Identification of Traffic Bottlenecks in Central Dhaka Through Spreading Graph-Based Congestion Analysis

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Abstract: The persistent traffic congestion in Dhaka, Bangladesh, calls for innovative and efficient solutions tailored to its unique urban dynamics. This study introduces a novel approach to traffic bottleneck identification that combines congestion levels and their potential to spread, addressing the critical need for targeted traffic management. Our methodology integrates traffic data collection through Google Maps snapshots, congestion intensity mapping, congestion spreading graphs (CSG), maximal spanning trees (MST), and applying Naïve Bayes' theorem to calculate congestion costs. These tools identify bottlenecks by quantifying both congestion impact and propagation costs within the urban road network. Key findings highlight three major bottlenecks: Kawran Bazar, Mohammadpur Bus Stand, and Dhanmondi 32 intersections, validated using the SUMO simulation platform. These points exhibit significant congestion spread and network-wide delays. The proposed methodology not only identifies critical bottlenecks effectively but also offers actionable insights for urban planners and policymakers to devise targeted interventions. This research bridges existing gaps, providing a cost-effective, adaptable framework for mitigating traffic challenges in resource-constrained cities like Dhaka.

1 INTRODUCTION

An intelligent transportation system (ITS) aims to offer significant advancements for enhancing the functionality of a public transportation system; nevertheless, the magnitude of these advantages may be constrained by several aspects and difficulties. Traffic congestion is one of them, which impacts nearly every aspect of urban life, from daily commuting to the cost of living. For example, in the USA, travelers spend about seven billion additional hours (42 hours per traveler) locked in their cars every year, as well as it also costs billions in Europe (Jamil et al., 2020). In Dhaka, Bangladesh, one of the world's most densely populated cities with over 20 million residents, the impact of traffic congestion is even more pronounced (Macrotrends, 2024). Traffic congestion costs five million working hours every day, leading to an annual loss of 200- 550 billion BDT in Dhaka city (Haider, 2018), (Ali et al., 2022). This challenge is only expected to grow as Dhaka's population continues to rise, placing even more strain on the city's transport infrastructure.

One of the main contributors to traffic congestion is bottlenecks—specific points where the road is always congested and capacity is heavily restricted, causing delays and impeding the smooth flow of vehicles (Hale et al., 2016). (Administration, nd) indicates that bottlenecks are the leading cause of traffic congestion, contributing 40% of significant factor, followed by traffic incidents (25%), bad weather (15%), work zones (10%), poor signal timing (5%), and special events or other factors (5%). Thus, it indicates that the bottleneck is the major source of traffic congestion. Based on the reason for the occurrence, a bottleneck can be classified into two categories: i) recurrent and ii) non-recurrent bottleneck. Demand fluctuations, network topologies, off-ramps, on-ramps, poor road alignment, road width narrowing, etc, cause recurrent bottlenecks. On the other hand, nonrecurrent bottlenecks are caused by random and unpredictable events (Yuan et al., 2014).

There are extensive studies on traffic signal control, signal optimization, and traffic prediction for congestion mitigation, but studies on bottleneck identification are not focused on that much (Karim and Nower, 2024). The initial study (Long et al., 2008) on bottleneck identification is based on the cell trans-

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mission model (CTM)–based congestion propagation model where the average trip velocity (AJV) is used to calculate bottleneck. Bottleneck identification method for Kaohsiung city is proposed in (Yue et al., 2018) where causal congestion tree is used on loop detector data. In addition, a map data-driven bottleneck identification approach is presented in (Mirzahossein et al., 2024) for Tehran city. Besides these, wavelet-based bottleneck detection for Washington (Ke et al., 2018), congestion propagation-based method for Taipei (Li et al., 2020), and bottleneck detection approach for Wisconsin (Jin et al., 2012) are proposed. Though these existing approaches provide valuable insights, their dependency on sophisticated technology, high costs, or lack of adaptability to highly congested, resource-limited urban settings makes them unsuitable for Dhaka city. In addition, there is minimal infrastructure to collect traffic congestion data for Dhaka city. Apart from the lack of traffic data, every city has a unique road layout and transportation system (Rahman and Nower, 2023). These factors significantly impact traffic congestion, as a result, we cannot simply apply other bottleneck detection approaches in our capital city Dhaka.

Dhaka is the fifth most congested city in the world with an estimated 17 million people living in an area of 1,528 square kilometers. According to the Asian Development Bank (ADB), average speeds in some places have dropped to as low as 7–10 km/h during peak hours because of severe traffic congestion (Moshiur Rahman and Nower, 2024). As a result, bottlenecks, as the most contributing factor to traffic congestion, are necessary to identify for this city. Bottlenecks are created by several factors in this city: inadequate road infrastructure, an ever-growing number of private vehicles, poor traffic management, etc. These choke points not only slow down traffic but also lead to ripple effects across the entire network, where even a minor delay at a bottleneck can create significant congestion downstream. The cumulative effect of these bottlenecks exacerbates the congestion problem, making it challenging to maintain consistent traffic flow throughout the city (Hossain and Nower, 2022). Thus we need a cost-effective, adaptable method for bottleneck identification tailored to the constraints and unique congestion patterns of Dhaka, aiming to bridge the gap left by existing research methods.

To address this gap, this study proposes a novel urban traffic bottleneck identification approach based on Congestion Spreading Graph (CSG) and Maximal Spanning Tree (MST) analysis using traffic intensity data calculated from Google Map snapshots. The proposed approach collects traffic data using our previously developed tool (Hossain and Nower, 2022) by processing Google map snapshots. By leveraging traffic data and advanced algorithms, our approach aims to identify specific bottleneck points accurately throughout Dhaka's road network. This data-driven solution can offer affordable solutions and actionable insights to policymakers and urban planners, helping them to create targeted interventions that address Dhaka's unique traffic challenges more effectively. Our primary contributions are as follows:

- A novel methodology is developed using a combination of snapshot processing, graphical models, maximal spanning trees, and Markov analysis to model and analyze congestion spreading in urban roads. It offers an effective way to quantify both the spread of congestion and the congestion costs of individual road links.
- Validation using SUMO demonstrates that the proposed method identifies Dhaka city's bottlenecks properly.

2 RELATED WORK

With the increase in urban dynamics, the urban transport system is becoming more crucial in the citizen's daily life. The bottleneck, the most critical road segment is one of the main reasons for traffic congestion. Thus, these critical road segments, or bottlenecks, must be identified in road networks. Once the congestion on the identified bottlenecks is reduced by using these sophisticated traffic control/management techniques, the overall traffic network's conditions will be effectively and efficiently improved. The existing bottleneck identification studies on different cities are highlighted in this section.

Numerous methods have been developed to identify traffic bottlenecks in different transport network settings. (Long et al., 2008) introduced a congestion propagation model for urban networks using the cell transmission model (CTM), incorporating link and node models to simulate flow propagation and identify bottlenecks. The model estimates average journey velocity (AJV) and demonstrates, through simulations on the Sioux Falls network, that increasing traffic demand is a key factor in bottleneck formation, influenced by link position, flow composition, and network demand. While their approach identified bottlenecks, the study was limited by a lack of real-time data and relied heavily on predefined thresholds which can be highly varied from city to city. Moreover, this method cannot effectively represent traffic congestion propagation under special conditions or manage traffic congestion control.

The author of (Jin et al., 2012) developed an algorithm to tackle noise and error issues in freeway detector data, aiming at recurrent bottleneck identification on Wisconsin freeways, which, when tested on field data, outperformed existing methods by reducing false alarms, particularly in severe congestion scenarios. They identified recurrent freeway bottlenecks by analyzing loop detector data to pinpoint bottlenecks' locations, timing, and activation rates. However, the major limitation is that it focused on test sites in Wisconsin, which lack the large-scale congestion seen in major metropolitan areas, limiting generalizability.

The paper (Ke et al., 2018) introduced a wavelet-based framework for automating bottleneck identification on Washington's I-405. This novel method effectively distinguished recurring bottlenecks and quantified their impacts using daily delay and congestion indicators. However, their proposed approach utilizes wavelet-based transformation on various loop detector data which is not feasible in the resource-constrained city Dhaka.

Another bottleneck identification approach is presented in (Yue et al., 2018) where causal congestion graphs are utilized for Kaohsiung city. They proposed a new definition of urban bottlenecks that combines congestion propagation costs and congestion weights of road segments. Using causal congestion trees and graphs, the method identifies bottleneck groups based on data from urban inductive loop detectors. To validate the results, the study enhances road capacity at these bottlenecks and compares congestion levels and propagation ranges before and after the enhancements. A major shortcoming of this paper is its inability to pinpoint the most significant bottleneck within each identified bottleneck group based on congestion level and congestion costs. This limitation restricts the effectiveness of targeted interventions, as it fails to prioritize the bottlenecks with the highest impact on overall congestion.

The authors of the paper (Li et al., 2020) developed a congestion propagation-based traffic bottlenecks identification method in Taipei by evaluating congestion costs, considering both road segment congestion and the spread of congestion to adjacent segments. The model employs graph theory and maximal spanning trees and uses Markov analysis to estimate the probability of congestion transfer between segments. Simulations on the SUMO platform and experiments with real-world data from Taipei demonstrate the method's effectiveness. The major shortcoming of this paper is its lack of integration between traffic data and detailed road characteristics, limiting its ability to identify specific congestion sources effectively. Their data collection method is very expensive for a mega city like Dhaka. A cost-effective method is necessary for the traffic bottleneck identification process for Dhaka.

Typically, fixed detectors on the road, including speed cams, loop detectors, video cameras, sensors, etc., are used to gather traffic data. However, there is not much reliable architecture in Bangladesh to collect traffic data as a result, research on traffic congestion, gridlock, and bottleneck analysis in the fifth most congested city Dhaka is not so extensive. For example, (Momin et al., 2023) used their recorded video to gather traffic statistics for just three hours, and then they applied Kalman filtering for prediction. Another study (Rahman et al., 2018) provides a traffic pattern analysis of Dhaka using GPS data collected for only 15 days. Due to a dearth of traffic data, (Al Noor and Mehanaz, 2022) used a questionnaire survey to collect responses from 721 different road users to investigate the dynamics of journey times in Dhaka.

As far as we know, till now no studies have systematically identified traffic bottlenecks in Dhaka that could provide insights for alleviating the city's severe traffic congestion. This lack of targeted research represents a significant gap in the existing literature, highlighting the need for focused investigations to understand and address the underlying causes of congestion in this rapidly urbanizing environment. Our proposed novel traffic bottleneck identification process will help to overcome the existing shortcomings of the mentioned works as well as the need for such studies for Dhaka city.

3 PROPOSED BOTTLENECK IDENTIFICATION APPROACH FOR DHAKA CITY

This section presents a systematic approach to identifying road traffic bottlenecks in Dhaka by analyzing traffic intensity snapshots. In this proposed bottleneck identification approach (as shown in Fig. 1), a Google map image of a road network for a certain interval is taken as input and then continues with image cropping and color masking to extract the traffic features, followed by a grid-based analysis that assigns intensity values to each grid cell using color codes. Congested lanes are then identified based on their traffic intensity value. Next, a correlation analysis is performed among the adjacent lanes within a specific time window, forming a Congestion Spreading Graph (CSG) to visualize the spread of congestion. In the CSG,

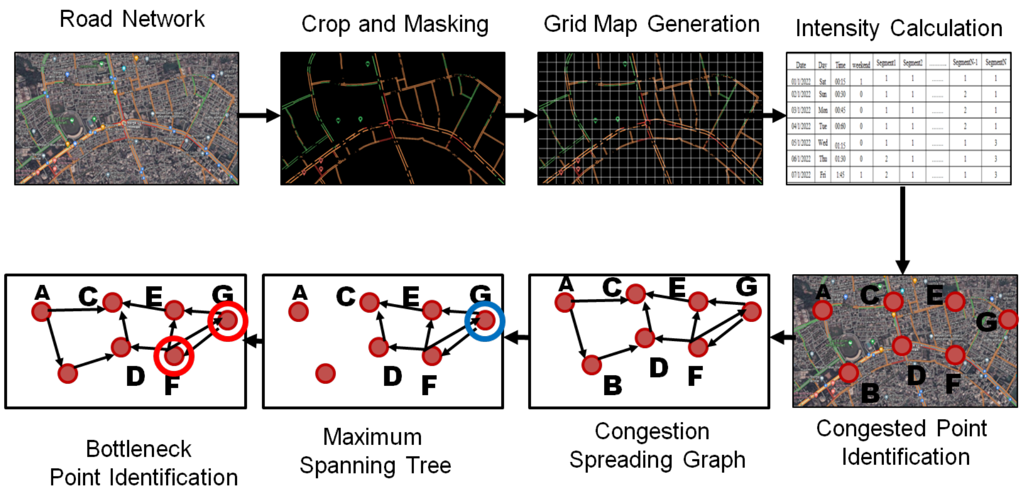

Figure 1: Proposed bottleneck identification process.

maximal spanning trees are applied to identify critical connections in this graph. Then, Naïve Bayes' Theorem is used to calculate the contagion cost for each lane of the CSG. Finally, the bottleneck is identified by summing up the lane cost and contagion cost. This integrated approach allows for precise detection of high-traffic areas, helping to predict and manage congestion, and making it useful for traffic control and infrastructure planning. Figure 1 presents the overall bottleneck identification process.

3.1 Traffic Data Collection from Road Network

For data collection, we have used our previously proposed tool (Moshiur Rahman and Nower, 2024; Hossain and Nower, 2022), which uses the Selenium Web Driver to capture screenshots from Google Maps. Finally, these screenshots are processed using image-processing techniques to extract road traffic information. Using that tool, we can extract traffic data for any place and any duration.

3.2 Image Cropping and Masking

The original traffic images from Google Maps were cropped to a standardized size of 940x1440 pixels to focus on the relevant road area and minimize unnecessary data. This size was chosen to encompass the usable road region where traffic flow was most concentrated. A color masking technique was employed to isolate traffic-related elements in the images. We have applied different masking HSV (Hue, Saturation, Value) values for default and satellite map types to extract traffic data from captured images. These masking values help to identify the relevant color regions indicating traffic congestion levels, enabling the extraction of necessary information from the images. All colors except red, yellow, and green were converted to black, effectively highlighting the key traffic indicators: Red HSV (0-10, 100-255, 100-255) = High intensity, Yellow HSV (20-30, 100-255, 100-255) = Medium intensity, Green HSV (35-85, 100-255, 100-255) = Low intensity and Black HSV (0-180, 0-255, 0-50) = No traffic.

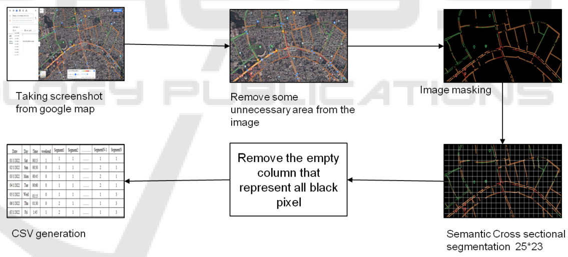

Figure 2: Image preprocessing for analysis.

3.3 Grid Map & Intensity Calculation

Each cropped image is subdivided into a grid of 20x20 pixel segments, yielding a total of 3,384 grid cells per image. Traffic intensity for each grid cell was determined independently based on the predominant color present, with a defined color scale used for classification: red is assigned an intensity value of three, yellow is assigned a value of two, green a value of one, and black a value of zero. The overall intensity for each snapshot is then calculated by summing the intensity values across all grid cells, resulting in a comprehensive and granular measure of traffic conditions at each time point. In this way, we have collected the intensity of each lane of the road network and stored it in a CSV file as shown in Fig. 2.

3.4 Congestion and Congestion Correlation

Based on the previously calculated intensity value congestion and congestion correlation are determined. Congestion refers to the condition where traffic demand exceeds roadway capacity, leading to slower speeds, longer travel times, increased vehicle density, and associated impacts such as reduced safety, higher fuel consumption, and greater environmental pollution. In this research, we use a definition of congestion based on traffic intensity which is used as the metric of traffic congestion in Dhaka city.

Definition 1- Congestion: From our field study, a specific lane is considered congested if its traffic intensity exceeds 10 percent of its average value. The formula for detecting congestion is given by:

$$C = \frac{CTI - MTI}{MTI} > 0.10 \quad (1)$$

Where:

- C represents the congestion status of the lane,
- CTI is the current traffic intensity at a given time,
- MTI is the mean traffic intensity over the observation period. $\mathrm{MTI} > 0$

Traffic intensity refers to the volume of vehicles passing through a specific point over a given period, offering a direct measure of road usage and demand. By setting thresholds for traffic intensity, one can determine when the flow of vehicles surpasses the road's capacity, leading to congestion. When the real-time traffic intensity on a road segment exceeds the predefined threshold, it indicates that the road is congested. Congestion correlation, on the other hand, analyzes the congestion-spreading relationship among the adjacent road segments. This concept is crucial as the onset of congestion on one road segment can have a significant effect, disrupting traffic patterns on adjacent road segments in urban areas like Dhaka city and contributing to increased congestion in the surrounding regions as well. It establishes the necessity of examining the relationships between congestion levels across various road segments. Thus, this definition of congestion correlation focuses on the spatial-temporal dynamics between two road segments, as outlined below:

Definition 2 Congestion Correlation Between Two Road Segments: Congestion on road segment A is correlated with congestion on road segment B if the following requirements are satisfied.

Spatial Threshold: Node A and node B are connected roads and adjacent in a given road network.

Temporal Threshold: The congestion spreading time between node A and node B should be within a predefined interval in the given road network.

In this paper, we consider that congestion at two different road segments is correlated only if both the spatial and temporal thresholds are met. The spatial threshold requires that node A and node B are connected and adjacent in the given road network, while the temporal threshold specifies that the traffic propagation delay between node A and node B is no more than 40 minutes. This congestion correlation definition offers two advantages: first, using the spatial threshold based on the connectivity of adjacent nodes reflects the actual congestion propagation path and direction in the traffic network; second, the temporal threshold better captures the relationship between congestion propagation and the time it takes for traffic delays to spread.

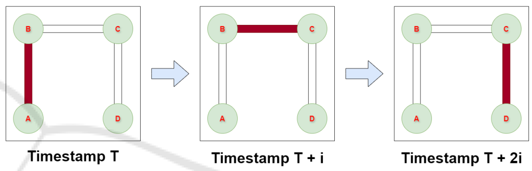

Figure 3: An illustration of the congestion correlation between road segments.

An example is shown in Figure 3, where congestion occurs on road segment A at 8:00 AM, and we need to investigate the correlated congested road segments for road segment A based on the proposed congestion correlation definition. According to the spatial threshold, we first identify the road segments adjacent and directly connected to congested road segment A in the road network, as shown in Figure 3 Road segments B and C are connected to the road segment A, satisfying the spatial threshold. Next, we consider the temporal threshold, which states that the traffic propagation delay between two segments is 40 minutes. Congestion on road segment C occurred at 8:55 AM, not meeting the temporal threshold of 45 minutes. Therefore, congestion on road segment C is not considered to be correlated with congestion on road segment A. In contrast, congestion on road segment B occurred at 8:45 AM, making it likely that congestion on road segment B is correlated with congestion on road segment A. Thus, considering both the spatial and temporal thresholds, only the congestion on road segment B is correlated with congestion on road segment A, and we can establish the causal relationship: "congested road segment $A \rightarrow$ congested road segment B.

3.5 Congestion Spreading Graph and Maximal Spanning Tree

In this subsection, we construct Congestion-Spreading Graphs (CSG) by connecting correlated road segments based on their spatial and temporal relationships, as defined earlier. After identifying congested road segments, they are connected as directed edges, and these connected segments are added to form a directed graph. Afterward, we apply a maximal spanning tree algorithm to the graphs, forming a set of trees that maximizes the number of edges and efficiently captures the causal congestion-spreading relation at different road segments within the selected transport network.

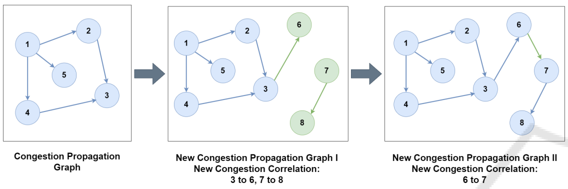

Figure 4: An illustration of the construction of congestion spreading graphs.

An example is shown in Figure 4 to illustrate the construction of the congestion spreading graph generation process. Suppose we have constructed one disjoint congestion propagation graph, and we need to add the other three new correlations 3 -→ 6, 7 -→ 8, and 6 -→ 7 into the graphs. As depicted in the congestion propagation graph I of Figure 4, if either road segment in a correlation relation already exists in the current graphs, such as correlation 3 -→ 6, we can connect the correlation to the corresponding graph. Suppose none of the two road segments in a correlation relation are in the existing graphs, such as correlation 7 -→ 8. In that case, this edge (and the associated vertices) should form the first edge of a new graph, as shown in the congestion propagation graph I. Moreover, suppose one road segment in a correlation is in a graph, and another road segment in a correlation is in another graph, such as correlation 6 -→ 7. In that case, we can join the two graphs together and form one graph, as shown in the congestion propagation graphs II. However, if two road segments in a correlation are both in the same graph, then we can delete this correlation. In this way, we can construct several disjoint congestion propagation graphs using the correlation, as mentioned earlier. The outcome of constructed congestion propagation graphs and maximal spanning trees is the input used in calculating the congestion cost of each road segment of each spanning tree.

Definition 3- Maximal Spanning Tree: A maximal spanning tree is a tree with a maximal set of directed edges (i.e., correlations) such that there is a unique (directed) path from the root of the tree (i.e., a road segment) to any other vertex (i.e., the endpoint of an edge) of the tree. To measure the congestion-spreading effects of a road segment, we calculate its spreading cost by applying Breadth First Search (BFS). In this approach, each road segment is treated as a root node to construct a maximal spanning tree from the congestion propagation graphs. An example is provided to demonstrate the construction of these maximal spanning trees.

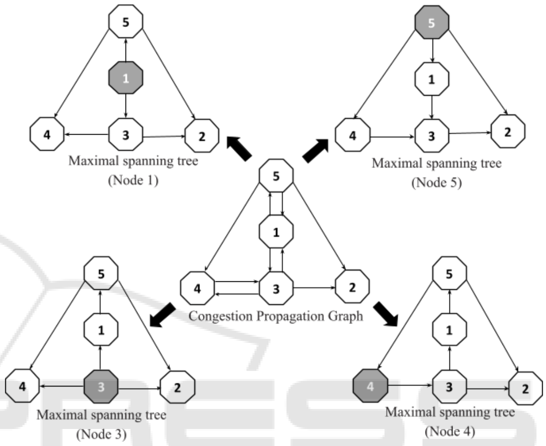

Figure 5: An illustration of the construction of maximal spanning trees from the congestion-spreading graph.

As depicted in Figure 5, a conceptual congestion spreading graph is presented based on our proposed method. The graph consists of five road segments and nine directed edges (correlations). Regarding road segments 1, 2, 3, 4, and 5 as the root of a tree respectively, we can get five different maximal spanning trees (because congestion on road segment 2 does not propagate to the other road segments, the fifth tree only consists of a root node, i.e., road segment 2). These maximal trees indicate the congestion propagation path and influence areas during congestion.

3.6 Bottleneck Identification

Bottlenecks are critical points in a road network, making their identification essential. We describe the process for identifying bottlenecks by calculating both the congestion cost of individual road segments and the contagion cost. To identify long-term bottlenecks and assess their network-wide impact, we calculate the congestion level of each road based on traffic intensity. Using Naïve Bay's Theorem and maximal spanning trees, we also estimate the cost of congestion spreading to neighboring roads. Thus, the following definitions of congestion cost and urban bottlenecks are proposed in this research.

$$B- > A = \frac{N_{AB}}{N_A} \tag{2}$$

where:

- N_{AB} is the number of instances where lane A is congested at time t and lane B becomes congested at time t + threshold
- N_A is the total number of time instances where lane A is congested.

Definition 4- Congestion Cost: Traffic congestion cost of a road segment indicates the quantification of congestion on this road segment that causes the negative influence on the whole road network, which can be expressed as the sum of the congestion level cost of the road segment itself and the congestion propagation cost that the congestion may propagate to other road segments.

Definition 5- Bottlenecks in Urban Areas: The lanes that have contagion costs greater than a certain value are marked as Bottleneck points.

In our work, the contagion cost for each lane was calculated using Naïve Bayes' Theorem to assess the probability that congestion in one lane would spread to adjacent or connected lanes. This probabilistic approach allowed for the quantification of how likely it was that congestion in a given lane would propagate throughout the road network. The contagion cost represents the cumulative risk of congestion transmission, with higher values indicating lanes that are more prone to causing network-wide traffic issues. Lanes with a contagion cost exceeding a certain value were flagged as potential bottleneck points, meaning they were critical to the overall traffic flow and posed a heightened risk of exacerbating congestion.

4 SIMULATION AND DISCUSSION

In this section, we have applied our proposed bottleneck identification approach to one of the busy areas of the capital city, Dhaka. We chose a road network covering eight major areas with twenty-three lanes as a study area. Finally, we have validated our proposed bottleneck identification approach using a widely used traffic simulator, Simulation of Urban MObility (SUMO).

4.1 Data Description

Our work focused on identifying traffic bottlenecks in eight major areas in Dhaka by analyzing a network of connecting twenty-three lanes. Table 1 shows the name, geographic location, and direction of connected lanes of the selected eight major traffic nodes within the study area. This area (as shown in Fig. 6) is a crucial hub for traffic flow, as it experiences heavy congestion almost daily, particularly during peak hours. Its strategic importance, serving commuters from various city sectors, makes this area an ideal candidate for bottleneck identification work. To identify the bottleneck in the area, we have collected snapshots from Google Maps for three months (January 2024- March 2024) using our tool (Moshiur Rahman and Nower, 2024) in ten-minute intervals. These collected snapshots are processed by cropping, masking, and grid map generation and finally generate the intensity of each road in ten-minute intervals. Our collected data set comprises 13104 (91 Days * 24 Hours * 6 Snapshots per hour) data instances for each road segment. Thus, we have a data set of a total of 13104*23 = 301392 instances for twenty-three road segments with intensity values. From this intensity value of the road segment, we calculate congestion cost and contagion cost.

Figure 6: Location of the selected eight nodes.

4.2 Simulation for Bottleneck Identification

1) Simulation on Bottleneck Identification: In this subsection, we first calculate the costs of all twenty-three lanes based on our congestion spreading graph and maximal spanning tree. The result is shown in Table 2.

Table 2 shows that the estimated cost varies from 0.36 to 17.82. Unlike traditional lane-specific analysis, this study aggregates lane-wise costs to determine the overall congestion impact at each intersection, providing a comprehensive view of traffic dy-

Table 1: Name, Location, and ID of connected lanes of the selected eight nodes.

Selected Nodes	Name	Geographic Position	Direction of Connected Lanes
1	Kawran Bazar Intersection	23.749876°N, 90.393197°E	1-2, 1-4, 1-5, 1-7
2	Shahbagh Intersection	23.738136°N, 90.395844°E	2-1, 2-3, 2-8
3	Shahed Captain Mansur Ali Sarani (Kakrail)	23.737350°N, 90.404211°E	3-2, 3-4
4	FDC Intersection	23.753535°N, 90.400696°E	4-1, 4-3, 4-5
5	Farmgate Intersection	23.758640°N, 90.389878°E	5-1, 5-4, 5-6
6	Mohammadpur Bus Stand	23.756996°N, 90.361499°E	6-5, 6-7, 6-8
7	Dhanmondi 32	23.751288°N, 90.378258°E	7-1, 7-6, 7-8
8	Science Lab Intersection	23.738840°N, 90.383451°E	8-2,8-6

Table 2: Traffic Contagion Cost for Each Lane in the first quarter of 2024.

Lane No	Lane Direction	Cost - January	Cost - February	Cost - March	Average Cost January - March
1	1-2	4.82	7.04	7.71	5.98
2	1-4	9.12	5.40	9.79	8.93
3	1-5	3.45	2.98	2.74	5.41
4	1-7	11.90	15.82	10.20	14.09
5	2-1	8.93	14.59	7.02	10.21
6	2-3	6.61	6.38	5.95	6.24
7	2-8	9.04	7.95	4.42	7.72
8	3-2	2.48	1.62	1.26	1.56
9	3-4	6.91	6.53	9.56	8.84
10	4-1	10.97	19.56	13.29	12.47
11	4-3	0.49	0	0.94	0.81
12	4-5	6.45	3.44	10.38	8.34
13	5-1	3.54	4.49	8.89	5.66
14	5-4	0.29	10.87	0.91	0.69
15	5-6	12.22	18.46	13.25	17.48
16	6-8	22.18	18.43	11.83	14.78
17	6-5	13.45	1.99	1.11	1.99
18	6-7	22.64	19.62	10.61	12.45
19	7-1	10.78	17.17	20.49	16.95
20	8-6	3.35	3.55	Not Correlated	3.44
21	7-6	2.65	3.64	1.42	3.17
22	7-8	7.85	6.86	3.53	5.55
23	8-2	0.92	0.78	Not Correlated	0.67

namics.

The total propagation cost for each intersection is calculated by summing up the individual lane-wise costs associated with that intersection. This approach considers the cumulative congestion effect stemming from all connected lanes, allowing for a holistic identification of critical traffic bottlenecks. Traffic data was collected over three months (January to March 2024) at 10-minute intervals, ensuring the analysis captures both temporal and spatial variations in congestion.

We set a bar that only the lanes with a contagion cost greater than fifty will be considered Bottlenecks. Let C_i represent the contagion cost for Point i, and let B_i be a binary variable indicating whether a point i is a bottleneck. This condition is expressed as :

$$Bi = \begin{cases} 1, & \text{if Ci } > 50 \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In Figure 7, we present the estimated costs for each intersection along with the bottleneck's minimum cost line for these three months (January - March).

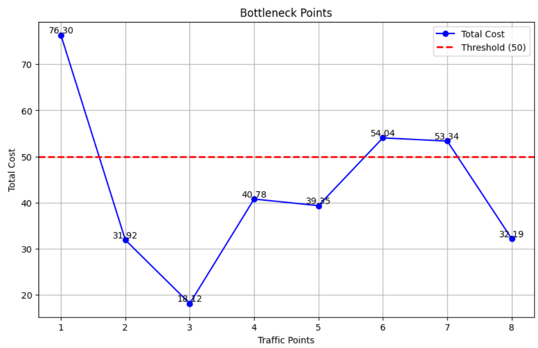

Figure 7: Estimated costs of all the traffic points.

Figure 7 clearly shows that only three points ex-

Table 3: Total propagation costs for selected traffic intersection points.

No	Intersection Point	Geographic Position	Total Propagation Cost
1	Kawran Bazar Intersection	23.749876°N, 90.393197°E	76.30
2	Shahbagh Intersection	23.738136°N, 90.395844°E	31.92
3	Shahed Captain Mansur Ali Sarani (Kakrail)	23.737350°N, 90.404211°E	18.12
4	FDC Intersection	23.753535°N, 90.400696°E	40.78
5	Farmgate Intersection	23.758640°N, 90.389878°E	39.35
6	Mohammadpur Bus Stand	23.756996°N, 90.361499°E	54.04
7	Dhanmondi 32	23.751288°N, 90.378258°E	53.34
8	Science Lab Intersection	23.738840°N, 90.383451°E	32.19

ceed the minimum cost line of bottleneck: Intersection Point 1 (Kawran Bazar), Intersection Point 6 (Mohammadpur Bus Stand), and Intersection Point 7 (Dhanmondi 32). Using a combination of field data and traffic simulations, these three lanes have been identified as primary congestion bottlenecks in the study area, demonstrating frequent delays that propagated to neighboring segments and exacerbated network-wide delays. The congestion analysis highlighted these lanes as high-impact zones where merging traffic flows, pedestrian crossings, and vehicle stoppages at intersections created significant disruptions.

Intersection Point 1 from Kawran Bazar Intersection to Dhanmondi 32 along the Panthapath corridor demonstrated significant congestion, particularly during peak hours, attributed to high volumes of merging traffic from adjoining feeder roads. This lane serves as a critical artery, connecting major hubs such as Farmgate, Kawran Bazar, Tejgaon, and Dhanmondi, making it highly susceptible to traffic buildup. The convergence of vehicles from these secondary routes intensified local delays, which subsequently spread to adjacent lanes, impacting the broader network flow.

Intersection Point 6 (Mohammadpur Bus Stand) shows high pedestrian activity and frequent stoppages by public transport, which contribute to significant delays at this node. Its role as a transit hub for buses and other vehicles amplifies congestion impacts on the surrounding network.

Intersection Point 7 (Dhanmondi 32) serves as a junction for multiple feeder roads. This intersection suffers from persistent delays due to traffic merging. The limited capacity to handle peak-hour traffic inflows further compounds the congestion issues, making it a critical bottleneck.

2) Verification of Identified Bottleneck:

Traffic simulations were conducted using SUMO to validate the identified bottlenecks. The simulations modeled traffic flows across the twenty-three lanes. Using SUMO we can confirm that three bottlenecks identified need congestion mitigation measures, such as signal timing optimization, lane reconfiguration, and pedestrian flow management. The results confirmed that among all the central nodes, only the following three are the critical bottlenecks— Intersection 1 (Kawran Bazar), Intersection 6 (Mohammadpur Bus Stand), and Intersection 7 (Dhanmondi 32). The impact of traffic bottlenecks is evident in the connected intersections. Figure 8-10 shows the intersections facing bottleneck effects.

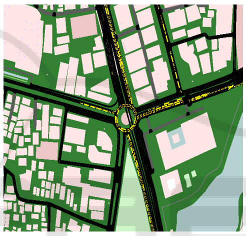

Figure 8: Kawran Bazar Intersection.

Figure 9: Mohammadpur Bus Stand.

Figure 10: Dhanmondi 32.

SUMO analysis also showed that the remaining five major traffic nodes are not congested, which validates our findings from the traffic intensity-based congestion calculation process using CSG and Maximal Spanning Tree.

5 CONCLUSION

In our paper, we introduced a novel approach to identifying bottlenecks in urban road networks by calculating road congestion levels based on traffic intensity. First, we gathered traffic intensity data to assess the

(a) (b) (c) (d) (e)

Figure 11: (a) Shahed Captain Mansur Ali Sarani (Kakrail); (b)Shahbagh Intersection; (c) FDC Intersection; (d) Science Lab Intersection; (e) Farmgate Intersection.

severity of congestion on individual road segments. We then proposed an algorithm to connect congestion correlations between road segments, forming CSG that maps the spread of congestion across the network. To analyze these graphs, we constructed maximal spanning trees to identify critical connections between congested areas. Using the road congestion intensity, we calculated the congestion costs for road segments, allowing us to pinpoint bottlenecks in the network. Our method was validated through simulation using SUMO, demonstrating that bottlenecks at three key intersection points caused a cascading effect, leading to delays throughout the surrounding area. This approach offers a more refined technique for identifying traffic bottlenecks, providing actionable insights for improving road capacity and mitigating congestion which can be applied to other major urban cities. In the future, we aim to integrate more detailed road characteristics, such as type, length, shoulder width, narrowness, etc, into the analysis to achieve finer-grained identification of bottlenecks and further enhance urban traffic performance.

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