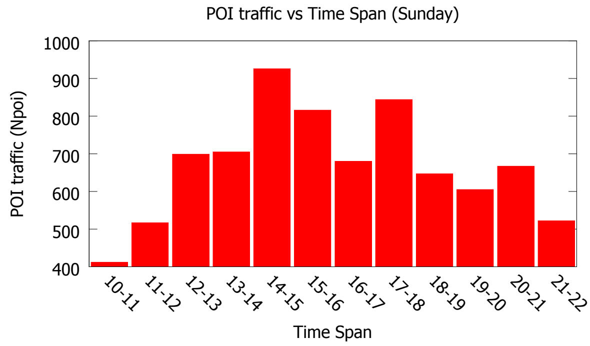
(d) Area

Figure 5.7: Shopping Mall for Saturday

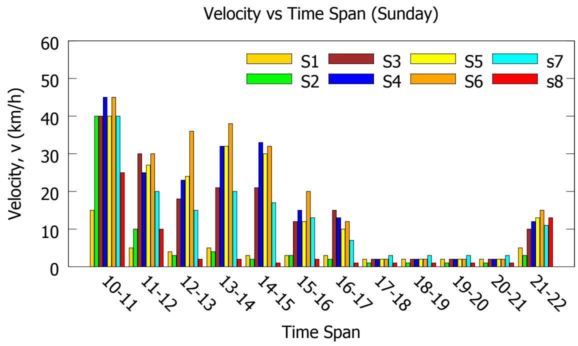
nearest to farthest from POI). S1, the nearest substream which is used for entering into POI premises, maintains a constant velocity (5km/h or less) to the entering point or to the exit. We observe that S2, S7 and S5 are affected more than that of the remaining substreams. These substreams are used by visitors to get in or get-off from their vehicles. Also, we see that the velocity is the lowest during the most active time (5PM-9PM)of the POI.

Figure 5.6(c) shows the average headway of the eight substreams on Friday. Again S2 and S7 are the most affected substreams as shown in the figure. This is because S1 had a higher number of entering or exiting POI vehicles, and S8 was blocked by the parking vehicles and thus had higher headway values than that of other substreams.

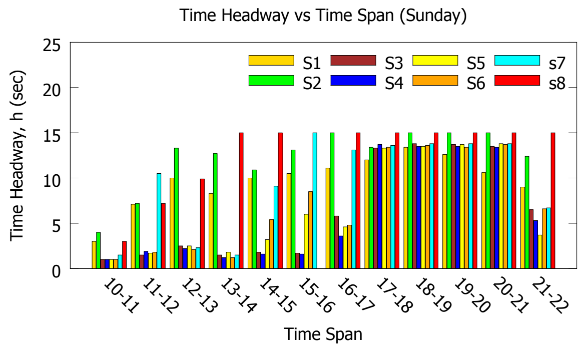
Figure 5.6(d) shows the average affected area in different substreams at different time spans on Friday. We find that S1, S2, S7 & S8 have significantly higher values than the other sub-



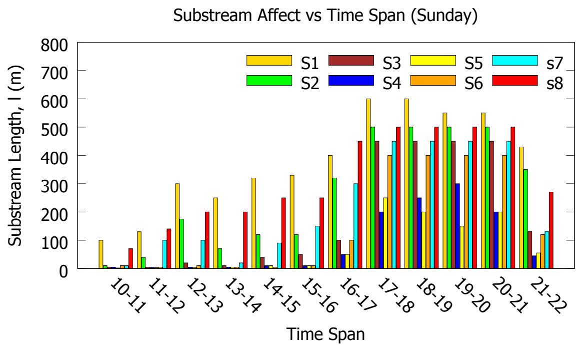
(a) POI traffic



(b) Velocity



(c) Time headway



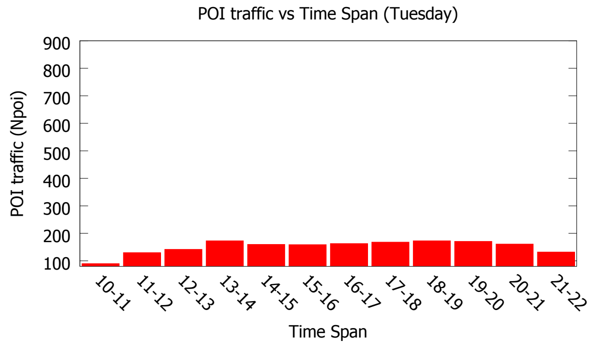
(d) Area

Figure 5.8: Shopping Mall for Sunday

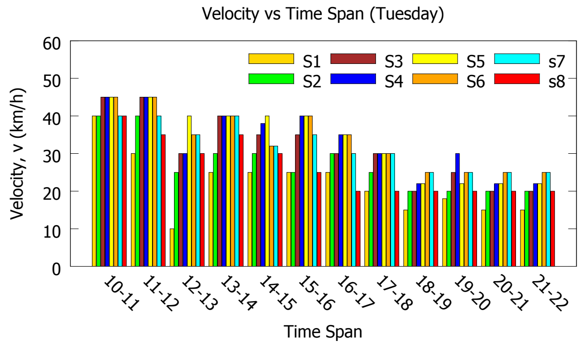
streams as these substreams are affected by the POI traffic most. However, in the most active period all substreams become congested due to the heavy POI traffic.

Similarly, Figure 5.10 shows POI traffic of Bashundhora City Shopping Mall and its impact on road congestion on Wednesday. Figure 5.10(a) shows that the POI traffic is 15%-20% lower than that of the Friday (as the day is week day). However, Figure 5.10(b) and (c) show that the velocity and headway are almost similar to that of the Friday. This is because on other days of the week this road remains busy due to regular traffic (other than POI traffic).Figure 5.10(d) show that during the most active time the road traffic contributes significantly in the congestion.

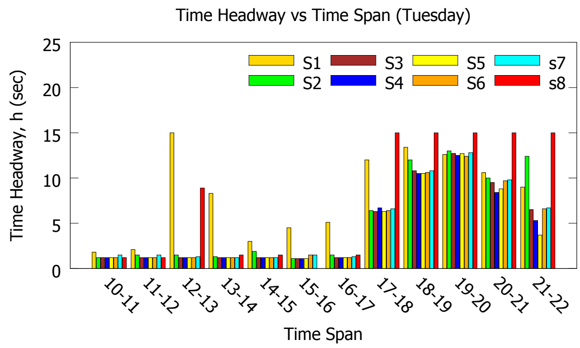
Figure 5.9 shows the impact of POI traffic in the road congestion on Tuesday. As Tuesday is the weekly holiday for the POI, Bashundhora City Shopping Mall, the POI traffic can be assumed to be zero in this day. However, Figure 5.9(a) shows that some traffic interacted with



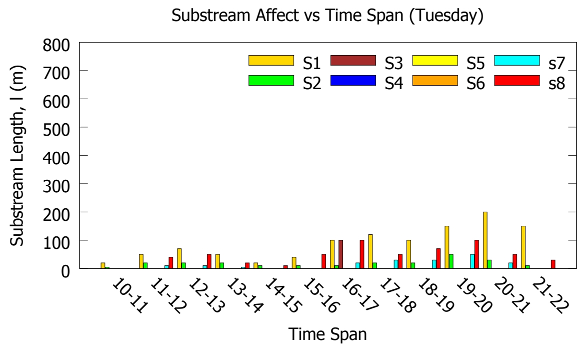
(a) POI traffic



(b) Velocity



(c) Time headway



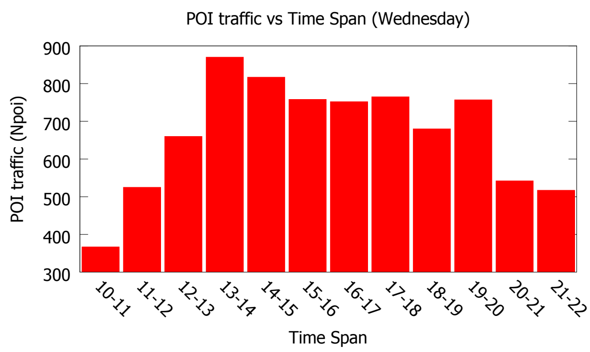
(d) Area

Figure 5.9: Shopping Mall for Tuesday

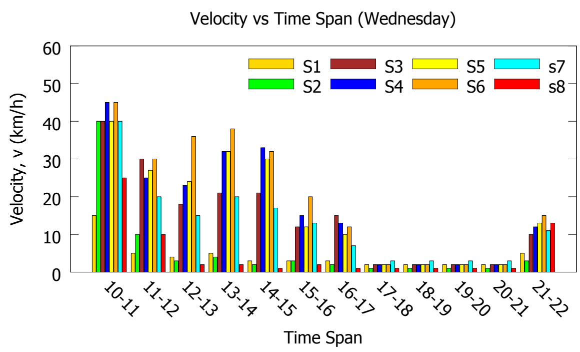
the POI. This is because some people enters to the POI FOR cleaning and maintaining the POI structure. Moreover, there was an conference in the early night (8PM-10PM). Still we find that the number of POI traffic is on average 80% lower than that of the other days.

Figures 5.9(b) and (c) show substream per velocity and headway for each substreams. These values are significantly high(around $55\% - 65\%$) than that of other days. However, we find that these values decrease significantly during 5PM-9PM which is also the POIs most active time. Since the POI is closed on Tuesday, the decreased value of velocity and headway are due to the regular traffic congestion.

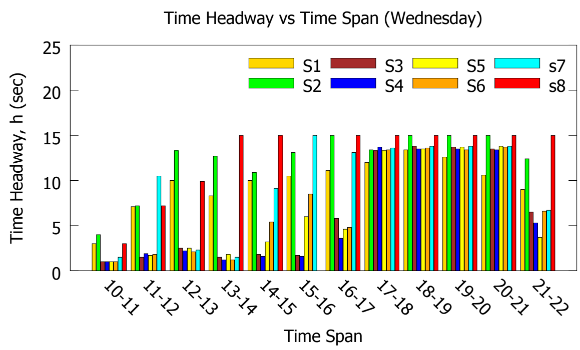
On the other hand, Figure 5.9(d) shows the affected area. Figure shows that the affected area is around 90% less than that of any other days of the week as there is no POI traffic on Tuesday.



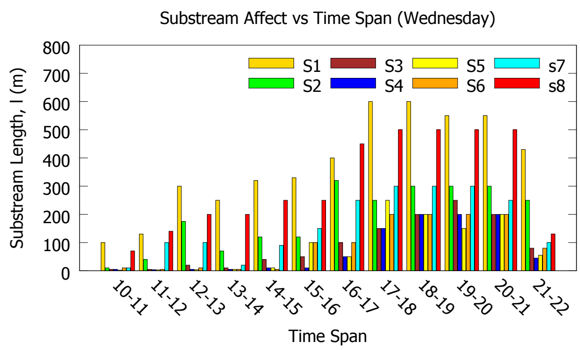
(a) POI traffic



(b) Velocity



(c) Time headway



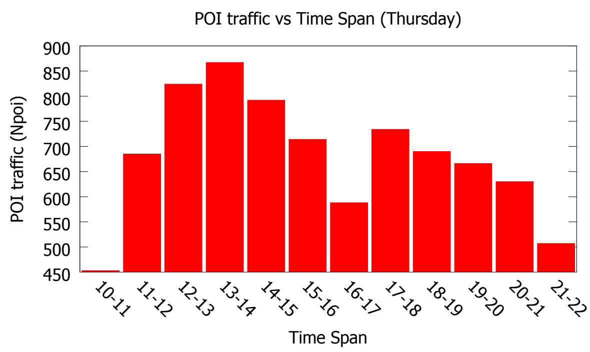
(d) Area

Figure 5.10: Shopping Mall for Wednesday

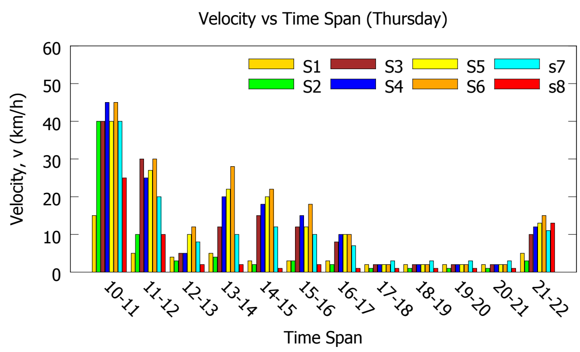
5.3 Evaluation of the Prediction Model

In this section, we evaluate the performance of our developed prediction model. We divide our collected data into training and test sets as shown in Table 5.3. We first show the impact pattern predicted with our model and compare them with the actual pattern achieved during our case studies in Section 5.2. Then we compute the substream wise prediction accuracy with respect to the test set for our developed model.

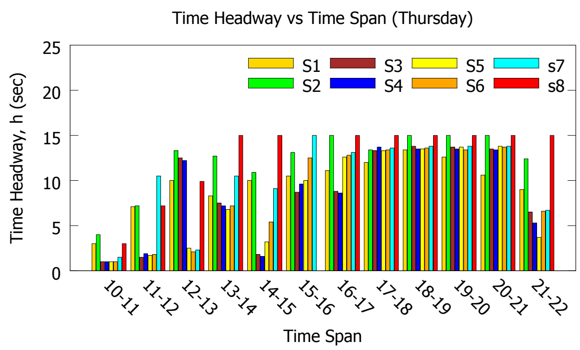
We present the predicted impact for Wednesday for both POIs. Figure 5.12(a) and Figure 5.12(b) show the predicted substream wise impact length for Popular hospital and Boshundhora city shopping mall, respectively. Figure 5.4(d) and Figure 5.10(d) show the actual substream wise impact length for Popular hospital and Boshundhora city shopping mall, respec-



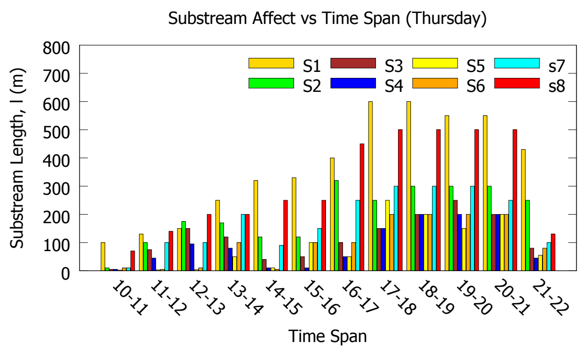
(a) POI traffic



(b) Velocity



(c) Time headway



(d) Area

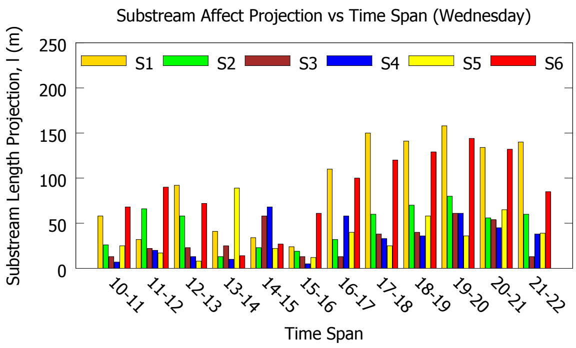
Figure 5.11: Shopping Mall for Thursday

Table 5.3: Traffic parameter measurement

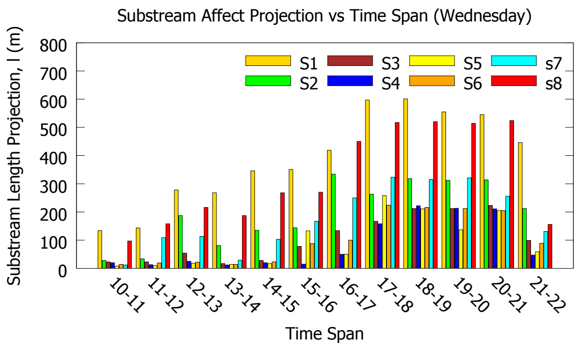
POI Name	Training Dataset	Test Dataset
Popular Hospital and Diagonstic Center	Monday	Wednesday
Boshundhora City	Sunday Monday	Wednesday

tively. In all these graphs, for both predicted and actual cases, we find that the nearest and furthest lanes are mostly affected.

Now if we take a closer look at Figure 5.12(a), we observe that in the early hour time span (10:00 AM to 1:00 PM) there is small impact because only people, who take early medical



(a) Popular Hospital



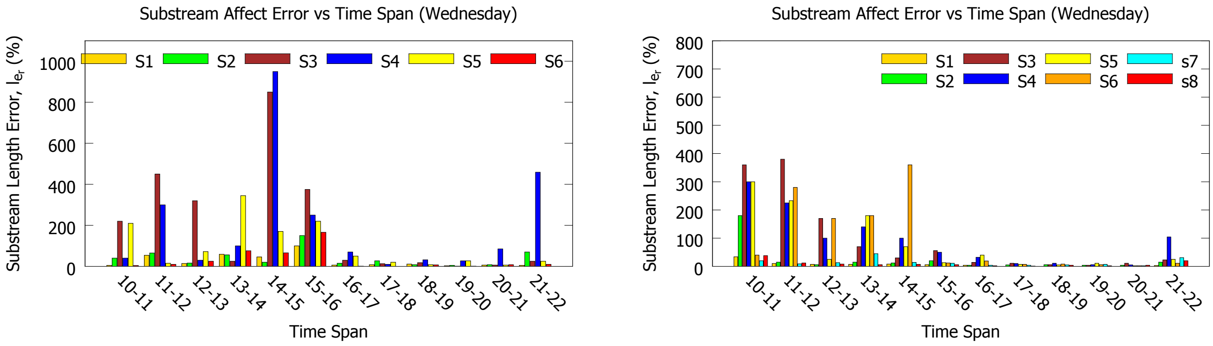
(b) Bashundhora City

Figure 5.12: Substream wise projection

diagnostics or see the doctors in outdoor section, interact with the POI. The POI also remains less busy during the time span from 1:00 PM to 4:00 PM. Figure 5.12(a) also shows the similar affect in terms of the predicted impact length. After that, during the time span 4:00 PM to 10:00PM, the POI becomes busy as several activities (e.g., hospital's visiting hours, private practice, high diagnostic rate etc.) occur during that period. Figure 5.12(a) shows that the impact length continuously increases and becomes the maximum during 6:00PM to 8:00PM, and then again starts to decrease. The actual pattern of impact lengths in Figure 5.4(d) also shows the similar behavior during different time spans.

Similarly, Figure 5.12(b) represents the prediction for Boshundhora City shopping mall. During the early hour time span, the predicted impact is low, which is actually the case because less people come to the shopping mall. Then the impact gradually increases and comes to the peak. At the time of the market's closing hour, the impact starts to decrease and becomes negligible during the last time hours. In Figure 5.10(d), the actual pattern of impact lengths does not show any significant difference with respect to our predicted pattern.

Next we measure the prediction accuracy of our model using the test set. First we measure the error rate for our prediction model using the conventional formula and show the result. Then we discuss why the conventional formula to measure the error rate is not applicable for our scenario and change the formula to adopt the considered scenarios. We also present the substream wise error rate according to the new formula.



(a) Popular Hospital

(b) Bashundhora City

Figure 5.13: Substream wise error

Let l_r and l_p represent the real and predicted impact length of a substream. The conventional way to measure the percentage error rate is as follows:

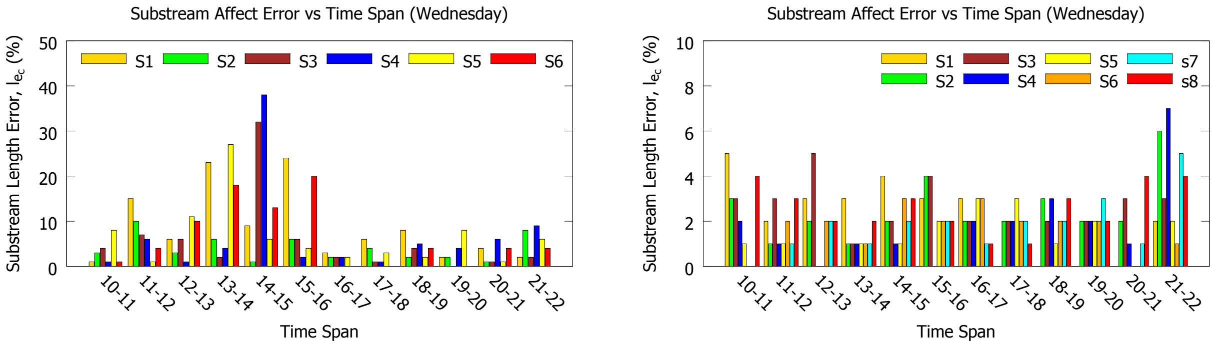
$$error\ on\ substream, l_e = \frac{|l_r - l_p|}{l_r} * 100\%$$

Figure 5.13(a) and Figure 5.13(b) show the error rate in percentage for every substream of the road for the Popular hospital and the Bashundhora city shopping mall, respectively. From the figures, we observe that sometimes the error rate becomes significantly high but it does not reflect the actual scenario due to ignoring the road segment length in measuring the error rate. Assume that we have $l_r = 5m$ and $l_p = 13m$ and the error rate as 160%. This error rate looks like very high but in reality, it is not significant with respect to a road length 250m. On the other hand, if we measure the error with respect to whole road segment, the error rate is 3.2%. This is more acceptable as the error represents only the length for two cedan cars.

To address the limitation of the conventional formula, we consider the road segment length l_c and modify the formula to measure percentage error rate as follows:

$$error\ on\ substream, l_e = \frac{|l_r - l_p|}{l_c} * 100\%$$

Figure 5.14(a) and Figure 5.14(b) show the error rate in percentage for every substream of the road for the Popular hospital and the Boshundhora city shopping mall, respectively. For the Popular hospital, during the early hours, the error is near 12% or less. In the middle of the



(a) Popular Hospital (b) Boshundhora City

Figure 5.14: Substream wise error

time span, the error is near 40%. This happens because of the noise in our training dataset due to the impact of a nearby POI (City College) in the considered road. However, during the peak hour our model can predict more correctly and the error rate is near 10% or less.

On the other hand, for the Boshundhora city shopping mall, the early time span shows the error as 4%. In the middle time span along with the peak period our model provides better results as the error is only 2%. However, during the last hours, the error goes high as 7%. The reason of this high error rate is explained as follows.

There is a 4-way junction nearby the Boshundhora city shopping mall, and among the 4 ways, two ways are freed more frequently than the other two less priority ways. The mentioned POI stands on the less priority way. Therefore, in that road section, along with the POI traffic there is always pressure for regular traffic. That is why substreams nearest to the road divider on both sides show the similar behavior most of the time in the weekday. During 8:00 - 10:00 PM, the traffic stays in the same place for a long time and our prediction model gets confused whether it is road traffic or POI traffic.

Chapter 6

Conclusion

In developing countries, POIs are not established in a planned manner and cause road traffic congestions. In this thesis, we have identified the traffic congestion pattern caused by POI traffic and developed two models: (i) a model to quantify the impact of POI activities on road traffic congestion, and (ii) a model to predict the impact of POI activities on road traffic congestion. We performed case studies for two POIs, a diagnostic center with hospital and a shopping center, located at busy areas of Dhaka city and collected sample datasets for these two POIs and their surrounding road networks. Our analysis show that POI traffic have significantly high impact on road traffic congestion. We divided the collected POI and traffic datasets into two parts: training and test datasets. Experimental results using test datasets of Dhaka city show that our developed model based on training dataset can predict the impact of POI activities on road traffic congestion with a high accuracy.

Our POI impact quantification and prediction model can be applied in selecting location for a new POI, changing activity time of POIs, and suggesting alternative routes to avoid road traffic congestions.

Selection of a location for a new POI: Knowing the active time, effect period, and estimated POI traffic, our model can predict and quantify the POI Impact Area of the new POI. The larger POI Impact Area shrinks the remaining space of the road for regular traffic and increases the probability of traffic congestions. Thus, based on the predicted impact level of the new POI derived using our model, the authority can decide whether the selected location is an appropriate place for the new POI.

Changing activity time of POIs: It is a common scenario in developing countries that multiple POIs are established on a single road and act as an dominant cause of traffic congestions. Applying our model we can determine POI Impact Area by combining POI traffic of all POIs situated on a single road. If the POI Impact Area becomes large enough to cause traffic congestions for regular traffic during a time period, the authority may consider to change effect period of POIs, i.e., the time period when vehicles interact with the POI. For example, if the visiting hour of a hospital and the closing time of an office overlaps, and their integrated POI traffic cause a large POI Impact Area, then either the visiting hour of the hospital or the closing time of the office can be shifted to reduce the road traffic congestion.

Suggesting routes based on POI impact: It is possible to construct a spatio-temporal color map for already established POIs with our POI impact quantification model. The map will represent the POI Impact Area of every POI for different time period and the color variation may represent the intensity of traffic congestions in terms of speed change ratio and time headway. This map can be used by city commuter to plan their trips from their source to destination locations and avoid traffic congestions.

6.1 Limitations and Future Works

This thesis is the first attempt to investigate the impact of POI activities on road traffic congestion in developing countries and opens new directions for further research. In the future, we plan to extend our case studies in other areas of Dhaka city and collect large scale POI data to further reduce the error rate of our developed models. In this thesis, we could not collect data in a large scale due to our budget constraint. The accuracy of the collected data can be improved by using sensors and increasing the number of video cameras.

However, this thesis has several limitations, which we leave for our future work. We have only considered entry and exist points to the POI at the main road and quantify the impact of a POI on the main road. However, a large POI like Boshundhora City has several side lanes which are also impacted due to parked public transport (e.g., rickshaws and cars). We also have not considered the effect of U-turn points or road junctions nearby a POI. In the future, we aim to extend our models to handle complex road structure including U-turn points and road junctions. In addition, we will incorporate the effect of other factors in the impact of POI traffic like weather condition, VIP movement and festive occasions.

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