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# Identifying Critical Mid-block Locations for Incidents in an Urban Road Network

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**Abstract**

One of the major challenges regarding development of a traffic incident management plan is the response to the incident which greatly depends upon the location of the incident. Therefore, it is necessary first to identify the potential locations of incident in the study network for developing the micro-simulation platform for incident modelling. It is quite difficult to simulate incident on each and every point in a road network as theoretically the solution space would be infinite in that case. To address this issue, a set of 'critical' locations is identified within the network where traffic management would become extremely difficult and complicated during an incident. For identifying the critical locations, the factors governing the selection of critical locations are identified. Then expert opinion surveys are done to assess the relevance of those factors for a pool of pre-selected locations. Then on the basis of the analysis, ranking of the locations conforming to being critical is done. This result from the expert opinion survey is then compared against the result obtained from incident simulation analysis using a calibrated micro-simulation model of the study network. The final outcome includes ranking of different critical mid-block locations within the network on the basis of the comparative study. These critical locations serve as the locations for incident simulation in the micro-simulation model developed for dynamically replicating the field scenario.

*Keywords:* Critical location; AHP-Fuzzy; Micro-simulation; Ranking; Delay; Maximum Queue Length.

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## 1. Introduction

India is experiencing rapid urbanization and growth of private vehicles in urban areas. The urban population in India has gone up significantly from 62 million in 1951 to 377 million in 2011 and is estimated to be around 540 million by the year of 2021. In terms of percentage of total population, the urban population has increased from 17% in 1951 to 31.2% in 2011 and is expected to increase up to around 37% by the year of 2021 (Padam and Singh, 2001; Ghosh and Maitra, 2017). This significant growth in urban population and corresponding private vehicles, constrained by space and cost, has already resulted in a growing imbalance between demand and supply of transport, leading to multi-faceted problems such as congestion, road accidents, pollution, etc. This adverse urban scenario is further aggravated by non-recurrent congestion caused by traffic incidents which act as major congestion contributor and pose a significant threat to urban mobility and safety (Ozbay et al., 2005).

Traffic incident may be defined as any non-recurring event that causes a reduction of roadway capacity or an abnormal increase in demand. Such events include traffic crashes, disabled vehicles, spilled cargo, fire, road debris, explosion, highway maintenance and reconstruction projects, and special non-emergency events (Farradyne, 2010). The immediate effect of the incident propagates to the surrounding road network as shock wave resulting in blockage; which eventually may spread over a larger network if efficient measures are not taken immediately (Ghosh and Maitra, 2016).

Traffic incident management is an essential component of every transportation network management program. Most of the available research studies have considered development of micro-simulation models for incident modelling and evaluating the performance of the network under different incident scenarios (Ozbay and Bartin, 2003; Gomes et al., 2004; Ozbay et al., 2005; Gursoy et al., 2009; Fellendorf and Vortisch, 2010; Martin et al., 2011; Tasic, 2012). One of the major challenges regarding the development of a traffic incident management plan is the response to the incident which depends upon the location of the incident (Martin et al., 2011). It is necessary first to fix the locations of an incident in the micro-simulation platform for incident generation. It is quite difficult to simulate incident on each and every point in a road network as theoretically the solution space would be infinite in that case. To address this issue, a set of ‘critical’ locations is needed to be identified within the network for incident modelling. Critical locations are the locations on the network that are difficult to manage under traffic incident conditions. The choice of critical locations does not simply focus on the locations with the most frequent incident occurrence; rather it considers the complexity regarding traffic management during incidents (Tasic, 2012). Incidents on these critical locations would result in serious traffic disruptions. From the traffic operators’ points of view, responding to incidents on the critical locations would be a challenging task.

Most of the available incident modelling studies have attempted to replicate on-field scenarios in accordance with homogeneous traffic operations. However, in emerging economies such as India, absence of lane marking, no lane discipline, haphazard movement near intersections, disorganized movement of a varied mix of vehicle types, are commonly observed phenomena which is quite different from the ideal scenario and difficult to replicate accurately (Mathew and Radhakrishnan, 2010). Unfortunately, adequate investigations have not been carried out in Indian context for developing a framework to identify critical incident locations and formulating rational traffic management strategies on the basis of real-time traffic state. The current practice regarding traffic management during incidents is primarily based on experience and judgment of key personnel (say, local traffic police) involved in the decision-making process. In light of the present scenario, this paper aims to develop a methodological framework for identifying critical incident locations required for incident simulation in a road network. The present study is conducted with reference to Kolkata metro city, India using the traffic micro-simulation software, PTV VISSIM 8.00. For simplicity, the scope of this study is confined to mid-block locations only; intersections are not considered to be identified as critical locations.

In addition to the micro-simulation analysis, this manuscript also investigates the scope and validity of expert opinion based survey techniques on the selection of critical locations within the network. As many past studies have focused on using expert opinion analysis as a tool to identify different key governing factors (motivators or deterrents) related to a transportation decision making process, the contextual requirement is to seek the key influencing factors and measure their relative importance in terms of their impact on critical location choice (Ghosh and Maitra, 2017).

The manuscript has been structured in 6 Sections. A brief introduction to the research problem has been presented in this section and the methodology adopted in the study is discussed in the following section. In the next section, the study area is briefly described. The fourth section focuses on different aspects related to the development of the micro-simulation model. The proposed methodology is then applied to the study network and analysed in the subsequent section. Finally, the major findings and outcomes of the study are summarized in the conclusion section.

## 2. Methodology

The broad methodological framework of this study is presented in Figure 1. The various tasks involved are briefly described below:

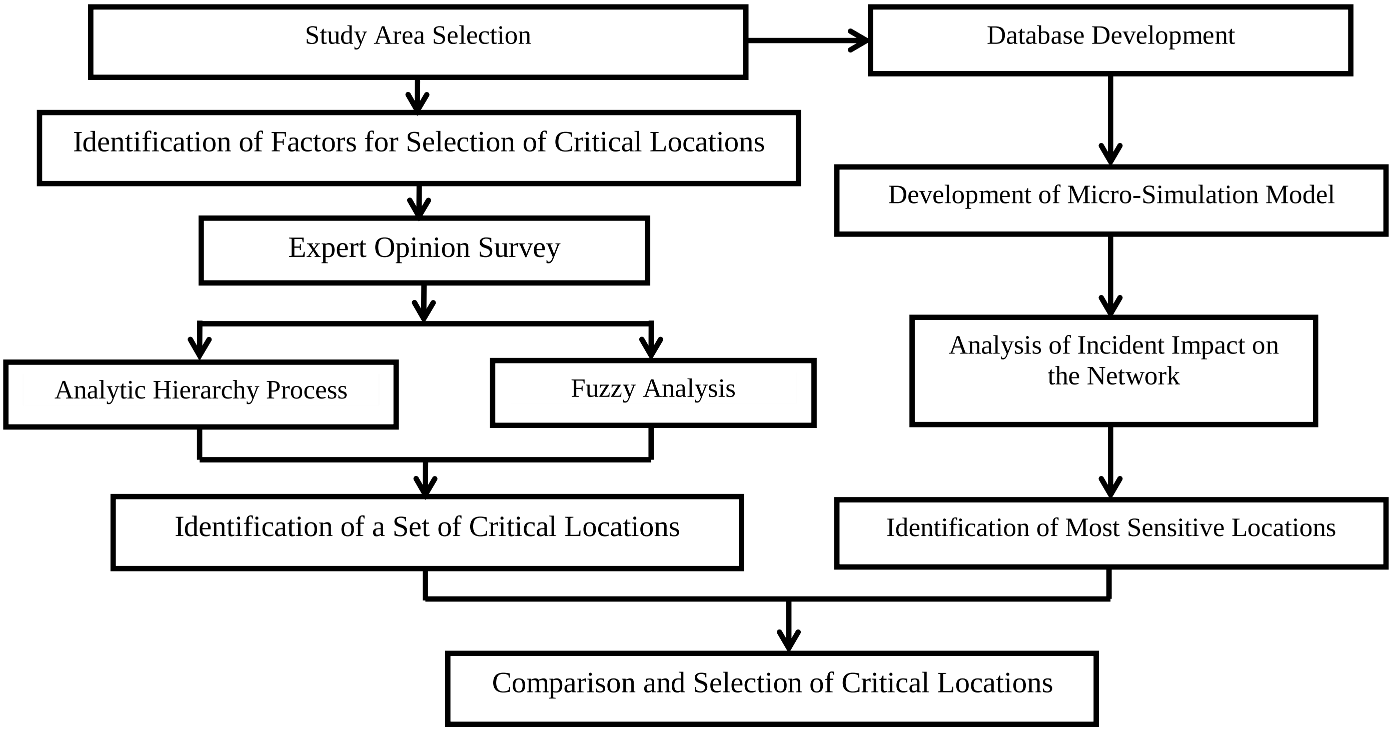

Fig. 1. Methodological framework of the study

### *2.1. Study area selection*

Firstly, a study area, over which the proposed methodology is to be applied, is selected and its geographical boundary is properly defined. A brief description of the study area is provided in section 3.

### *2.2. Database development*

A comprehensive database is developed for constructing a micro-simulation model of the study network. For developing the micro-simulation model, different types of traffic data and network geometry data are collected on-site. The collected raw data are properly extracted and refined as per the needs. The existing traffic circulation pattern and the current practice regarding incident management are also noted.

### *2.3. Development of micro-simulation model*

The various steps in developing a micro-simulation model are mentioned below.

#### *2.3.1. Network coding*

This step involves coding of the study network in the micro-simulation platform. The database required for coding the network include network geometry data (carriageway width, lane configuration, width of median etc.), link traffic volume, turning movements, vehicle composition, vehicle routing decisions and traffic signal control data (signal cycle length & its variation over different hours of a day, number of phases, green splitting, change interval, clearance interval etc.) associated with the study network.

### *2.3.2. Simulation with default parameter values*

Once the study network is properly coded, a set of initial simulation runs is performed with default parameter values to compare the model outputs with the observed field values. A significant variation between model outputs and observed field values warrants for model calibration.

### *2.3.3. Preliminary site-specific model adjustments*

There are a few site-specific model parameters that require modifications in order to replicate certain traffic stream characteristics onto the micro-simulation platform. These parameters include the desired speed distributions of respective modes, the lane changing and lateral behaviour, especially of smaller vehicles, etc. This stage includes identification and modification of such parameters to improve the model performance with respect to the field conditions (Bhattacharya et al., 2018).

### *2.3.4. Identifying sensitive parameters for calibration*

A micro-simulation platform generally caters a large set of adjustable input parameters. However, adjusting all the parameters will make the calibration process hugely complex and tedious (Ge & Menendez, 2014). Therefore, some selected parameters sensitive to the Measures of Effectiveness (MOE) are identified for the calibration purpose.

### *2.3.5. Calibration*

This step involves optimization of the selected parameters to replicate the on-field scenarios as precisely as possible. There are different approaches and techniques reported in literature for parameter optimization in the context of traffic micro-simulation (Park & Schneeberger, 2003; Kim et al., 2005; Manjunatha et al., 2013; Maheshwary et al., 2016).

### *2.3.6. Validation*

The final step involves the process of validation where an independent check on the calibrated model is performed. To achieve this, two sets of observed data are needed while developing the micro-simulation model. One set of data is used in calibrating the model, and the other is used to verify that the performance of the calibrated model agrees to that set of observed data (Sykes, 2010).

## *2.4. Analysis of incident impact on the network*

In this stage, the impact of incident is quantified and analysed on the basis of repeated simulation runs. For the evaluation purpose, a pool of pre-selected important mid-block locations within the network are selected as the incident locations and a number of simulation runs for each incident scenario are conducted. Only the incidents resulting in full closure across a road-stretch are considered for incident simulation.

Most of the existing literatures have considered travellers' delay as the MOE to predict the impact of incident (Fu and Rilett, 1997; Fu and Hellinga, 2002; Ngassa, 2006; Gursoy et al., 2009). Some studies have also used queue length (Zografos et al., 1993; Ghosh-Dastidar and Adeli, 2006; Wang et al., 2012), travel time (Zografos et al., 1993; Yang and Koutsopoulos, 1996; Mahmassani, 2001), number of stops (Martin et al., 2011) etc. as the MOEs to quantify the incident impact on the network. For this study, average aggregate network delay and average maximum queue length are considered as the MOEs.

## *2.5. Identification of most sensitive locations*

From the analysis results, the sensitive locations are identified based on the potential incident impact on the network and ranked in order.

### 2.6. Identification of factors for selection of critical locations

On a parallel approach, based on the past research findings, various key influencing factors are identified for the selection of critical locations. Some of the studies suggest use of traffic volume and provision of alternative route(s) for detouring purpose as attributes influencing the choice of critical locations (Martin et al., 2011; Tasic, 2012). Route related attributes such as route topography, presence/ absence of signal (Stinson and Bhat, 2004), average slope, length of route (Jason et al., 2010), roadway condition (Litman, 2013) and link related attributes such as availability of proper parking facility, dedicated mode facility, provision of traffic calming measures (Majumdar and Mitra, 2015) are considered in various related transportation studies. Once identified, these factors are further subjected to expert opinion based analyses.

### 2.7. Expert opinion survey and identification of a set of critical locations

During this stage, expert opinion surveys are conducted to get the perceived importance levels of the factors associated with a particular location. Multi Criteria Decision Making (MCDM) techniques such as Analytical Hierarchy Process (AHP) (Cheng and Li, 2002; Wong and Li, 2007; Shelton and Medina, 2010), TOPSIS (Sadhukhan et al., 2014), Fuzzy-AHP (Sun, 2010) and a combination of these (Sun, 2010; Shelton and Medina, 2010; Ho et al., 2012) are some of the most popular methods in this regard. Among these approaches, AHP performs pair wise comparisons between the attributes in terms of numeric values that can be processed and compared in the context of the given problem while maintaining the consistency of the dataset (Kong, 2010). AHP nowadays is widely used as an MCDM tool & as an approach for estimating priorities (Saaty, 2010) and remains as a popular choice for the measurement of intangibles along with tangibles (Saaty et al., 2003). In addition, some studies have preferred to make the judgments fuzzy while handling decisions in complex and uncertain environments (Laarhoven & Pedrycz, 1983; Dubois, 2011). According to these studies, 1–9 fundamental AHP scale is a scale of crisp numbers and that scale needs to be fuzzified for decision making purposes. By incorporating fuzzy judgments (such as triangular, trapezoidal, interval and fuzzy numbers) instead of the regular 1–9 fundamental scale for making pairwise comparisons, often result in a better decision model (Buckley, 1985b; Chang, 1996). This idea of fuzzifying the judgements is extensively used in AHP applications to make applications with apparently greater validity.

This stage involves two different tasks which are described below.

#### 2.7.1. Analytic Hierarchy Process (AHP)

AHP is generally used for deriving weightages of different criteria associated with a single goal on the basis of pair-wise comparisons. This gives us an ordered hierarchy having numerical weights for different factors under each criterion by deriving local and global weight for all associated factors (Majumdar and Mitra, 2015). The step-wise procedure is discussed below.

Firstly, a survey is conducted to obtain data on various factors influencing critical location choice. A questionnaire is prepared containing all possible pair-wise comparisons of those factors. The experts (transport researchers, academicians and professionals) are asked to give their responses on a fundamental nine-point scale (1 – ‘equally important’; 9 – ‘extremely important’) against each pair of options. The survey questionnaire does not include questions on their sociodemographic profile. Then geometric means are calculated for all of the responses to prepare the consolidated matrix. Then the consolidated matrix is normalized and multiplied repeatedly with itself until a unique Eigen Vector is obtained. A consistency check is required to be conducted on the collected responses to make it fit for the analysis. So, the overall consistency check is performed on the basis of the consistency ratio (CR) for each of the scenarios, where the CR is a function of the Random Index (RI) and the order of the matrix as expressed below (Majumdar and Mitra, 2015).

$$CI = (\lambda_{max} - n) / (n - 1) \tag{1}$$

$$CR = (CI) / (RI)(n) \tag{2}$$

Where CI = Consistency Index, CR = consistency ratio, n = order of matrix, RI = Random Index, $\lambda_{max}$ = Principal Eigen value. If the consistency ratio is less than or equal to 0.1, only then the responses are regarded to be consistent

(Saaty et al., 2003). Finally, weightages for each factor are derived and noted. A large sample is not necessary in case of a subjective method such as AHP to be used in the context of research pertaining to a specific issue. Moreover, as per Cheng and Li (2002), AHP method may be proven impractical for a survey with a large sample size as ‘cold-called’ respondents tend to have a great tendency to provide arbitrary responses which can lead to a high degree of inconsistency among the results.

### *2.7.2. Fuzzy analysis*

After getting the weights of each of the factors, for each location, the measures are assessed qualitatively based on fuzzy logic of analysis. Firstly, data are collected from the experts in terms of fuzzy variables. The experts are asked to define the range of the fuzzy variables on a scale of 0-100 as per their perceptions. Then they are asked to rate the factors for each location on that fuzzy scale to get the membership functions of the corresponding fuzzy sets. This process is called fuzzification (Ross, 2004). Then defuzzification is done to convert the fuzzified outputs into single quantifiable crisp values with respect to fuzzy sets. The defuzzified value in FLC (Fuzzy Logic Controller) represents the action to be taken in controlling the process (Saade and Diab, 2004). For this study, defuzzification is performed by using centroid of area (COA) method (Chu and Tsao, 2002). This method provides a crisp value based on the centroid of the fuzzy set. The total area of the membership function distribution used to represent the combined control action is divided into a number of sub-areas. The area and the centre of gravity or centroid of each sub-area is calculated and then the summation of all these sub-areas is taken to find the defuzzified value for a discrete fuzzy set (Saade and Diab, 2004; Mogharreban and DiLalla, 2006).

After getting the weightages from AHP analysis and the defuzzified values of the factors for a pool of pre-selected locations, overall scores of those locations are calculated; and based on this scoring, ranking of the locations conforming to being critical, is done.

### *2.8. Comparison and selection of critical locations*

Both the results from micro-simulation analysis and expert judgement analysis are compared against each other on the basis of the statistical significance of the similarities between the ranks coming out of the analyses. Finally the top ranked mid-block locations are selected as critical locations based on the comparative study. This comparative study is conducted to juxtapose the perceptions of transportation experts with the findings from micro-simulation model.

## **3. Study area**

Fig. 2. Outline of the study area

The study area considered in this research is the Central Business District (CBD) area of Kolkata city and it is selected in consultation with the local law enforcement agency (Kolkata Traffic Police). The area is marked with some busy and congested streets where some old and vulnerable buildings and factories are located, thereby, making this area highly sensitive to incidents. The boundaries of the area are defined by four major arterial roads namely, Chittaranjan (C.R.) Aveneue on East, Strand Road on West, Mahatma Gandhi (M.G.) Road on North, and S. N. Banerjee Road on South. The study network consists of 131 intersections, 32 of them being signalized ones and the rest 99 intersections are minor and unsignalized. A few extremely important buildings and infrastructure facilities (Writers Building, Raj Bhawan, Kolkata Police Headquarters, General Post Office, SBI Headquarters, Regional Passport Office, The Lalit Great Eastern Hotel, Central and Chandni Chawk metro railway stations etc.) are located in this area, making this area highly attractive in terms of trip generation. The outline of the area is shown in Fig. 2.

This area is marked with a wide variation in carriageway widths. Some of the important roads within the study area are listed below.

Table 1. Important roads and their characteristics

| Sl. No. | Name of the Road | Length (m) | Width (m) | Carriageway Type | Flow Pattern |
|---|---|---|---|---|---|
| 1. | Strand Road | 2160 | 15.2 | Undivided | One-way |
| 2. | M. G. Road | 1161 | 14 | Undivided | Both-way |
| 3. | C. R. Avenue | 2050 | 22.8 | Divided | Both-way |
| 4. | Rashmoni Avenue | 430 | 17.5 | Divided | Both-way |
| 5. | Shahid Khudiram Bose Road | 465 | 11.4 | Undivided | Both-way |
| 6. | Kiran Shankar Roy Road | 584 | 10.2 | Undivided | Both-way |
| 7. | Hare Street | 309 | 10 | Undivided | One-way |
| 8. | BTM Sarani | 269 | 10.2 | Undivided | One-way |
| 9. | Fairlie Pl. | 206 | 10.5 | Undivided | Both-way |
| 10. | Biplabi Ras Behari Sarani | 714 | 7 | Undivided | One-way |
| 11. | Raja Woodmount Street | 249 | 11 | Divided | Both-way |
| 12. | Netaji Subhas Road | 1222 | 20 | Divided | Both-way |
| 13. | Rabindra Sarani | 925 | 10.5 | Undivided | One-way |
| 14. | Maulana Saukat Ali Street | 462 | 7 | Undivided | One-way |
| 15. | New CIT Road | 745 | 10.5 | Undivided | One-way |
| 16. | B. B. Ganguly Street | 962 | 10.5 | Undivided | One-way |
| 17. | Ganesh Chandra Avenue | 650 | 12.4 | Undivided | Both-way |
| 18. | Prafulla Sarkar Street | 501 | 8 | Undivided | One-way |
| 19. | Sido Kanhu Dahar | 310 | 13.2 | Undivided | One-way |
| 20. | Bentinck Street | 670 | 12.3 | Undivided | One-way |
| 21. | BBD Bag East | 240 | 18 | Divided | One-way |
| 22. | BBD Bag South | 215 | 16 | Undivided | One-way |
| 23. | Brabourne Road | 860 | 14 | Divided | One-way |
| 24. | Marx Engels Beethi Road | 644 | 21 | Divided | Both-way |
| 25. | Government Palace West | 388 | 24 | Divided | Both-way |
| 26. | Council House Street | 212 | 16 | Divided | Both-way |

## 4. Development of the micro-simulation model

The test network for the study area for incident modelling is developed in VISSIM using network coding. The developed study network is presented in Figure 3.

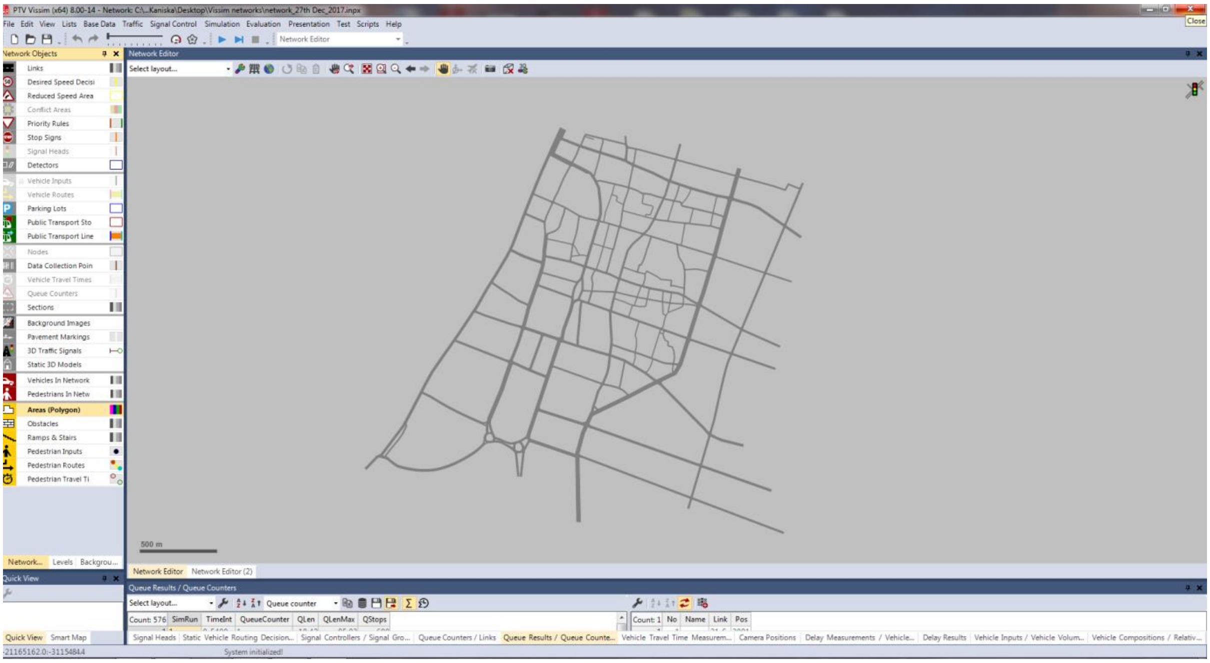

Fig. 3. Study network in VISSIM

All the network geometry data, signal control data and existing traffic circulation patterns are collected on-site with the help of Kolkata Traffic Police. Capacities of all the roads in the study network are calculated in accordance with IRC: 106-1990. Several assumptions are considered while developing the microsimulation model:

- The impact of land use, drivers' familiarity with the network, weather conditions and maintenance on route choice is not included in this model.
- The presence of pedestrians is not considered in the model.
- Travellers' characteristics are not included in this model.
- Secondary incidents are not included in this model.
- Drivers' response to traffic intervention is instantaneous.

For conducting this analysis, only the peak-hour traffic conditions are considered throughout the network. As heavy vehicles are not allowed to enter Kolkata during that period, the vehicle composition considered includes car, bus and bike (motorized 2-wheeler) as the existing modes.

As part of the preliminary site-specific model modifications, adjustments are made to the desired speed distribution for each mode under study. The desired speed distributions were modified as per the field-observed free flow speeds of different modes obtained during the early morning lean periods. In order to replicate Indian mixed-traffic stream condition in VISSIM, the parameters pertaining to the lane changing and lateral behaviour models are also modified for the respective modes. Calibration of driving behaviour parameters is done by calibrating some of the Wiedemann '99 car-following model parameters incorporated in VISSIM, for each of the existing modes. These parameters include CC0, CC1, CC2, CC3, CC7, CC8, "Maximum Look Ahead Distance", and "Observed Vehicles". A detailed description of all these parameters is available in the literature (PTV, 2015).

Incident in VISSIM simulation is defined by installing time-dependent speed reduction areas and signal heads. Incident Location is represented by placing a traffic signal head to model the incident. Lane Closure is represented by the number of signal heads, with one signal head for each lane closed at the incident location. Incident Duration defines the “red” time of the signal head used for incident modelling. Speed reduction areas are defined before and after the traffic signal to ensure that the vehicles comply with incident conditions and slowdown near the area of lane closure.

As mentioned earlier, 45 mid-block locations are considered for this analysis. Each of these mid-block locations is considered as the incident location in turns for the simulation study and for each incident location, twenty different simulation runs are conducted. Then the outputs over those simulation runs are averaged for analysis purpose. These incident simulation scenarios are also compared against a base simulation with ‘no incident’ scenario where the network is simulated without consideration of any incident, keeping all other input parameters constant. Here only the incidents resulting in full lane closure are assumed to take place at the designated incident locations in the micro-simulation model. For simplification, a buffer period of 600 seconds during which traffic flows in its normal state, is provided at the start of a simulation run. The duration of incident is considered as 3600 seconds, followed by a cooling period (traffic flow is back to its normal state after incident recovery) of 1200 seconds, leading to the duration of a simulation run to be 5400 seconds. All the 45 mid-block locations (numbered as 1-45) marked on the micro-simulation model network are shown in Figure 4.

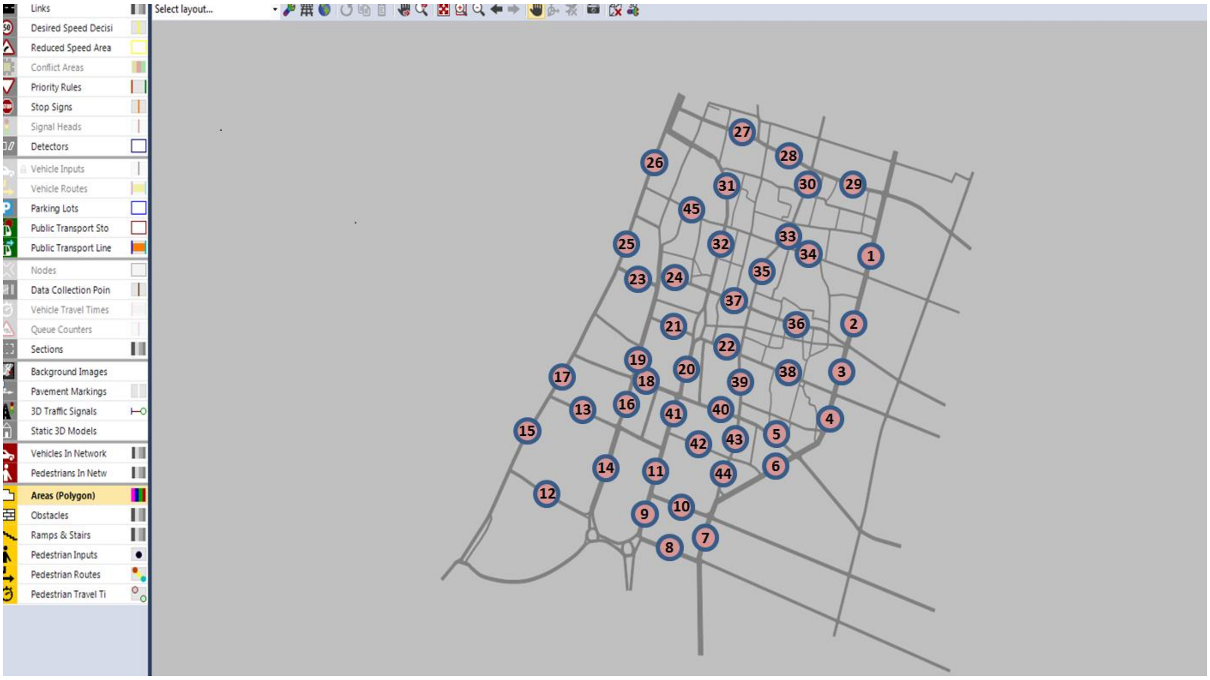

Fig. 4. Test mid-block incident locations in VISSIM

## 5. Analysis

### *5.1. Identification of factors for selection of critical locations*

As stated earlier, the selection of the critical locations should be rational and logical. Based on the available literatures (discussed in the methodology section) coupled with the knowledge regarding the geographical and traffic features of the study area, the following six key factors are identified, namely (i) Traffic Volume, (ii) Scope of Diversion to Alternative Route, (iii) Distance to Traffic Signal, (iv) Distance to Major Intersection, (v) Number of Lanes in Each Direction, and (vi) Traffic Flow Direction. These factors are briefly described below.

#### *5.1.1. Traffic volume*

Traffic volume represents the actual number of vehicles observed to pass the given location on the roadway in a given time. Here, only the peak-hourly traffic volume at the incident location is considered for the analysis.

#### *5.1.2. Scope of diversion to alternative route*

Presence of alternative route(s) near the location is an important feature in context of traffic incident management as it can be used for traffic diversion in case of an incident. This factor represents how far the alternative routes are located from the respective incident locations.

#### *5.1.3. Distance to traffic signal*

This factor measures the distance from the incident location to its nearest traffic signal heads. Incident in the vicinity of a signalized intersection is likely to have more impact on the traffic stream than that of an unsignalized intersection.

#### *5.1.4. Distance to major intersection*

Major intersection means an intersection of two major streets. It generally caters a large traffic volume. This factor measures the distance from the incident location to the nearest major intersection.

#### *5.1.5. Number of lanes in each direction*

Carriageway configuration plays an important role in traffic management aspect. More number of lanes and presence of median facilitate in emergency traffic management.

#### *5.1.6. Traffic flow direction*

This factor represents that whether the road is one-way or two-way. Unidirectional movement generally facilitates in implementing emergency traffic management measures as the capacity of the roadway increases in that case.

### *5.2. Expert opinion survey*

After identifying the factors, expert opinion survey is done to assess the relevance of those factors for a pool of pre-selected locations. The pool of pre-selected locations includes 45 important mid-block locations within the network. In this stage, experts are asked to judge the importance of the factors on different scales. For this study, experts are asked to consider only the peak hour characteristics of the locations. This analysis is done in two parts. In the first part, Analytic Hierarchy Process (AHP) is used to find the weightage of each factor. In second part, Fuzzy Logic is applied to find the defuzzified score of each factor for each location. Then Overall Score is calculated; and based on scoring, ranking of the locations conforming to being critical, is done. Overall Score (Y) for each location is calculated by using the following equation:

$$\boldsymbol{Y = a_1x_1 + a_2x_2 + \ldots + a_nx_n} \tag{3}$$

Where $a_i$ = weightage of factors obtained by AHP, $x_i$ = values obtained by defuzzification of the variables collected from the expert survey, and n = number of factors.

#### *5.2.1. AHP analysis*

Here AHP survey is done by using twenty experts’ ratings. The experts (transport researchers, professionals and academicians) are asked to submit their responses on a nine-point scale (1 – ‘equally important’; 9 – ‘extremely important’) against each pair of options. Since there are 6 factors, so each expert respondent has to compare a total of ${}^6C_2$ = 15 responses. To check the consistency in perceptions of different experts, this analysis is done in three ways: (i) considering the judgement of first 10 experts ($W_{10}$), (ii) considering the judgement of first 15 experts ($W_{15}$), and (iii) considering the judgement of all 20 experts ($W_{20}$). The results are found to be consistent. Then all the three results are averaged to estimate the final weightages ($W_{avg}$). The calculated weightage of each factor is summarized below.

Table 2. Weightage of factors based on AHP

| **Factors** | **$W_{10}$** | **$W_{15}$** | **$W_{20}$** | **$W_{avg}$** |
|---|---|---|---|---|
| Traffic Volume | 0.205 | 0.219 | 0.216 | **0.213** |
| Scope of Diversion to Alternative Route | 0.233 | 0.222 | 0.224 | **0.226** |
| No. of Lanes in Each Direction | 0.144 | 0.162 | 0.174 | **0.160** |
| Traffic Flow Direction | 0.144 | 0.126 | 0.113 | **0.128** |
| Distance to Traffic Signal | 0.111 | 0.118 | 0.118 | **0.116** |
| Distance to Major Intersection | 0.163 | 0.154 | 0.155 | **0.157** |

According to the AHP analysis, ‘Scope of Diversion to Alternative Route’ (22.6%) is found to be the criterion with the strongest influence on the selection of critical location. ‘Traffic Volume’ (21.3%) is found to be the next important factor to consider followed by ‘Number of Lanes in Each Direction’ (16%), ‘Distance to Major Intersection’ (15.7%), ‘Traffic Flow Direction’ (12.8%), and ‘Distance to Traffic Signal’ (11.6%).

### *5.2.2. Fuzzy analysis*

As two of the influencing factors (No. of Lanes in Each Direction and Traffic Flow Direction) are cardinal variables, analysis is done on the basis of normalized ranking for those two factors. For the remaining four factors, which are considered as ordinal in nature, data are collected from the experts based on fuzzy variables for each factor for each pre-selected location. Though ‘Traffic Volume’, ‘Distance to Major Intersection’ and ‘Distance to Traffic Signal’ are measurable, here these factors are assumed to be ordinal to capture the variation in perceptions amongst the experts on judging the parameters. The experts have to define the range of fuzzy variables on a scale of 0-100 based on their perceptions. Then they are asked to rate the factors for each location in terms of fuzzy variables (fuzzification). The fuzzy variables for each of the factors are listed below.

Table 3. Variables used in Fuzzy analysis

| **Factor** | **Variables** |
|---|---|
| Traffic Volume | Very High, High, Medium, Low, Very Low |
| Scope of Diversion to Alternative Route | Very Difficult, Difficult, Normal, Easy, Very Easy |
| No. of Lanes in Each Direction | 1,2,3,4 |
| Traffic Flow Direction | One-way, Two-way |
| Distance to Traffic Signal | Very Far, Far, Medium, Near, Very Near |
| Distance to Major Intersection | Very Far, Far, Medium, Near, Very Near |

Using the weightage and fuzzy values, defuzzification is done using centroid of area method. Subsequently final score is obtained for each location. Based on final scores, all the locations are ranked respectively. Here Fuzzy analysis is done by collecting opinions of five experts who have adequate knowledge of the network. The rankings of the 45 locations with their respective overall scores are presented in Table 4.

Table 4. Ranking of mid-block locations on the basis of expert opinion analysis

| Rank | Location No. | Overall Score | Rank | Location No. | Overall Score | Rank | Location No. | Overall Score |
|---|---|---|---|---|---|---|---|---|
| R 1 | 32 | 82.43 | R 16 | 44 | 52.14 | R 31 | 39 | 42.37 |
| R 2 | 7 | 71.13 | R 17 | 41 | 50.53 | R 32 | 14 | 42.22 |
| R 3 | 10 | 68.26 | R 18 | 25 | 49.72 | R 33 | 20 | 41.58 |
| R 4 | 28 | 65.44 | R 19 | 15 | 49.04 | R 34 | 36 | 41.13 |
| R 5 | 38 | 64.33 | R 20 | 11 | 48.88 | R 35 | 31 | 40.08 |
| R 6 | 17 | 62.21 | R 21 | 12 | 47.76 | R 36 | 4 | 39.67 |
| R 7 | 26 | 61.86 | R 22 | 19 | 46.91 | R 37 | 33 | 38.25 |
| R 8 | 27 | 60.67 | R 23 | 22 | 46.83 | R 38 | 24 | 37.32 |
| R 9 | 9 | 60.26 | R 24 | 16 | 46.73 | R 39 | 30 | 36.64 |
| R 10 | 8 | 59.38 | R 25 | 37 | 46.51 | R 40 | 45 | 36.16 |
| R 11 | 6 | 57.32 | R 26 | 18 | 46.01 | R 41 | 35 | 35.85 |
| R 12 | 29 | 56.20 | R 27 | 43 | 45.03 | R 42 | 34 | 35.46 |
| R 13 | 2 | 56.07 | R 28 | 42 | 44.19 | R 43 | 13 | 34.43 |
| R 14 | 1 | 53.95 | R 29 | 3 | 44.05 | R 44 | 23 | 34.09 |
| R 15 | 5 | 52.94 | R 30 | 40 | 42.81 | R 45 | 21 | 34.02 |

### *5.3. Analysis on the basis of micro-simulation model*

For this analysis, average aggregate network delay and average maximum queue length are considered as the MOEs. A total of 12 travel time sections are installed to cover the spatial impact of incidents throughout the network and 24 queue counters are placed at strategic locations to properly cover all of the high density parts of the network. After fixing all the model variables, input, and output parameters, the micro-simulation model is used to quantify the impact of incident over the network.

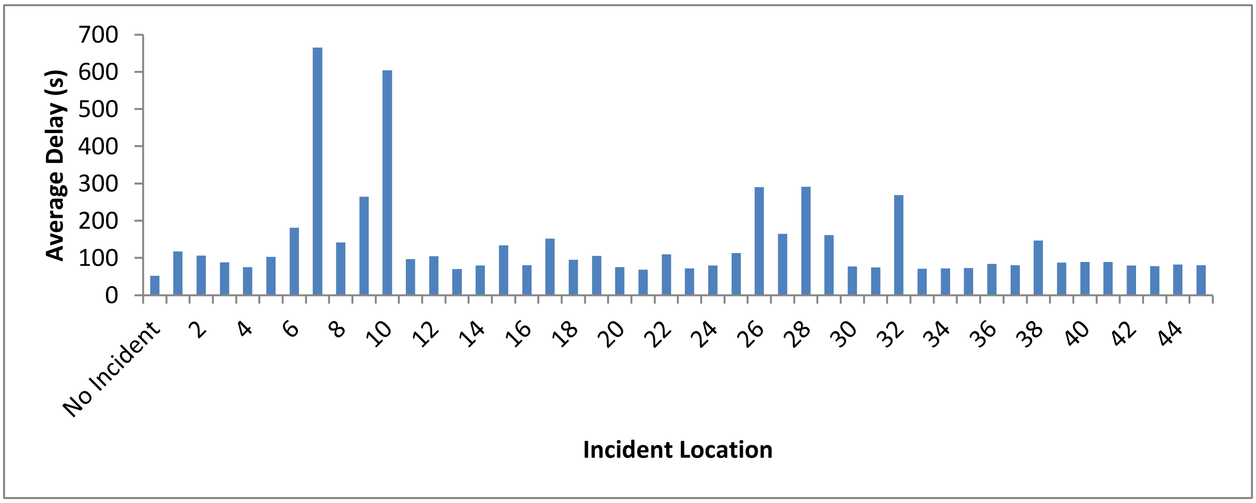

Fig. 5. Average delay comparisons for different incident locations

As mentioned earlier, 45 mid-block locations within the study network are selected for the incident impact analysis where each of these locations is considered as incident location in turn. Each of these 45 scenarios is subjected to 20 simulation runs. The average values of the MOEs for those 45 locations are compared against the base case of ‘no-incident’ scenario. The average aggregate network delay and average maximum queue length comparisons for different incident locations are presented in Fig. 5 and 6 respectively.

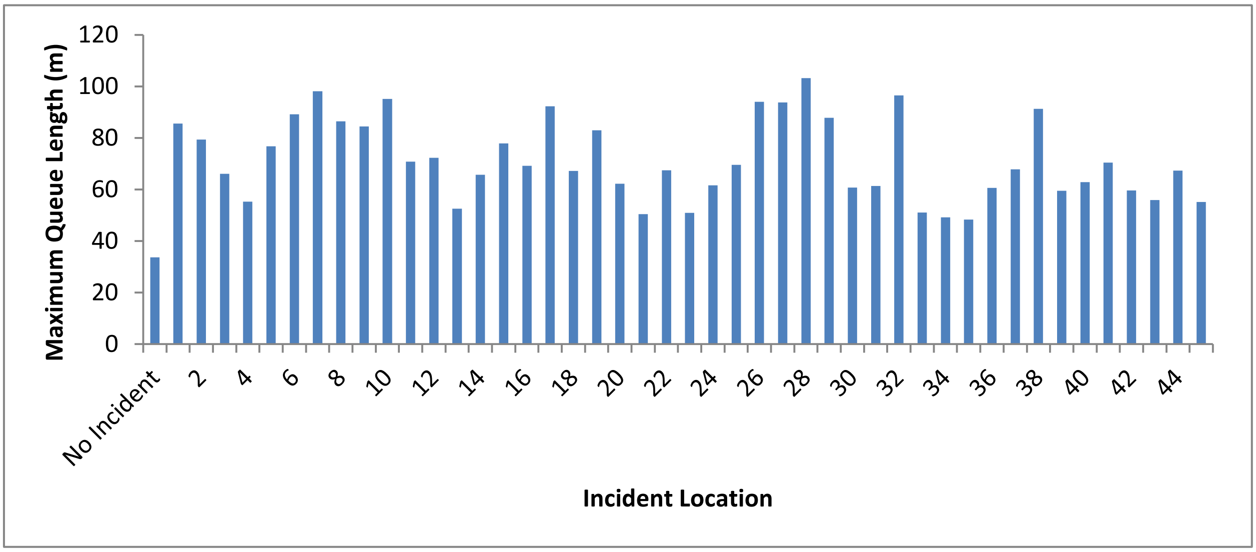

Fig. 6. Average maximum queue length comparisons for different incident locations

The rankings of the 45 mid-block locations on the basis of average delay and average maximum queue length are estimated and shown in Table 5 and 6 respectively.

Table 5. Ranking of mid-block locations on the basis of average delay

| Rank (Delay) | Location No. | Rank (Delay) | Location No. | Rank (Delay) | Location No. |
|---|---|---|---|---|---|
| R1 | 7 | R16 | 22 | R31 | 37 |
| R2 | 10 | R17 | 2 | R32 | 42 |
| R3 | 28 | R18 | 19 | R33 | 24 |
| R4 | 26 | R19 | 12 | R34 | 14 |
| R5 | 32 | R20 | 5 | R35 | 43 |
| R6 | 9 | R21 | 11 | R36 | 30 |
| R7 | 6 | R22 | 18 | R37 | 4 |
| R8 | 27 | R23 | 40 | R38 | 20 |
| R9 | 29 | R24 | 41 | R39 | 31 |
| R10 | 17 | R25 | 3 | R40 | 35 |
| R11 | 38 | R26 | 39 | R41 | 34 |
| R12 | 8 | R27 | 36 | R42 | 23 |
| R13 | 15 | R28 | 44 | R43 | 33 |
| R14 | 1 | R29 | 16 | R44 | 13 |
| R15 | 25 | R30 | 45 | R45 | 21 |

Table 6. Ranking of mid-block locations on the basis of average maximum queue length

| Rank (QL) | Location No. | Rank (QL) | Location No. | Rank (QL) | Location No. |
|---|---|---|---|---|---|
| R1 | 28 | R16 | 15 | R31 | 24 |
| R2 | 7 | R17 | 5 | R32 | 31 |
| R3 | 32 | R18 | 12 | R33 | 30 |
| R4 | 10 | R19 | 11 | R34 | 36 |
| R5 | 26 | R20 | 41 | R35 | 42 |
| R6 | 27 | R21 | 25 | R36 | 39 |
| R7 | 17 | R22 | 16 | R37 | 43 |
| R8 | 38 | R23 | 37 | R38 | 4 |
| R9 | 6 | R24 | 22 | R39 | 45 |
| R10 | 29 | R25 | 44 | R40 | 13 |
| R11 | 8 | R26 | 18 | R41 | 33 |
| R12 | 1 | R27 | 3 | R42 | 23 |
| R13 | 9 | R28 | 14 | R43 | 21 |
| R14 | 19 | R29 | 40 | R44 | 34 |
| R15 | 2 | R30 | 20 | R45 | 35 |

In order to check the correlation between these two sets of rankings, Spearman’s rank order correlation coefficients were calculated and found to be statistically significant at the 99% confidence level, indicating a positive rank order relationship among these two rankings (Table 7).

Table 7. Nonparametric correlations between rankings

**Correlations**

| | | | Delay | Maximum QL |
|---|---|---|---|---|
| Spearman's rho | Delay | Correlation Coefficient | 1.000 | .941** |
| | | Sig. (2-tailed) | | .000 |
| | | N | 45 | 45 |
| | Maximum QL | Correlation Coefficient | .941** | 1.000 |
| | | Sig. (2-tailed) | .000 | |
| | | N | 45 | 45 |

**. Correlation is significant at the 0.01 level (2-tailed).

### *5.4. Comparative study*

The rankings of 45 mid-block locations, as per the micro-simulation analyses, are compared against the same found from the expert opinion analysis. It is found that the results of simulations study and AHP-fuzzy analysis are mostly in agreement, with slight variations among the internal order of the locations. These sets of rankings are statistically compared against each other on the basis of **Wilcoxon signed-rank test**. **Asymp. Sig. (2-tailed)** values of **0.925** and **0.787** are obtained between Expert Opinion-Delay comparison and Expert Opinion-Maximum Queue

Length comparison respectively, which also indicate that the rankings are consistent and not statistically significantly different.

Now, as the Expert Opinion-Delay comparative statistic value is found to be greater than the Expert Opinion-Maximum Queue Length comparative statistic value, the Expert Opinion-Delay comparison is considered as the representative comparative study between the expert opinion analysis and micro-simulation analysis. Any of the rankings obtained from expert opinion analysis (Table 4) or delay analysis (Table 5) can be used as the ranking of critical mid-block locations (as those sets of rankings are consistent and not statistically significantly different). Ultimately, for this study, the ranking based on the expert opinion analysis is chosen as the ranking of critical mid-block locations in the study network. The top 15-20 ranked locations can be selected as the critical mid-block locations for incident modelling purpose.

## 6. Conclusions

This paper has developed a methodological framework to identify different critical mid-block incident locations within a network for incident modelling purpose. This paper has also compared the relative importance of different attributes influencing the selection of critical incident locations from both experts' perception and simulation analysis.

Analytic hierarchy process (AHP) has been used to analyze the relative importance of various attributes influencing selection of critical incident locations from expert's point of view whereas a Fuzzy analysis has been performed to evaluate overall scores for a pool of pre-selected important locations. The expert opinion analysis has revealed the superior importance of 'Scope of Diversion to Alternative Route' as compared to the other factors for selecting critical locations. 'Traffic Volume' has also been found to be an important factor from experts' point of view. The other factors have been perceived by the experts accordingly.

Evaluation results from the micro-simulation model have revealed that the rankings of locations obtained on the basis of delay and maximum queue length are statistically not different from each other. Finally the rankings of locations obtained from the expert opinion analysis and the micro-simulation analysis are compared which are found to be consistent and statistically not different. The consistency between the results indicates the capability of expert judgements to successfully predict the critical mid-block locations within the network, coinciding with the results coming from the micro-simulation analysis.

The future study may include the variations between peak hour and off-peak hour analyses. The correlation among the key influencing factors for identifying the critical locations may also be investigated. For analysis using micro-simulation model, considerations of more MOEs can also be explored.

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