AN INTEGRATED INCIDENT DETECTION METHODOLOGY WITH GPS-EQUIPPED VEHICLES

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ABSTRACT

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Recurrent congestion in urban traffic networks, especially on arterials, is a growing problem. Non-recurrent congestion, mainly due to incidents, only aggravates the problem. Any solution requires monitoring of the network, for which many developing countries, such as Turkey, do not have the traditional surveillance systems on arterials mainly due to high costs. An alternative solution is the utilization of Global Positioning System (GPS) technology, which is increasingly used in traffic monitoring. It is easy and cheap to obtain the GPS track information, even in real-time, from a probe-vehicle or a fleet of vehicles; and spatial variation of speed and travel time of the vehicle(s) in a network can be determined. GPS-based data, especially with only one probe-vehicle, would not provide information on the concurrent states of upstream and downstream traffic, needed to define the state of traffic in a network. To overcome this obstacle, a methodology based on statistical analysis of archival traffic conditions obtained through different sources is proposed to analyze traffic fluctuations and identify daily traffic pattern. As a result, bottleneck and resulting queues can be detected on a corridor. Thus, it enables detection of non-recurrent congestion and queues that may result from incidents.

The proposed methodology is tested on a corridor the roadway between METU and Kızılay of İnönü Boulevard. The results show that the methodology can effectively identify bottleneck locations on the corridor and also an incident observed during the data collection is detected correctly by the proposed algorithm.

Keywords: Incident detection, Bottlenecks, Intelligent Transportation Systems, GPS, GIS

ÖZ

GPS TEÇHİZATLI ARAÇLARLA BÜTÜNLEŞİK VAKA TESPİTİ YÖNTEMİ

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Kentsel trafik ağlarında, özellikle de arterlerde tekrarlayan sıkışıklıklar artan bir sorun teşkil etmektedir. Genellikle vakalardan kaynaklanan tekrarlanmayan sıkışıklıklar ise bu sorunu daha da kötüleştirmektedir. Bu konuda önerilebilecek herhangi bir çözüm trafik ağının izlenmesini ve Türkiye gibi gelişmekte olan ülkelerde ana arterlerinde yüksek maliyet nedeniyle mevcut olmayan trafik denetim sistemlerini gerektirmektedir. Trafik izlemede artarak kullanılan alternatif bir çözüm ise Küresel Konumlandırma Sistemi (GPS) teknolojisinin uygulanmasıdır. GPS takip verisinin bir tahkikat aracından yada araç filolarından gerçek zamanlı olarak bile elde edilmesi kolay ve ucuzdur; aynı zamanda araçların hız ve seyahat sürelerinin mekansal değişimi de belirlenebilir. GPS verisi, özellikle tek bir tahkikat aracıyla, traffik durumunun belirlenmesi için gerekli olan aşağı ve yukarı akım trafik koşullarının eş zamanlı durum bilgisini sağlamaz. Bu engelin üstesinden gelmek için, trafikdeki dalgalanmaları analiz etmek ve günlük trafik şablonunu belirlemek için, değişik kaynaklardan elde edilen arşivsel trafik durumlarının istatistiksel analizine dayanan bir metodoloji önerilmiştir

Böylelikle bir koridorda dar boğazlar ve bunun sonucu olarak oluşan kuyruklar belirlenebilir. Bu sayede tekrarlanmayan sıkışıklıklar ve vakalardan kaynaklanan kuyruklarin belirlenmesi de sağlanılabilir.

Önerilen metodoloji, İnönü Bulvarının ODTÜ ve Kızılay arasındaki kalan bölümü üzerindeki koridorda test edilmiştir. Sonuçlar, metodolojinin koridordaki darboğazları etkili bir şekilde belirlediğini göstermiş, hatta veri toplama işlemi sırasında karşılaşılan bir vakanın tesbiti önerilen algoritmayla doğru şekilde yapılmıştır.

Anahtar Kelimeler: Vaka tespiti,Dar boğazlar, Akıllı Ulaşım Sistemleri, GPS, CBS

To

My Family

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LIST OF ABBREVIATIONS

ACN	Automatic Crash Notification
ANN	Artificial Neural Network
ARIMA	AutoRegressive Integrated Moving Average
AVI	Automatic Vehicle Identification
AVL	Automatic Vehicle Location
BM	Benchmark
DR	Detection Rate
FAR	False Alarm Rate
GIS	Geographic Information Systems
GPS	Global Positioning System
HIOCC	High Occupacy
ITS	Intelligent Transportation Systems
SND	Standard Normal Deviate
TCCD	Time-dependent Corridor Characteristics Database
TTD	Time To Detect
POI	Point of Interest
VIP	Video Image Processing

CHAPTER 1

INTRODUCTION

Congestion in urban traffic networks, especially on arterials, is a growing problem. Congestion due to incidents only exacerbates the problem. But, the major difference between everyday traffic congestion and incident induced one is that the former is recurrent while the latter, non-recurrent. Although both results from situation of “flow exceeding capacity”, daily congestion is generally due to regular high demand levels, whereas, incidents are mostly due to capacity losses, irregular and can not be forecasted a priori. Therefore, different strategies are needed for recurrent and non-recurrent congestion. Recurrent congestion might be solved by demand management policies such as diverting vehicles to an alternative route, or by supply management strategies, such as lane reversals, etc. Such solutions unfortunately cannot be used for incident-based congestion as they require preplanning and organized deployment, most likely location-based.

Incidents may cause long queues on the roadway, slowing down or even stopping of traffic flow. Previous research by Sullivan (1997) and Ozbay et al. (1997) shows that delays due to incidents are related with the type and duration of the incident, the number of lanes blocked, and the number of vehicles involved. When an incident blocks one or more lanes of traffic flow, a queue builds in the upstream of the incident. This queue grows and so do the delays until the incident is cleared and traffic flow is restored. Developing any strategies for incident management requires the understanding of basic characteristics of traffic flow and their interactions under incident conditions.

Incident detection can be regarded as the most crucial step of the overall incident management activities. Because, any delay in this step can cause longer queues, consequently longer incident recovery period and secondary accidents. Incident detection necessitates a reliable surveillance system, which may include one or more of available incident detection technologies; sensor-based, probe-based and driver-based.

Among various incident detection technologies, sensor-based ones are generally integrated in the roadway infrastructure system. Since they are embedded in pavement or installed roadside, they give fixed point or short-section traffic information extracted from vehicles passing the sensors (Parkany and Xie, 2005). Most popular of these technologies is the loop detectors and they are primary component of traffic management and incident detection systems on freeways in developed countries such as the USA. Even in the USA, they are not generally extended to arterials and for a developing country such as Turkey; the problem is more difficult, due to lack of availability of such technologies except for very limited use. Probe-based technologies are mobile and use sensors carried in vehicles to gather traffic information. In addition to sensor-based and probe-based technologies, incident detection can be made via mobile reports which are reports of incidents from drivers and service patrols.

1.1 Problem Definition

Although they are widely used, there are some drawbacks of sensor-based technologies. First, they are not easily expandable and adding more measuring devices to a surveillance system is extremely costly (Petty, 1997). Secondly, there are high maintenance costs due to excessive wear as they are installed in or near a roadway. Third and most important disadvantage of these systems is that they are fixed at one point, so information from a sensor is location based. This information is not sufficient to realize traffic flow on arterials where spatial variation of traffic flow is very complex. Therefore, there is a need for an incident detection system which is cheap and capable of capturing the spatial variation of traffic flow on arterials.

With current advances in information, computing and communication technologies, GPS-based traffic data collection is becoming a cheaper way when compared with cost of installing sroadway based sensors. Furthermore, Quiroga & Bullock (1999) states that GPS provides consistency, automation, finer levels of resolution, and better accuracy in measuring travel time and speed than traditional techniques (Quiroga & Bullock, 1999). From this perspective, probe vehicle methods using Global Positioning System (GPS) devices, provide a good alternative to traditional point-based sensors. A GPS device in a probe vehicle can transmit the vehicle's position and velocity information with time tag at a pre-selected frequency to a control center. When this GPS track data is associated with the underlying traffic network the obtained traffic information can be used for traffic monitoring and even for incident detection.

The main drawback of traffic surveillance with GPS especially by a single probe vehicle is that while spatial variation of traffic flow in the network can be monitored, downstream and upstream traffic conditions cannot be determined concurrently. In other words, unlike fixed sensors, the traffic flow cannot be monitored at multiple locations simultaneously. However, historical traffic information of network can be used to forecast expected traffic conditions and compared with current conditions to overcome this shortcoming. In such an approach, bottlenecks causing recurrent congestion must be detected in order to differentiate between queues due to incidents and recurrent ones.

The goal of this study is to develop an integrated and low-cost incident detection methodology, applicable for both freeways and arterials using GPS equipped probe vehicles. Such a method requires selection of a corridor to be studied. It might be reasonable to choose a main corridor since it can be monitored without further investment for dedicated probe vehicles and has a high possibility and priority for incidents. The network representation of the corridor is important, as well as the segmentation of it, which should be performed based on physical and operational changes, characteristic reasons such as “black spots” along it.

An essential part of the proposed methodology is the creation of an archival database for the corridor. The archival data needed includes determination of time-dependent traffic characteristics of the corridor links for selected time windows and confidence intervals for them, link speed variation parameters, slow regime parameters. These data are needed mainly to perform a retrospective bottleneck analysis necessary to determine recurrent congestion locations in the corridor. In this step, bottlenecks and their impact zones are detected by a search algorithm to avoid detecting a recurrent bottleneck falsely as an incident. Finally, a real-time incident detection algorithm is proposed which utilizes and integrates information produced in previous steps to detect incident with a single GPS equipped vehicle.

1.2 Organization of the Thesis

In Chapter 2, first, the review of incident management and necessary steps are summarized and the popular technologies and techniques used in incident detection are presented. Then, the literature on incident detection algorithms is reviewed in detail, followed by a review of GPS/Geographic Information Systems (GIS) use in traffic management and incident detection.

In Chapter 3, challenges in incident detection are discussed and the proposed methodology is described in detail. The steps to develop an integrated methodology for incident detection with GPS equipped vehicles are presented. The proposed algorithms for bottleneck and incident detection are studied step-by-step in this section.

In Chapter 4, the developed methodology is tested for a selected study corridor, a portion of İnönü Boulevard in Ankara. The probe vehicle data analyzed to derive to corridor characteristics is checked. The methodology is tested using the corridor characteristics and the results of bottleneck analysis. Finally, incident detection algorithm is tested by a real-life incident witnessed during data collection.

Chapter 5 presents conclusions and recommendations for future research. The improvements to increase the applicability of the methodology are discussed.

CHAPTER 2

LITERATURE REVIEW

Traffic congestion and delays are two major problems that we face in traffic management. Increasing rate of car ownership exacerbates the situation and makes it an everyday problem. Building new roads or increasing the capacity of the existing ones offers a partial solution, however a) it may not be economically and physically feasible for the most urban arterial roadways and b) the delays may not stem from persistent lack of capacity, such as in the case of incidents.

Before suggesting any long-term and big-budgeted solutions for incident management, it is important to study the traffic congestion phenomenon and its possible causes. One way to classify traffic congestion is to look at the frequency of the problem categorized as i) recurrent and ii) non-recurrent congestion. Recurrent congestion is the delays in the peak-hour traffic mostly due to high demand compared to existing capacity, while non-recurrent congestion is caused by traffic incidents, such as vehicle disablements, cargo spills, and accidents (Ozbay and Bartin, 2003). Incident management efforts deal with minimization of non-recurrent congestion, as non-recurrent congestion can be decreased by proper utilization of resources.

In this chapter, first the steps of incident management are summarized. Then, the technologies used in incident detection are briefly explained. Literature on freeway and arterial incident detection algorithms is reviewed and finally potential of GPS in transportation studies are investigated and the studies on GPS-based incident detection are reviewed.

2.1 Incident Management

Incident management aims minimization of impacts of an incident (such as lack of safety and delay). Four stages of an incident management approach are commonly defined as: *i)* incident detection, *ii)* incident response, *iii)* incident clearance, and *iv)* incident recovery which are summarized in Figure 2.1 and discussed in further detail below.

At first, these four stages can be seen only sequential but they, in most cases, may be carried out at the same time. For example, while an incident response team is dispatched; alternative routes can be offered to motorists. Figure 2.2 shows the flow of incident management process.

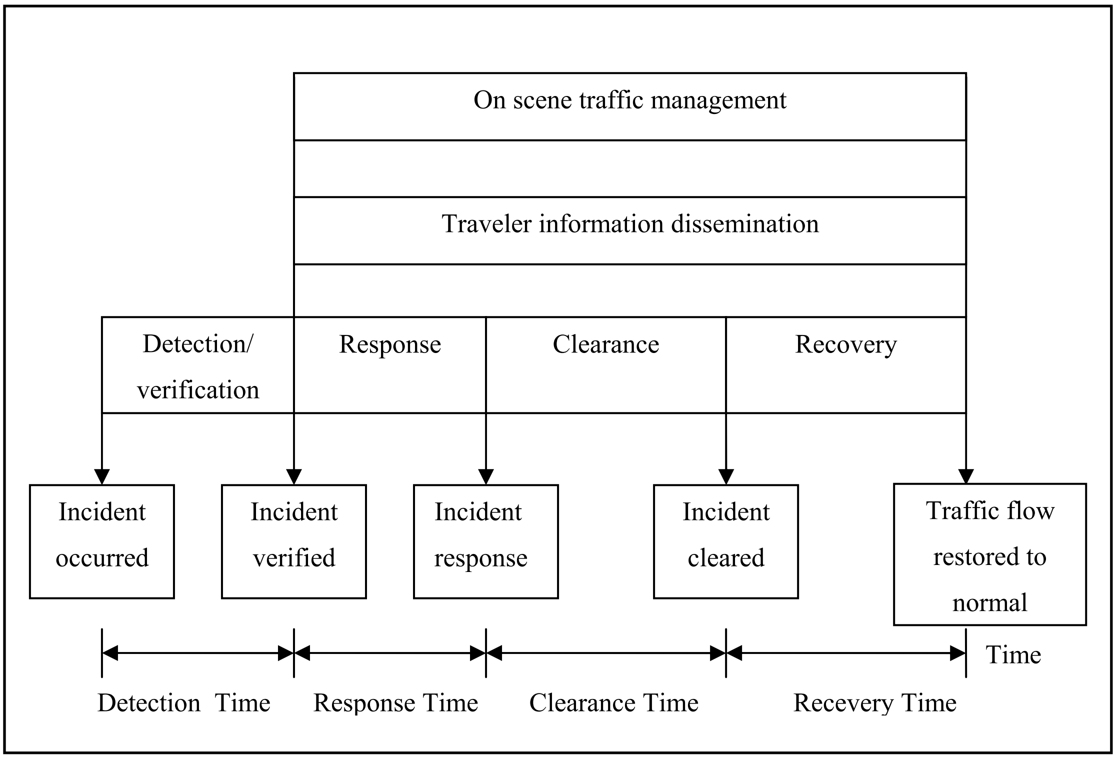

Figure 2.1 Steps of incident management (Ozbay & Kachroo, 1999)

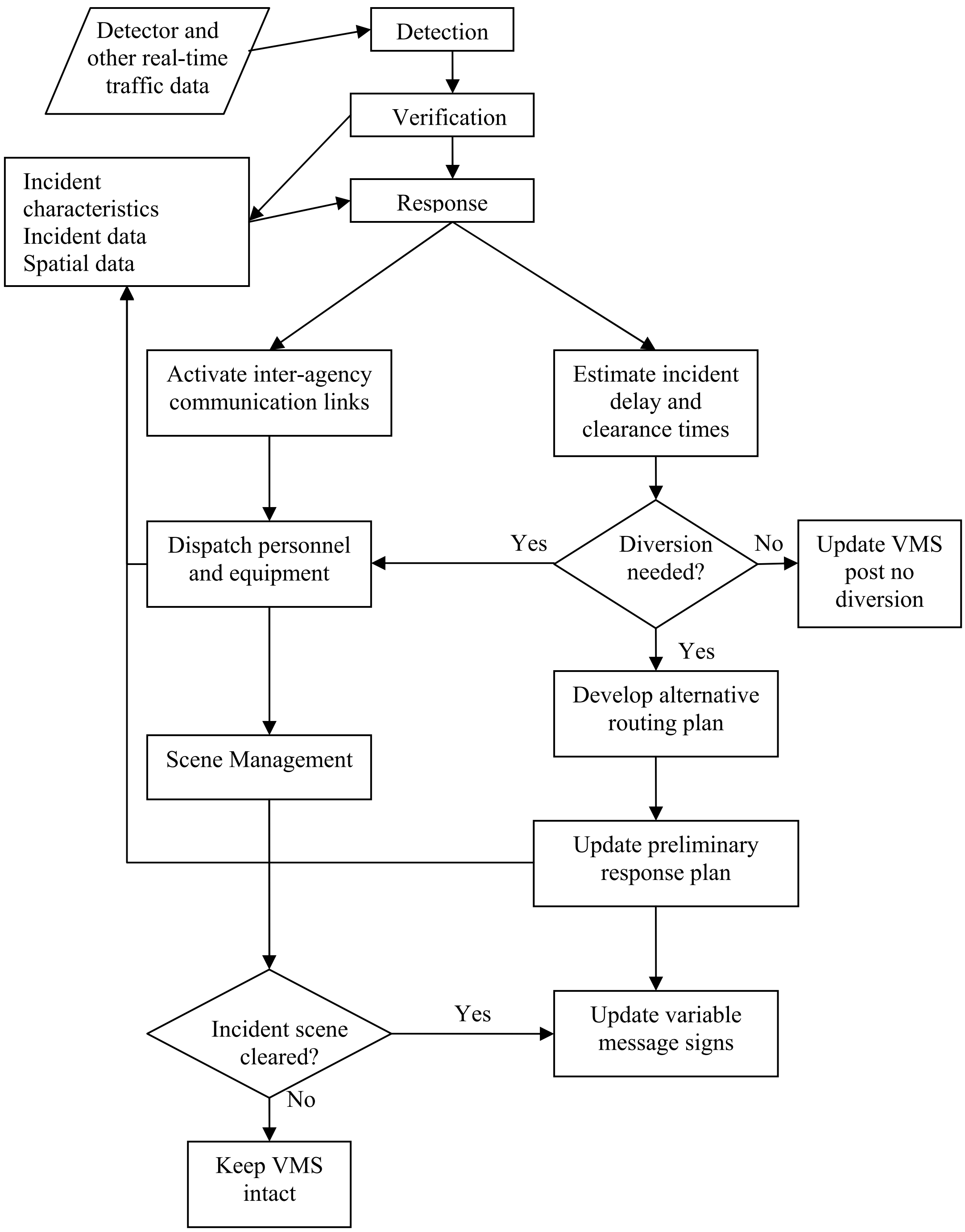

Figure 2.2 Incident Management Framework

(adapted from Ozbay and Kachroo, 1999)

i) Incident Detection/Verification

This phase is the start point of incident management activities. To generate a response strategy, first the incident should be detected. Detection can be automatized by using relevant traffic data processed by computer-based algorithms. Such algorithms mostly use detector data from freeways comparing traffic conditions between upstream and downstream flows to decide about a potential incident at a given location. Alternatively, detection can be made by other drivers passing through or by police patrols. Reports made by other drivers, mostly via cell phones, are not always reliable, as certain specific information on an incident is necessary for generating quick and proper response. On the other hand, whenever available, closed circuit cameras might be very useful for verification of incident information, which provides exact location, severity, type, existing traffic conditions.

One major aspect in this phase is the congestion effecting and effected by the detection. Most major incidents are detected within 5-15 minutes; however, minor incidents may go unreported for 30 minutes or more (Cambridge Systematics, 1990). On the other hand, early detection of an incident is important for preventing congestion, since early detection allows early response and recovery actions. Otherwise, significant traffic queues build up due to lane blockage and bottlenecking in case of incidents, especially during peak hours.

ii) Incident Response

In *Traffic Incident Management Handbook* (2000), incident response is defined as "dispatching the appropriate personnel and equipment, and activating the appropriate communication links and motorist information media as soon as there is reasonable certainty that an incident is present". Since the most important objective is safety, whenever needed, emergency response teams and equipment should be dispatched to an incident scene as soon as incident verified. This may require interagency communication between police, fire department, rescue units, and others.

In current incident management practice, the process of calling in different agencies is carried out by a dispatcher at traffic operations center (Ozbay and Kachroo, 1999). Meanwhile, incident-related information can be disseminated by means of commercial radio broadcasts, variable message signs, route guidance systems, etc. Moreover, the decision should be made on whether any traffic flow would be diverted, based on estimated incident delay, number of lanes blocked, and type and severity of the incident. During off-peak hours and minor incidents, demand may not exceed the capacity and the impact would be less. In such cases, although the flow is disrupted, it may not be necessary to divert if the remaining capacity is enough for traffic operations to continue. In the case of major incidents, diverting traffic flow can be important for network efficiency and public safety, as well as to protect the incident scene and provide for rapid and safe clearance (Sawaya et al., 2005). If the flow is to be diverted, it is important to choose alternative routes with enough capacity in order not to create excessive congestion on the alternative routes.

iii) Incident Clearance

Incident clearance involves timely handling of incident scene. This operation may include tow truck operations, the removal of wreckage, and the cleanup of material spills and debris. In case of some special incidents, like hazardous material (HAZMAT) spills, incident clearance takes more than usual cases as HAZMAT teams are required for response.

iv) Incident Recovery

Recovery consists of three tasks: a) restoring traffic flow at the site of the incident; b) preventing more traffic from flowing into the area and c) preventing congestion from spilling across the traffic network (PB Farradyne, 2000). Diverting upstream traffic to an alternative route(s) in the response step can decrease recovery period. However, capacity of an alternative route may not be sufficient; or there may not be an alternative route at all. At this point, other steps become more vital, as decreasing recovery period totally depends on duration of other steps.

2.2 Technologies Used in Incident Detection

Incident detection requires collection and processing of traffic data. Type of technologies used in data collection affects the reliability of the data and, consequently the reliability of incident detection. In this section, data collection technologies are classified based on the source of information as sensor-based, probe-based and mobile reports. Capabilities and characteristics of these are discussed in detail below.

2.2.1 Sensor-based Technologies

These technologies are generally built as a part of infrastructure system. They might be embedded into pavement, or installed near roadside. Sensor-based technologies provide fixed point or short section traffic information from the vehicles passing over them.

Loop Detectors

The oldest and most widely used sensor technology is the inductive loop detector. This sensor is composed of two main parts: a controller cabinet and an inductive loop which is embedded beneath the pavement (Petty, 1997). When a vehicle passes over the loop, the electrical properties of loop changes (PB Farradyne, 2000) and then this change is recorded by controller. This record can be used to calculate volume and occupancy. Occupancy, related to density, can be defined as the percent of time that a detector is indicating a vehicle presence over a total time period, and it can change depending on vehicle spacing (FHWA, 1990). Although they are in use for decades, they suffer from poor reliability due to continuous weathering and their maintenance might lead to serious disruption of traffic flow especially at congested roadways (Petty, 1997).

Magnetometers

This technology was initially developed as an alternative to loop detectors for special locations where steel adversely affects loop detector performance such as bridges (PB Farradyne, 2000). Similar to loop detectors, they detect presence of a vehicle when the earth's magnetic field around them is disturbed. Magnetometers are easier to install and more maintainable than loop detectors (Parkany & Xie, 2005). However, their main disadvantage is that they cannot measure occupancy.

Microwave Radar

Microwave radar detectors mainly have been used in law enforcement and traffic management to monitor vehicle speeds (FHWA, 1997). These sensors transmit microwave energy onto a detection area and vehicle presence and speed are detected by frequency changes in the return signal (FHWA, 1997 & PB Farradyne, 2000). Unlike aforementioned sensors which require dismantling the pavement, microwave radar is a non-intrusive detector, which can be mounted on a structure above the roadway surface. They are relatively smaller, and easier to install than loop detectors and magnetometers and they can detect traffic flow on multiple lanes. However, they can interfere with other microwave devices in their vicinity (Parkany & Xie, 2005).

Infrared Sensors

Infrared sensors are also non-intrusive detectors. There are two types: active and passive sensors. Active infrared sensors direct a beam of energy toward a background and a portion of that beam is directed back to its source, which detects vehicles according to changes in returning signal. On the contrary, passive infrared sensors do not transmit energy but measures amount of energy emitted by objects to sense vehicles in their field of view. Active infrared sensors can measure presence, speed, volume, and occupancy and vehicle classification. Passive infrared sensors measure the same traffic parameters except for speed. Although they may give very accurate information, infrared sensors are very sensitive to environmental conditions such as vibrations, fog, rain, and dust (PB Farradyne, 2000).

Ultrasonic Sensors

Ultrasonic sensors transmit electronic sound wave signals and a receiving unit detects vehicles. Similar to microwave radar, they detect presence of a vehicle on the basis of shifts in the return signal (FHWA, 1990). These sensors can measure speed, presence and classification of vehicles. Ultrasonic sensors are reliable, durable and require little maintenance (Parkany & Xie, 2005). However, their performance can be affected by air turbulence and environmental conditions.

Acoustic Sensors

These passive sensors utilize microphones along with signal processing technology to associate audible sounds with vehicles for detection. These sensors can measure presence, speed, volume and occupancy. They work well under all lighting conditions and in wide temperature and humidity ranges. Inference between the noises of multiple vehicles is the main drawback of this technology (FHWA, 1997).

Video Image Processing

Video image processing (VIP) systems sense presence of vehicles by monitoring specific zones in the video image of a traffic flow to determine changes between successive frames. VIP systems include one or more video cameras, a microprocessor system to digitize and to process the video images and software to interpret this data and to detect vehicles in traffic flow. The life cycle cost of VIP system is lower than loop detectors for most cases. Moreover, their installation and maintenance is easy and also their location is flexible. However, their performance can be affected by shadows from vehicles in adjacent lanes and light reflections from other objects. Also, the vehicles hidden by another vehicle cannot be detected by these systems.

2.2.2 Probe-based Technologies

These technologies employ devices such as GPS or electronic toll collection tags that have capability to locate position of probe vehicles carrying them and to transmit this information to roadside readers or a traffic management center. Their most important feature is that they can easily detect spatial variations in the traffic which cannot be captured by fixed point sensors.

Automatic Vehicle Location

Automatic Vehicle Location (AVL) systems are used for tracking location of a vehicle at a particular time. These systems include in-vehicle transponders which communicate with a reference point such as cellular phone towers, signposts or satellites to locate position of a vehicle. Travel time information can be computed at an information center by comparing the vehicles position at certain intervals and this information might be used as input for incident detection. The main advantage of these systems is that they can be easily expanded by increasing the number of equipped vehicles (Wang and Sisiopiku, 1998). AVL systems use following technologies for locating vehicles:

- **Dead reckoning and map-matching:** These systems make use of the internal compass and odometer, indicating distance traveled, of a vehicle and calculate its position by measuring its distance from a known starting point. Due to low accuracy compared to other AVL technologies, dead reckoning and map-matching are not widely used.
- **Signpost:** This is a relatively accurate and inexpensive AVL system used by vehicles which have a fixed route such as transit vehicles. Antennas which are placed on places on the vehicle's route record the time at which vehicle passes by.
- **Ground-based Radio Navigation:** These systems are based on series of a series of receiving antennas within a metropolitan area installed by an AVL vendor. AVL equipped vehicles broadcast a radio frequency signal to nearby receiving antennas. By measuring the time it takes for the signal to travel to the antenna, the distance between vehicle and antenna can be determined.
- **Global Positioning System:** The most commonly used AVL system is the global positioning system (GPS), operated by U.S. Department of Defense. GPS uses a network of 24 satellites to locate objects on earth. The position of an object is determined measuring how long a radio signal takes to reach the object from multiple satellites.

Automatic Vehicle Identification

Automatic Vehicle Identification (AVI) systems use an in-vehicle unit such as a tag or transponder and roadside transmitters to uniquely identify vehicles when they pass through a detection zone. This technology is used for electronic toll collection, electronic congestion pricing and fleet control (Parkany and Xie, 2005). Electronic toll collection systems are used in incident detection by Mouskos et al. (1999) and Hellinga and Knapp (2000) suggesting that AVI based incident detection can provide comparable performance to loop detector based incident detection methods.

2.2.3 Mobile Reports

This category includes the manual incident reports from service patrols and road users.

Highway Service Patrols

Highway service patrols are trained drivers who cover a particular area of highway, report a problem, monitor traffic operations (FHWA, 1997). Service patrols are used to monitor and assist vehicles and generally operate on freeways in the USA. The most important advantage of service patrols is that an incident is detected and verified at the same time. Moreover, service patrols can respond to incidents and this greatly minimizes verification, response and clearance time. However, due to the high cost of service patrols, this service cannot be expanded easily. Therefore, their coverage is generally very limited and the limitations on the number of service patrols result in long incident response time (Parkany & Xie, 2005).

Cellular Phone Reports

Since coverage and number of cellular phones used along roads increase everyday, cellular phone reports offer an alternative method for incident detection. There are several studies that evaluated the effectiveness of using cellular phones for incident detection (Skabardonis et al., 1998; Tavana et al., 1999; Mussa and Upchurch, 1999), showing that detection rate is closely related to traffic flow conditions, penetration of cellular phone ownership among drivers, willingness to report an incident and number of erroneous calls.

2.3 Incident Detection Algorithms

Incident detection algorithms can be divided into two categories: *i)* algorithms for freeway, which generally employ sensor-based technologies, and *ii)* arterials, which generally use probe-based technologies. Freeway incident detection algorithm studies starts as early as 1960s in the USA and many of incident detection algorithms are developed for freeways until 1980s. After that time, incident detection on arterials is started to be studied, since most of freeway algorithms cannot be readily transferred to arterial roadways. In this section these two categories are reviewed and the traditional technique for algorithm performance evaluation is discussed.

2.3.1 Freeway Incident Detection Algorithms

These algorithms generally utilize traffic measurements at one location to predict incidents. There is an extensive literature on freeway incident detection algorithms, of which some major studies are reviewed in this section.

Comparative Algorithms

Comparative incident detection algorithms compare the value of measured traffic characteristics at upstream and downstream detectors, such as occupancy or speed, to a pre-defined threshold value. These algorithms check occupancies at upstream and downstream detectors. The basic idea is that an incident causes significant increase in upstream occupancy while downstream occupancy decreases at the same time. The current values are compared with predefined threshold values using decision trees. An incident is declared by the algorithm, if threshold values are exceeded.

California algorithms are the most widely known comparative algorithms. In these algorithms, occupancy differences between two neighboring fixed detectors are analyzed in a decision tree structure. First, the occupancy difference between upstream and downstream detectors is compared. Then, the relative difference between upstream and downstream detector, which is the ratio between them, is compared with the upstream occupancy and the downstream occupancy. There are ten versions of California algorithm, among which some are reported to produce better results for detection with less time to detect (FHWA, 1990).

Statistical Algorithms

These algorithms utilize statistical techniques to investigate whether observed loop detector data is significantly different from predicted traffic characteristics. The two important statistical algorithms are the standard normal deviate (SND) algorithm (Dudek et al., 1974) and Bayesian algorithm (Levin and Krause, 1978).

The working principle of SND algorithm is that a sudden change in the traffic state suggests the occurrence of an incident. The SND is defined as the number of deviations of a value traffic control variable from its mean. The algorithm compares one minute average occupancy measurements with archival values of mean and the SND. If the SND exceeds a critical value, occurrence of an incident is reported.

The Bayesian algorithm uses Bayesian statistical techniques to determine the likelihood of an incident signal caused by a real incident. Like California algorithms, relative difference of the occupancies of upstream and downstream detectors used as traffic characteristic, however, conditional probability using Bayesian statistics is calculated in this case.

Time Series Algorithms

These algorithms assume that traffic flow follows a predictable temporal pattern and compare short-term predictions with the current traffic state. Two well-known time series algorithms are AutoRegressive Integrated Moving Average (ARIMA) model (Ahmet and Cook, 1980) and High Occupancy (HIOCC) algorithm (reviewed in Parkany and Xie, 2005).

In the ARIMA model, it is assumed that differences between a current traffic characteristic such as volume or occupancy and the characteristic in the last period can be predicted by averaging errors between the predicted and observed traffic characteristic in the last three time periods. The errors are expected to follow a normal pattern, whereas an abnormal error suggests occurrence of an incident. The confidence intervals are attached to short-term traffic forecasts and incident is detected if the observed values are outside the confidence interval.

Similarly HIOCC algorithm monitors the changes on detector data (occupancy), however, using a one-second time interval. The algorithm assumes that a vehicle moves slowly over a detector only if it is in a queue caused by an incident. However, traffic queues might be also related to shock waves or bottlenecks, this algorithm fail to identify the cause of a queue (Parkany and Xie, 2005).

Smoothing/Filtering Algorithms

These techniques try to eliminate short-term noises and irregularities which might cause false alarms from traffic data. After extracting short-term noises, such as compression waves, it becomes easier to detect incidents. The well-known algorithms in this category are double exponential smoothing algorithm, low-pass filter algorithm (Stephanedes and Chassiakos, 1993) and the discrete wavelet transform and linear discriminant analysis algorithm (Samant and Adeli, 2000).

The double exponential smoothing algorithm, proposed by Cook and Cleveland (1974), involves forecasting a traffic characteristic and comparing it to real observation. Incidents are detected using a tracking signal, which is the sum of errors between previous observations and forecasted values. The basic idea is that the tracking signal would be around zero under incident-free conditions (Petty, 1997).

The low pass algorithms, which are also known as Minnesota algorithms, discard sharp and high frequency characteristic fluctuations from the data and tolerate low frequency fluctuations which are related to incidents to pass through a filter. The algorithm basically compares the occupancy levels of two neighboring station according to 3-minute and 5-minute moving average occupancies and smoothing techniques reapplied to occupancies to better distinguish between incident and bottlenecks.

Discrete wavelet transform and linear discriminant analysis algorithm extracts incident-related conditions from the data to minimize false alarms. First, discrete wavelet transform, an effective tool used in signal and image processing, is applied to raw data and the finest resolution coefficients which represents random fluctuations in the traffic are discarded. Then, linear discriminant analysis is used on the filtered signal for further feature extraction and reducing the dimensionality of input data for incident detection.

Traffic Modeling/Theoretical Algorithms

Traffic modeling algorithms utilize the basic concepts of traffic flow characteristics to predict traffic behavior under incident conditions. The dynamic model (Willsky et al., 1980) and the McMaster algorithm (Forbes and Hall, 1990) are the main representatives of this category.

The dynamic model is based on the use of macroscopic dynamic model to predict traffic characteristics over sections of a freeway. Two methods are used in this model to describe flow-density relationships: the multiple model method for system identification and the generalized likelihood ratio method for detecting abrupt changes (incidents) in dynamic traffic system.

The McMaster algorithm, which employs the catastrophe theory to model abrupt changes in the flow, requires two dimensional analysis of traffic data. Catastrophe theory takes its name from the sudden discrete changes that occur in one variable of interest while other related variables exhibit smooth and continuous changes (Black and Sreedevi, 2001). This algorithm use the assumption that speed changes sharply when traffic changes between a congested state and free flow state while volume and occupancy changes smoothly to detect incidents which result in congestion on the roadway.

Artificial Intelligence Algorithms

Artificial intelligence techniques include a set of procedures that apply inexact or black box reasoning and uncertainty in decision making and data-analysis processes (Parkany & Xie, 2005). Most widely used artificial intelligence technique in incident detection is the artificial neural networks (ANNs). There are many researchers developed incident detection algorithms using ANNs (Ritchie and Cheu, 1993; Dia and Rose, 1997; Abdulhai and Ritchie, 1999; Adeli and Samant, 2000). ANNs contain many simple processing elements and neurons that are densely interconnected. The idea is to train the ANN by feeding it with input and corresponding output data like a human brain. Training process enable ANN to develop relation rules among its neurons. In the case incident detection, input data is traffic characteristics such as volume, speed or occupancy at upstream and downstream detectors and output data is decision about the state of traffic derived from the input data (Ozbay & Kachroo, 1999)

2.3.2 Arterial Incident Detection Algorithms

Unlike freeways, urban arterials feature a variety of traffic signals, turning movements and easy lane changing of vehicles; hence, they create a more complex and challenging conditions for incident detection (Khan and Ritchie, 1998). So far, there are a few studies in this area.

Han and May (1989) developed a comparative algorithm to detect incidents on arterial roadways using volume and occupancy data from loop detectors. The detector data is smoothed and passed through a module to identify problems from detector malfunctions. This algorithm has capability to detect type of operational problems (lane blockage, approach blockage, arterial blockage) from operating conditions of detectors in adjacent lanes.

The most well known study on arterial incident detection is the ADVANCE project (Bhandari et al., 1995). In this study, a data fusion algorithm used to process the data from three different data sources (loop detector, probe vehicle, anecdotal source) for incident detection, in which three sources are integrated and overall likelihood of occurrence of an incident is determined. The system also estimates the duration and the impact of incidents on link travel times as a function of the type of incident.

Khan and Ritchie (1998) used artificial neural networks in a modular architecture to detect different types of operational problems such as lane-blocking incidents, special events and detector malfunctions on signalized arterials. This algorithm is developed based on loop detector data collected cyclic basis. The modularity concept enables to decompose the task of detecting type of problems and produce an overall system of models which individually outperforms single neural network models.

A fuzzy logic-based incident detection algorithm for signalized diamond interchanges is developed by Lee et al. (1998). This algorithm is capable of detecting lane-blocking incidents as a part of a real-time traffic-adaptive control system. Fuzzy-logic approach is chosen to develop an effective solution to these systems which must operate in real-time, require approximate reasoning and exhibit uncertainty.

Most recently, Lee and Hwang (2001) utilize the multinomial logit model in arterial incident detection. They assume incident detection process as a discrete choice problem, where incident and incident-free conditions are two choices. In this algorithm, an incident index, representing the probability of occurrence of an incident, expressed as the utility of a multinomial logit model (Parkany and Xie, 2005). Volume and occupancy are used as traffic variables and the error term assumed to follow Gumbel distribution to estimate the probability of an incident.

Although the above algorithms produce good results, they are tested with specific detector configurations and in a particular network. The sensors may not always be installed to all arterials and the characteristics of traffic networks might be very different from others.

2.3.3 Performance Evaluation and Measures

There are three traditional measures used to evaluate the performance of incident detection algorithms: detection rate (DR), false alarm rate (FAR), and time to detect (TTD). DR can be defined as the ratio of the detected number of incidents to the actual number of incidents during a certain time period. FAR is number of incorrect detected incidents to the total number of algorithm applications. TTD is the average time between the occurrence of an incident and until the actual detection of it. Ideally, an effective incident detection algorithm is expected to minimize FAR and TTD at the same time to maximize DR.

These measures of performance cannot be treated as they are completely independent. There is tradeoff between shortening TTD and lowering false alarm rates. Another concern is that there is no standard in the evaluation methodology of incident detection algorithms. Therefore, it is not rational to compare the algorithm evaluation results (Ozbay and Kachroo, 1999). California Center for Innovative Transportation ITS Decision web page gives a summary of reported performance measures of different incident detection algorithms as can be seen in Table 2.1. It must be stated that there is no standard procedure for evaluation; therefore, actual performance of these algorithms can significantly vary from reported. Because, there are variety of factors may affect the performance of the algorithms in real life such as operating conditions, geometric conditions, environmental factors, etc. (Weil et al., 1998).

Table 2.1 Summary of reported performance measures of well-known algorithms (Black and Sreedevi, 2001)

Algorithm	DR (%)	FAR (%)	TTD (minutes)
California (Basic)	82	1,73	0,85
California #7	67	0,134	2,91
California #8	68	0,177	3,04
Standard Normal Deviate	92	1,3	1,1
Bayesian	100	0	3,9
Time Series ARIMA	100	1,5	0,4
Exponential Smoothing	92	1,87	0,7
Low-Pass Filter	80	0,3	4
Modified McMaster	68	0,0018	2,2
Multi-layer Feed Forward Neural Networks	89	0,01	0,96
Probabilistic Neural Networks	89	0,012	0,9
Fuzzy Set	Good	Good	Up to 3 minutes quicker than conventional algorithms
Logit- Based	96.3	5,3	Good

2.4 GIS/GPS Use in Incident Detection

GIS are computer-based systems which enable storage, manipulation, display and analysis of geospatial information. The integration of multiple functionalities within a seamless environment eliminates necessity to conquer all of the functions individually by users (Thill, 2000). Different from other database management tools, GIS can add geographic referencing to data and then visually display it with spatial distribution over a region. User-friendly environment and geospatial capabilities makes GIS a popular tool widely used by different disciplines such as geography, transportation, and city planning, archeology, etc.

GIS can create a suitable environment for conducting spatial analyses necessary for transportation management systems especially as a part of intelligent transportation systems (ITS). ITS require collecting and integrating large amounts of data and this data can be easily handled, accessed and displayed by a GIS if it is geographically referenced. GIS allow users to integrate transportation data such as accidents, pavement conditions and speed and relates those data to a point or a link in a geospatial referencing system (Ozbay and Kachroo, 1999).

GPS is a satellite-based navigation system which provides position, velocity and time information anywhere on the earth. The baseline constellation comprises 24 satellites uniformly distributed in six orbital planes approximately 20200 km above the earth. This configuration ensures that at least four satellites are visible at any time and anywhere on the earth. The current constellation has 27 satellites and guarantees at least seven satellites are visible at any location (Ochieng and Sauer, 2002). Although in the past, the system provided two different services, Standard Positioning Service for civilians and Precise Positioning Service for military users, today, civilians can access GPS signals free with an increased accuracy from 100 meters to 20 meters for 95 percent of time. Taylor et al. (2001) reported that this error is often much lower than this.

GPS receivers provide a fast and easy method for obtaining position information in real-time and this information can be easily employed within a GIS, since the basic GPS position data is compatible with common GIS location specifications (Taylor et al., 2000). It should be noted that position data can be referenced to roadway with the help of a GIS, whenever a digital road map is available.

2.4.1 GIS/GPS for Transportation

Due to ability to give spatio-temporal information in real-time, GPS is a good alternative for traffic congestion and management studies. Moreover, with current advances in information, computing and communication technologies, GPS-based traffic data collection is becoming a cheaper way when compared with traditional methods. Using the position and time information from GPS receivers, it is easy to obtain the travel time and speed data, and from this data additional congestion measures such as congestion index, acceleration noise, and mean velocity gradient can be derived (D'Este et al., 1999).

In transportation studies GPS receivers are used in probe vehicles to collect travel time and speed data. The probe vehicles can be either "active", equipped specifically for data collection or "passive", already in the traffic for other purposes. Generally, active probe vehicles are employed for data collection since a specific corridor or region chosen in traffic studies. Many researchers used GPS equipped probe vehicles for travel time studies (Quiroga, 1997; Quiroga and Bullock, 1998) and measuring traffic system performance (D'Este et al., 1999). In each of these studies, single active probe vehicle is employed to collect position and speed data assuming a probe vehicle represents average characteristics of traffic flow. Time dependent traffic characteristics, such as average speed, running time and acceleration noise are calculated by repeatedly running probe vehicle on a chosen route.

Nonetheless, GPS-based systems have some weaknesses as well. For example, satellite visibility is a must in order to use GPS devices. Obstructions such as high-rise buildings or clouds can easily affect satellite visibility and so the precision of GPS. New methods such as dead reckoning method, differential GPS method and map-matching method help to improve accuracy and reliability of GPS data and thus make GPS data more consistent (Guo et al., 2000).

2.4.2 GIS/GPS Use in Incident Detection

There is very limited research on the use of GPS equipped vehicles in incident detection. The first example of GPS-equipped probe vehicle use in incident detection is the ADVANCE (Advanced Driver and Vehicle Advisory Navigation Concept) project in Chicago (Bhandari et al., 1995). In this project, Bhandari and his colleagues used GPS equipped probe vehicles to collect travel time information and fused this information with loop detector data and anecdotal information. The data fusion proved to be more effective for incident detection than each source individually.

Li (2004) employed GPS equipped probe vehicles to collect traffic data and for incident detection. She used real-time GPS data for estimating travel time for incident detection and found that ral-time link travel times and differences in travel times between two adjacent time intervals were distributed bivariate-normally in incident free conditions. The outliers of the distribution were considered as incident. She developed a bivariate model for incident detection and reported satisfactory detection and false alarm rates. Moreover, she investigated the minimum number of probe vehicles for reliable travel time estimation. The results showed that in different traffic conditions, the sample size of probe vehicles is different and if the speed profile of probe vehicles is analyzed for travel time estimation, fewer probe vehicles than normally required are needed. Then, a fuzzy model was developed to analysis speed profiles, and travel time could be estimated using a single probe vehicle. Satisfactory estimates were obtained in both non-incident and incident conditions.

Another recent study in incident detection with GPS equipped vehicles is conducted by Basnayake (2004). In this study an automated incident detection system using transit vehicle equipped with GPS as a passive probe vehicle fleet was developed. The two important problems were addressed, namely the need for a GPS positioning technique that provides better performance in urban environments and an accurate probe-based incident detection algorithm. In the study High Sensitivity GPS, which offers better performance by providing higher level of system availability from conventional GPS, is suggested for positioning of transit probes in the city. Then, the bias introduced by using transit vehicles as passive probe vehicles minimized by proposed transit travel time modification algorithms which estimated total dwelling time at stops. The results of study showed that the algorithm was capable of detecting incidents less than 5 minutes and with a comparable detection rate to well-known incident detection algorithms but false alarm rate was very high.

Besides the potential in incident detection, GPS has some drawbacks: while spatial variation of traffic flow in the network can be monitored by GPS, downstream and upstream traffic conditions cannot be determined concurrently by a single probe vehicle and also GPS cannot give occupancy or volume data. These two problems make it difficult to apply and to adapt well-established incident detection algorithms which generally detect incidents using volume and occupancy data from two adjacent loop detectors. Therefore, there is a need for a GPS-based incident detection algorithm, which is capable of predicting current traffic state by using historical traffic data such as link speeds.

CHAPTER 3

METHODOLOGY

Incident management starts with incident detection, which can be performed in various ways including loop detectors, highway service patrols, etc. However, these methods and technologies are not always applicable everywhere either due to high installation costs or traffic conditions such as complex arterial flow patterns. In this chapter, the challenges of incident detection will be discussed first. Later, a method based on traffic monitoring via GPS equipped probe vehicles is proposed. As such a method requires constant comparisons with historical traffic conditions, an archival database of time-dependent traffic characteristics is needed, which is discussed in further detail.

3.1 Challenges of Incident Detection

There are several challenges in incident detection. Due their complex behavior of traffic flow on arterials, incident detection on these roadways is not as easy as controlled freeways. Moreover, due to the budget constraints, developing countries cannot invest on ITS, which are essential in incident detection. Although GPS might offer a cost-effective alternative in incident detection, it has some limitations that need additional consideration. Even above challenges are overcome, the cause of a queue (whether bottleneck related or incident related) is needed to be determined. In this section, these major issues of an incident detection algorithm are discussed.

3.1.1 Freeway versus Arterial Incidents

Much of the previous work on incident detection has focused on limited access highways. Since traffic flow generally is not interrupted much by geometric and operational constraints, it is expected that traffic on a freeway moves with a uniform speed. An unexpected event can alter this situation and irregularities occur in speed, occupancy and volume on a section of a freeway. Using the sensors densely installed on freeways along with an incident detection algorithm, incident can be easily detected

Although, types of incidents on arterials are not different than on freeways, there are factors that make it harder to develop incident detection methods for the former. Han and May (1989) identify the following differences between highways and arterial those prevent application of existing incident detection algorithms developed for freeways to arterial roadway:

- limited access points and reduced median and marginal friction on freeways
- fewer geometric constraints and a more homogenous vehicle mix on freeways than surface streets.
- more uniform traffic speed and flow on freeways than on arterials.
- more complex problem of managing incidents on arterials than on freeways.

Nonetheless, non-recurrent congestion due to incidents on arterials should be handled. Because, during the peak travel hours, traffic demand on the arterial roads in urban networks are used at or above capacity, and even a small disturbance can generate significant delay (Raub and Schofer, 1998). Moreover, delay brings associated costs of increased fuel consumption and pollution.

3.1.2 Case of Developing Countries

In developed countries with mostly complete transportation infrastructures and increasing use of ITS, such as in the USA, incident management can be handled efficiently on freeways and automated for certain tasks. For example, in California, closed circuit TV cameras, loop detectors and changable message sign units are used for assisting to incident management efforts. (Hall & Mehta, 1998)

However, these technologies are expensive to implement and to maintain. In addition to their high cost, there are other constraints for application of ITS. In Yokota (2004), these constraints are stated as follow: a) an underdeveloped road network, b) severe budged restrictions, c) explosive urbanization and growth, d) lack of human and physical resources for complicated maintenance and operation, e) high employment, coupled with less demand for automation. In addition to above problems, lack of archival traffic information on traffic network makes it difficult to employ ITS technologies even above problems are got over. This is because archival data is essential for calibration and proper operation of ITS tools. Thus, in order to able to apply ITS technologies in developing countries, a cheap and easy way should be found. Utilization of GPS, cellular phone networks and GIS might be a solution for developing countries to overcome the constraints above.

3.1.3 Incident Detection with GPS Technology

To develop incident detection tools using high technology with low cost options, probe vehicles might be equipped with GPS receivers. The collected GPS data can be automatically transferred to a traffic information center via cellular phone network, even in real-time. Using transit vehicle fleets might be a cost effective way of the data collection, since they are continuously moving in the network and mostly equipped with GPS devices for monitoring purposes already. The data can be related to roadway network in the information center using GIS and link speeds and travel times might be estimated and using special algorithms even incidents can be detected. There are some examples of usage of these systems in transportation in developing countries. 100 taxis equipped with GPS are used in a study of arterial speeds in Guangzhou, China, and the technique is found to be very powerful for estimating travel time (Zou et al., 2005).

One simple example, which can be related to incident detection, could be automatic crash notification (ACN) systems, which is introduced by automobile manufacturers to increase automobile attractiveness. In this system, when the airbags activate, an on-board cell phone automatically calls the emergency center and provides relevant authorities with the exact location of the crash by GPS, the name of the vehicle owner, and other registration information (Yokota, 2004). Bachman and Preziotti (2001) evaluated the ACN Field Operational Test conducted by National Highway Traffic Safety Administration and they reported potential benefits of an ACN system as reduced emergency center notification times, improved knowledge of the vehicle location, and estimates of crash severity and the probability of serious injury.

GPS equipped vehicles can fail to detect in two ways. First, an incident cannot be detected if it has little or no impact on the traffic, as the speed of GPS equipped vehicle is not affected by the incident. Secondly, incidents cannot be detected if no probe vehicle passes through the impacted zone of the incident while the fluctuations due to the incident last in the network. It is very difficult to detect incidents if it does not significantly affect traffic, or there are not enough probe vehicles covering the area of interest spatially and temporally. If the number of GPS equipped vehicles increase, their spatial distribution might improve and the probability of missing incidents in the space could be decreased.

3.1.4 Bottlenecks versus Incident Related Congestion

Another challenge that incident detection algorithms are faced with is that it might not always possible to predict the cause of slow traffic regime and queue formation on a section of a roadway. Actually, there might be two possible reasons: bottlenecks, activated at the same place at the same time due to recurrent congestion, and incidents, which are random events mostly decreasing capacity of roadways. A probe vehicle hitting a queue in the traffic would not know, if there is an incident in the downstream locations or simply daily congestion. Any method to separate chronic bottlenecks from incident related congestion should utilize historical information of traffic conditions at a location.

One critical issue on this subject is the time-dependent nature of bottlenecks. Due to time-dependent variability in the demand, bottlenecks can occur and cease in a time-dependent manner. While there may be regular congestion related queues during peak hours at a location, there may be incident-related ones at the same location during off-peak periods. Thus, existence and impact of bottlenecks have to be treated as time-dependent concepts, and consequently variables. After a time-dependent analysis of bottlenecks, a better distinction between them and incident related congestions might be made.

3.2 A Framework for Incident Detection Using GPS-Equipped Probe Vehicles

Using GPS technology in incident detection assumes that one or more probe vehicles equipped with GPS devices travel in the network. The required number of probe vehicle in the network is an open ended question. Ideally, if all vehicles in the network are probe vehicles equipped with GPS, we would not miss a single incident in the network (Parkany and Xie, 2005; Petty, 1997). This is very unlikely as even the most advanced computer systems currently cannot store and process such data. It is possible to have only one dedicated probe vehicle covering whole or a portion of the network, in which case it may take a long time to collect required traffic information. As an alternative, a fleet of vehicles equipped with GPS can give further information and even enables to determine the traffic conditions at different locations. It is very likely to have GPS data from vehicles that travel randomly in the network (such as, from taxi fleets or private cars) or along certain routes in the network (such as transit bus fleets).

When the number of probe vehicles on the same corridor increases, a better picture can be drawn due to better concurrent spatial information from the probe vehicles. The potential of multi-vehicle GPS traffic data collection producing a “temporary virtual loop detector couple” is a complex phenomenon which would depend on, the gap between vehicles, mean speed of the vehicles in the segment, and stimulus response functions of drivers, etc. Figure 3.1, depicts a schematic representation of multiple probe vehicle case, where some of their routes overlap along the same corridor. At certain points, where the headway between Probe 1 and Probe 2 is small enough, temporarily they can act as a couple for certain time periods and give simultaneous information about current state of traffic; this is very similar to loop detectors except the fact probe vehicles are moving, as well.

Unless Probe 1 and Probe 2 are dedicated vehicles to follow each other, they would have different routes with certain time/space headway on the same corridor, and the coupled behavior would cease after certain time/points, when the headway between the probe vehicles increases or one of them diverges from the shared route. In that case, they would act as two single probe vehicles. Therefore, even it is intended to use multiple probe vehicles on a corridor; first, an algorithm for a single probe vehicle data should be developed.

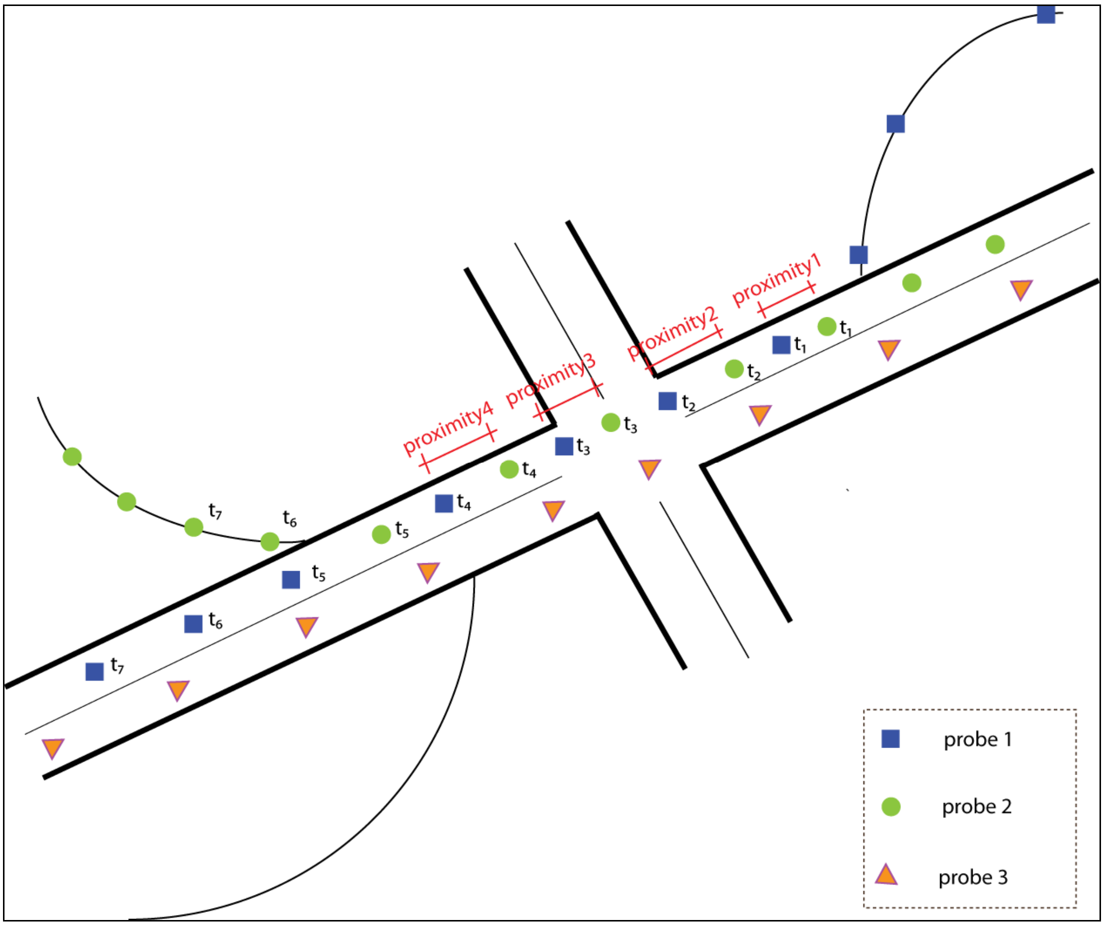

Figure 3.1 Coupling effect between two GPS-equipped probe vehicles

The GPS-based incident detection framework proposed in this study starts with the selection of a corridor to be monitored (see Figure 3.2). It is important to choose a corridor, which is continuously traveled by vehicles equipped by GPS devices already in order to minimize cost of monitoring and increase the probability of having a probe vehicle on the corridor. If any part of the corridor is not covered or traveled frequently enough by the available GPS equipped vehicles, dedicated probe vehicles are needed.

Then the selected corridor is divided into links (or even smaller segments) considering geographic and operational features of the network. This step is necessary to control and to limit the level of the detail lost by averaging the traffic measures over long links. This step is followed by corridor characterization using archival traffic data, which is necessary for a probe vehicle based methodology. It should be noted that, due to time-dependent nature of the traffic conditions as well bottlenecks and incident related queues, the traffic data collection and the required database has to be designed in a “time-dependent” fashion, as well. Time-dependent corridor characteristics database (TCCD) should include traffic measures, at minimum, travel times, link speeds, slow regime parameter, link, etc., which can be generalized to store more parameters regarding traffic safety measures, incident locations for further studies.

Retrospective bottleneck analysis enables the determination of chronic bottleneck locations. This step is crucial in incident detection, since the chronic bottlenecks might be falsely detected as incidents. Then, real-time data from the probe vehicles utilized to detect incidents. There might be two options: single source incident detection algorithm where multiple probe vehicles can be treated separately as single probe vehicles or multiple source incident detection algorithm where coupling effect between them is employed. As mentioned earlier, the coupling effect is a very complex and also a temporary phenomenon. Therefore, in this study, only single source incident detection algorithm will be developed. The incident detection algorithm will detect incidents using an acceptable lower limit for link speed, a statistical and time-dependent value derived for each link in time-dependent corridor characteristics database. Finally, an incident is reported if real-time link speed is considerable smaller than the acceptable lower limit in a link at a time when bottleneck is not expected.

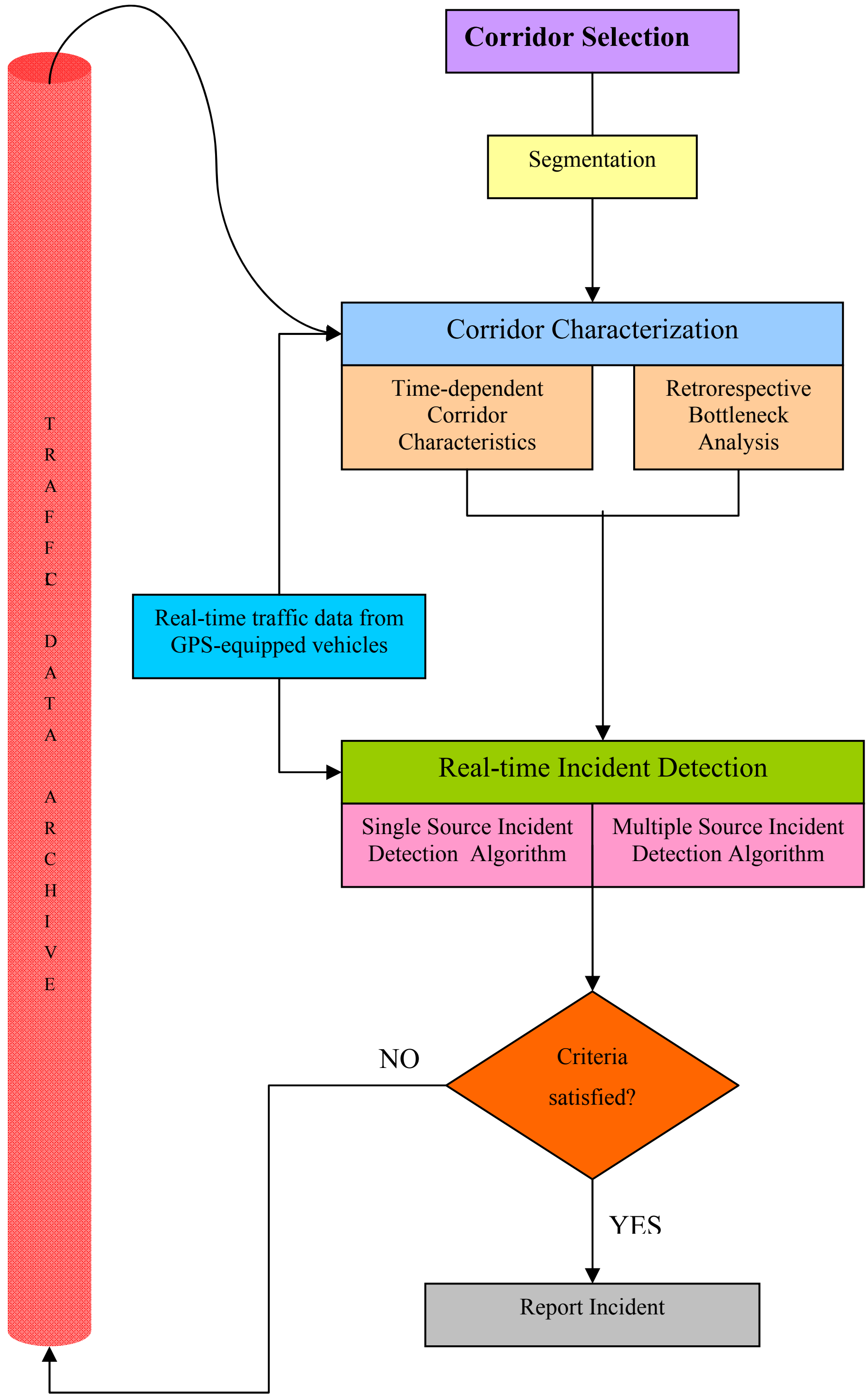

Figure 3.2 Proposed framework for incident detection with GPS technology

3.2.1 Corridor Selection

There might be links on a corridor covered by multiple vehicles, which is preferred from the point of statistical analysis. Also, the corridors studied are most probably main corridors on a network and can be monitored without further investment for dedicated probe vehicles, and possibility of congestion on those corridors is high.

One consideration in the selection of a corridor might be the level of service provided on the corridor. If the corridor includes a main arterial, most of the links are expected to be congested resulting in a low level of service. In such a corridor, an incident will definitely lead to long queues and even stoppage of service since congestion. Also the low level of service is associated with high traffic flow value, which is expected to be associated with high incident rate to some extend.

3.2.2 Corridor Representation and Segmentation

Once the corridor is selected, a proper traffic network preparation for it is necessary. While we can work with many representative graphs for certain traffic problems, a study based on GPS technology requires a geographically correct digital traffic network which can be obtained from registered satellite imagery or GPS track data collected on the study corridor. Because, the collected GPS data is going to be mapped on the network to derive link characteristics. Also, it is very crucial to include all physical and operational changes on this map which might be a possible reason for traffic queues. Moreover, some links on a corridor might be divided to smaller segments due to their length or characteristic reasons such as “black spots”.

Segmentation on a corridor would be based on geographic features such as, interchanges, ramps, intersections, roundabouts, etc as well as operational features such as traffic signals, one-way regime start and end points, etc. Besides such measures, the length of a link itself is an important factor affecting the success of incident detection. While it is practical and meaningful to exclude minor conflict points (such as, parking lot entrance/exit points to the corridor, or stop/yield signs) in the traffic flow, the level of aggregation should not exceed certain levels. According to Quiroga & Bullock (1998), traditional approach based on long segments connecting contiguous physical discontinuities (or links) is not sufficient to characterize localized effects of congestion properly with GPS. Especially, on highways, where entrance and exit points are very limited, long traffic queues can be stay undetected for an unacceptable time unless small segments are chosen as links.

Black spots might also be used as nodes to divide links into small segments. Since the probability of occurrence of an accident on these locations is higher than the other links, the probability of incident and lane blockage is also high. Hence, according to characteristics of a corridor, a more discrete traffic network might be generated if it is necessary.

3.2.3 Archival Data Warehousing

Without the archival data, probe vehicle information is only a route-based travel data. To identify current traffic state on a link –or a segment of a link- historical traffic conditions and patterns of the link –or the segment- has to be determined as a base case. While it is possible to get archival traffic data via other traffic measurement techniques, such as loop detectors, or infrared sensors, it is also possible and probably cheaper to generate it from track logs of GPS-equipped vehicles. There might be previous GPS data from fleets such as transit buses, taxis, cargo trucks, etc., where the vehicles are continuously tracked; if not, as a starting step, probe vehicles can be used to collect data to create a data warehouse for an acceptable time period. Data by GPS receivers cannot provide meaningful information that can be used directly to compute link speeds. The track data should be mapped onto a digital road map, for which a separate algorithm is needed.

Time-dependent Corridor Characteristics Database (TCCD)

As mentioned above, most of the data would be time-dependent, which requires a "time-dependent" data warehouse design. Time-dependent link speeds and their variation due to link characteristics are the main parameters for this study. In this methodology, an algorithm developed by Unsal (2006) is used to calculate time-dependent link travel times, used in the calculations of following parameters:

- **Link Speeds:** Instantaneous speed of a vehicle might fluctuate over the link length as well as over time as in "time of the day". While the latter captures the randomness of traffic conditions over time, the former represents a relatively small and negligible information in terms of traffic conditions, if link definitions are made appropriately. Therefore, for a chosen link of a selected length, the speed of a probe vehicle can be assumed constant with an average value equal to "length over link travel time (difference of link entrance and exit times as shown in Figure 3.3)". For the sake of simplicity, this "average link speed" value assumed constant along the link *i* itself, for a selected time window τ, will be called "link speed" from this point forward.
- **Slow Traffic Regime Parameter:** This parameter (γ_i^τ) is derived for retrospective bottleneck analysis, which is a control function taking Boolean values. $\gamma_i^\tau = 1$ indicates slow traffic regime on link *i* at time τ, if link speed is less than a limit value λ ($v_i^\tau \leq \lambda$) and other cases by 0.
- **Link Speed Variation Parameter:** This parameter (δ_i^τ) is derived for bottleneck detection algorithm and it defines the change in the link speeds between two consecutive links at time τ. It is calculated for every travel data as "0", "1" and "-1" corresponding to cases of constant speed, jump in speed, drop in speed between two consecutive links. Later, the average of the individual route-based speed variations is calculated to get the characteristic link speed variation values, δ_i^τ.

For every travel of the probe vehicle over the same link at a selected time window, the link speed may change due to uncertainties in the demand, traffic operation. To represent the characteristics of traffic on the selected link the statistical average of the link speeds can be selected, calculated from multiple trips of probe vehicles. In these calculations, link travel time is defined as the time required for a vehicle to enter and exit from a link. An enter time (t_{in}) and an exit time (t_{out}) is needed to be determined using map-matched tracked data for link travel time calculation. These t_{in} and t_{out} can be detected, interpolated or estimated according to spatial distribution of GPS track data (see Figure 3.4). If there are GPS track data points matched to nodes at link entrance or link exit points, then t_{in} and t_{out} can be detected. Enter time might also be calculated by linearly interpolating the last GPS track data before the entering the link and first data on the link using the shortest path connecting these two points. Exit time might be calculated in the same manner, using last GPS track data on the link and the first data after the exit node. The worst case in travel time calculation occurs when no GPS track data can be matched to a link, which might be because of its short length or high speeds of the probe vehicle. In this case, the last GPS track data on the route before entering a link and the consecutive GPS track data after link exit are used to estimate enter and exit time. Further details of this algorithm are available in Unsal (2006).

Using time-dependent link travel times from multiple observations calculated by TDA and link lengths, archival average link speed ${}_a\overline{v}_i^{\tau}$ and sample variance s for link i can be computed for a chosen time window τ by

$$ {}_a\overline{v}_i^{\tau} = \frac{1}{n}\sum_{j=1}^{n}(v_i^{\tau})_j \qquad (3.1) $$

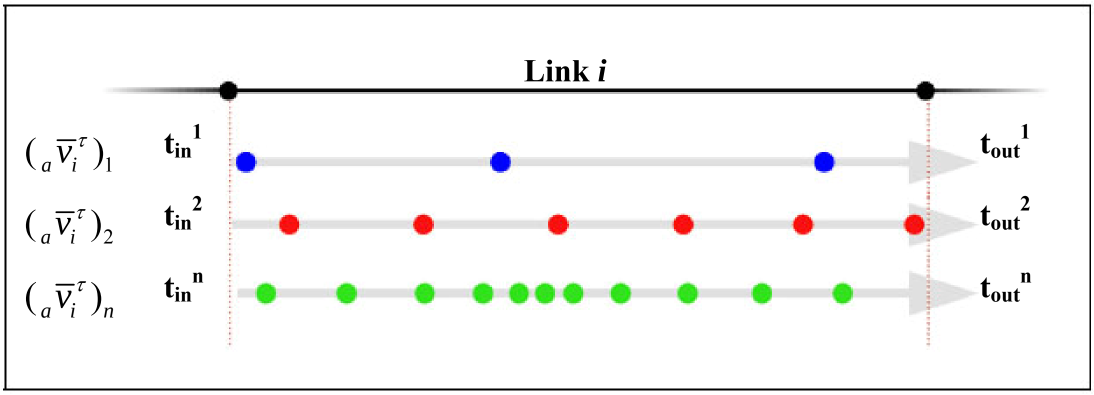

Figure 3.3 GPS track data on a link representing different traffic conditions (from Unsal, 2006)

where n is number of observations and subscript a stands for archival values, and the sample variance is

$$({}_a s_i^{\tau})^2 = \frac{1}{n-1}\sum_{j=1}^{n}\left[(v_i^{\tau})_j - {}_a\overline{v}_i^{\tau}\right] \qquad (3.2)$$

The average link speed ${}_a\overline{v}_i^{\tau}$ is a random variable that depends on the state of traffic, number of observations and other fluctuations along the link. True mean link speed for chosen time window can be estimated from observations. As sample size increases, the sampling distribution of sample means approaches that of a normal distribution. Therefore, if the sample size is large, it can be assumed ${}_a\overline{v}_i^{\tau}$ follows a normal distribution $N(\mu_i^{\tau}, \sigma_i^{\tau}/n)$ with a mean link speed of μ_i^{τ} and standard deviation of σ_i^{τ}. ${}_a\overline{v}_i^{\tau}$ and $({}_a s_i^{\tau})^2$ are unbiased point estimators of mean μ_i^{τ} and standard deviation σ_i^{τ}, respectively. But, if an interval value for the mean link speeds is needed, α-*percent confidence interval* can be determined where the z^*

value corresponds to z-score limits for $\alpha / 2$ making the area under the normal curve between $-z^*$ and z^* equal to α.

$$\Pr\left({}_a\overline{v}_i^{\tau} - z^* \frac{{}_a(s_i)^{\tau}}{\sqrt{n}} < \mu_i^{\tau} < ({}_a\overline{v}_i^{\tau}) + z^* \frac{{}_a(s_i)^{\tau}}{\sqrt{n}} \right) = \alpha \qquad (3.3)$$

For every link, the estimated mean link speed and its standard deviation might differ resulting in different α-*percent confidence intervals* as shown in. Figure 3.4.

Time-dependent corridor characteristics are calculated from the archival traffic data. However, traffic characteristics can evolve over time. Therefore, all values in the corridor characteristics are needed to be updated when there is a new data input such as real-time GPS track data which makes it easier to represent traffic characteristics more realistically.

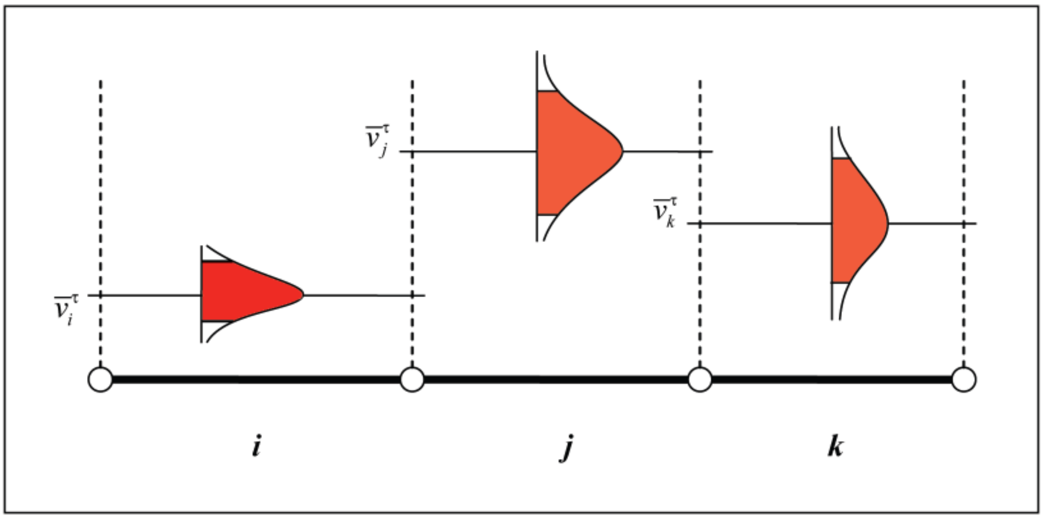

Figure 3.4 Average link speeds and their estimated confidence levels

3.2.4 Retrospective Bottleneck Analysis

Cassidy and Bertini (1999) states that flow rate can be 10% lower than that of prior to queue formation. At some locations a queue formed by a bottleneck affects other links so the perturbation in the network propagates to the other upstream links and even queues might be formed at these links which makes harder to characterize the traffic flow at the links. Also, locations of the bottlenecks on the corridor should be determined so that the algorithm will distinguish between recurrent bottlenecks and the non-recurrent incidents. This step is crucial in order to decrease false alarm rate of the algorithm.

In this methodology, a procedure for bottleneck detection is proposed in order to flag bottleneck locations and their approximate impact zones by a cross-link analysis. Bottlenecks are expected to cause low speeds or congested traffic conditions in the upstream followed by a sudden jump in the speed in the downstream. For this step, the data from the time-dependent corridor characteristics database is utilized. The proposed bottleneck algorithm is basically a search algorithm, which tries to detect bottlenecks by looking at the probability of a sudden speed jump at downstream. Then the detected bottlenecks are confirmed by the slow traffic regime on the upstream of the bottlenecks and slow traffic regime zone behind the bottleneck release is reported as bottleneck impact zone.

As introduced previously, link speed variation parameter (δ_l^τ) is a step function showing speed difference between two consecutive links at τ. For the j^{th} observation over a link l with a predecessor link k, if there is a jump in the speed of link l v_l^τ compared to link k v_k^τ, the function is equal to 1; if speed is approximately constant (that is within an interval of $(v_k^\tau)_i \pm \psi$), it is equal to 0, and if there is drop, it is equal to -1 as shown in Eq. (3.4)

$$\left(\theta_l^\tau\right)_j = \begin{cases} -1 \text{ if } & (v_l^\tau)_j - (v_k^\tau)_j < -\psi \\ 0 \text{ if } & -\psi < (v_l^\tau)_j - (v_k^\tau)_j < \psi \\ 1 \text{ if } & (v_l^\tau)_j - (v_k^\tau)_j > \psi \end{cases} \qquad (3.4)$$

For the above function, a threshold for significant change in speed ψ is defined to surpass temporal irregularities in traffic. Consequently, the link speed variation parameter ${}_a\delta_i^\tau$ is calculated by

$$\delta_l^\tau = \frac{1}{n}\sum_{j=1}^{n}\left(\theta_l^\tau\right)_j \qquad (3.5)$$

As the constant speed is represented by "0" and a speed variation by "1" and "-1" which the resulting average parameter enables us to observe the significant jumps or drops in speed over the observations. Since bottlenecks are recurrent in nature, $\delta_l^{\tau j}$ is expected to generate high positive value, by which a potential bottleneck location can be detected. Similarly, a high negative value (δ_l^τ close to "-1") might suggest joining a queue.

Finally, the algorithm matches the identified potential bottleneck locations with slow traffic regime at the upstream of these locations, using slow regime parameter γ_l^τ. The potential bottleneck locations without slow traffic upstream are discarded in the analysis. If there are multiple consecutive upstream links, where slow traffic regime is identified, these links are considered as the impact zone of the bottleneck, since it suggests that bottleneck related queue extends to those links. Bottleneck possibility index ϕ_l^τ at those links are set to "1", and the procedure ends.

The steps included in retrospective bottleneck analysis can be summarized as follows:

Step 1. Check speed variations between consecutive links

If there is constant jump, define a bottleneck release

Step 2. Check slow traffic regime on the upstream of bottlenecks

Match slow traffic regime with bottlenecks

Refine bottleneck locations by discarding unmatched locations

Step 3. Check continuous slow traffic regime upstream of bottlenecks

Add the consecutive links with slow regime to bottleneck impact zone

Set bottleneck possibility index to “1” for the links in the impact zone

Actually, it might be possible to estimate the length of probable impact zone of a bottleneck using probabilistic methods; however, this requires complex analyses and it is out of scope of this study.

3.3 An Incident Detection Algorithm

The final part of the methodology is the real-time incident detection algorithm. Similar to bottleneck analysis, where traffic state in the current link is compared with predecessor link, in the incident detection algorithm, basically current (real-time) link speed v_i^τ is compared with a lower limit derived from archival link speeds ${}_a v_{i,l}^\tau$. Unusual decrease in link speed is reported as a possible incident, if the location does not show a regular bottleneck potential for the given time window τ.

For this part, first, location of an active (moving) probe vehicle is needed to be checked against the boundaries of the selected corridor. If the probe vehicle is inside the boundaries of the corridor, a spatial search can be employed to determine the link at which it is traveling. As soon as the link travel time is observed, the real time link speed v_i^τ is computed for the most recent traveled link *i*, v_i^τ is checked against the acceptable lower limit ${}_a v_{i,l}^\tau$ which is defined as *lower limit for α-percent confidence* *interval* calculated in TCCD below which the probability occurrence of an observation is (100-α) percent. If the real-time average link speed is less than the acceptable lower limit, this means that the traffic flow is unexpectedly slow at that link. Then, the algorithm checks whether there is a bottleneck possibility index ϕ_i^τ associated to that link at that time of day or not. If the link is a known bottleneck location, then the algorithm reports bottleneck or incident related queue, which cannot be known conclusively. Otherwise incident possibility index η_i^τ is set to "1" at that link.

When incident possibility index is set to "1" at a link by the algorithm, an additional check is needed to determine whether the vehicle is really at the link where incident occurred or it is in the impact zone of a incident at the downstream. For this purpose, when possibility of incident is set to "1" by the algorithm at a link, this index is stored until a incident possibility index at a downstream link speed is "0". Then, the real-time link speed of consecutive link is checked against archival lower limit.If it is below the acceptable lower limit, then the incident possibility index set to "1" for this link. For the following downstream links same procedure is applied by keeping the incident possibility index of upstream links. When the real-time link speed exceeds the acceptable lower limit at a downstream link, the location of incident is reported as the last upstream link and the consecutive upstream links with incident possibility index "1" are considered as "impact zone" of the incident then the procedure is terminated. The pseudo code for the incident detection algorithm can be seen in Figure 3.5.

Incident detection based on real-time link speed compared to a confidence interval of the mean link speeds and bottleneck possibility may not be distinctive enough for certain traffic conditions: seasonal change in the demand levels and consequently the level of service on a link may result in significant low speeds below the lower limits, setting incident detection possibility index to "1" falsely. To avoid such false alarms, the time-dependent link speed lower limits defined based on the time-of-the-day (such as morning peak, noon off-peak, etc.) can be replaced by more precise measures that take additionally day-of-the-week, or the seasonal characteristics into account.

For the currently traveled link *i* in the time period τ ,

Step 1: Calculate link speed v_i^τ and check against the archival lower limit, ${}_a v_{i,l}^\tau$

Check the η_{i-1}^τ value to see if the link is in the impact zone of an incident

Step 2a: If $v_i^\tau < {}_a v_{i,l}^\tau$,

check bottleneck possibility value ϕ_i^τ

If $\phi_i^\tau = 1$,

report "***Bottleneck OR Incident related queue***"

Otherwise,

Set incident possibility $\eta_i^\tau = 1$

Select the consecutive link, go to Step 1

Step 2b: Otherwise

If the predecessor link $\eta_{i-1}^\tau = 1$

-Report possible incident for Link (i-1)

-Check η_k^τ s for every upstream link k until the first $\eta_k^\tau = 0$;

- report the impact zone as the sequence of links with $\eta_k^\tau = 1$

Figure 3.5 Pseudo-code for the proposed Incident Detection Algorithm

CHAPTER 4

CASE STUDY: İNÖNÜ BOULEVARD

The methodology developed in the previous chapter is tested on a corridor with high demand monitored via two probe vehicles equipped with GPS devices. In this chapter, after a brief description of the corridor and the data collection process, traffic characteristics of it are determined from GPS track data for morning and evening peaks and noon off-peak period. Later, the GPS track data is analyzed with proposed methodology, locating recurrent bottleneck locations and their impact zones as a base for incident detection on the corridor in the future.

4.1. Description of the Corridor

The study corridor, Inonu Boulevard, starts from A1 entrance of METU and extends to Kızılay with a total length of 11060 meters, mostly consisting of arterial roads, grade-separated intersections and some surface streets. Many of the governmental agencies and business centers are located in Kızılay make this region one of the main attraction zones in Ankara. Traffic flow patterns towards and from Kızılay differ significantly, thus will be studied separately. While METU to Kizilay direction is denoted as the "inbound" direction, Kizilay to METU direction denoted as the "outbound" direction from this point on. (see Figure 4.1a and Figure 4.1b)

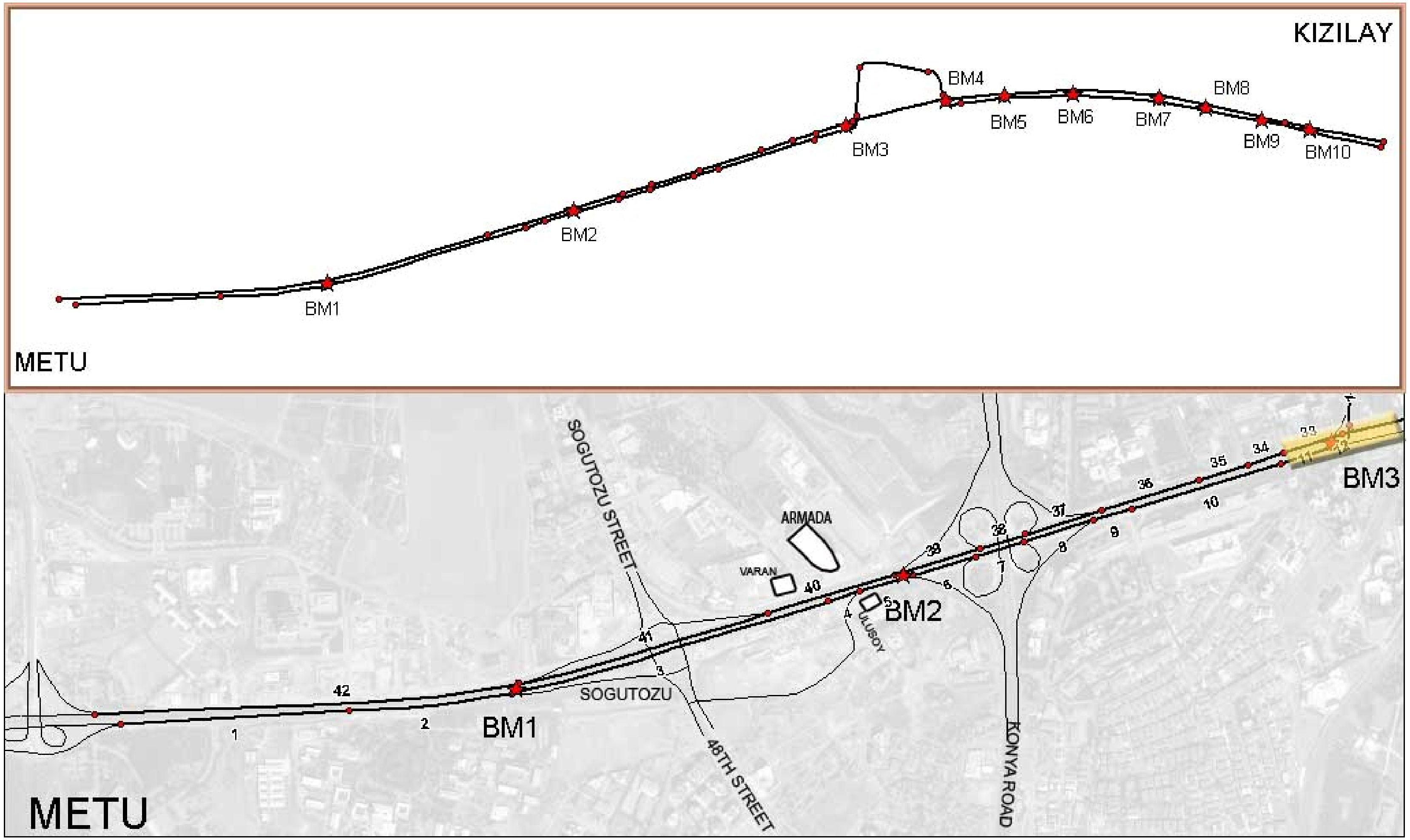

Figure 4.1a The Study Corridor from METU to BM3

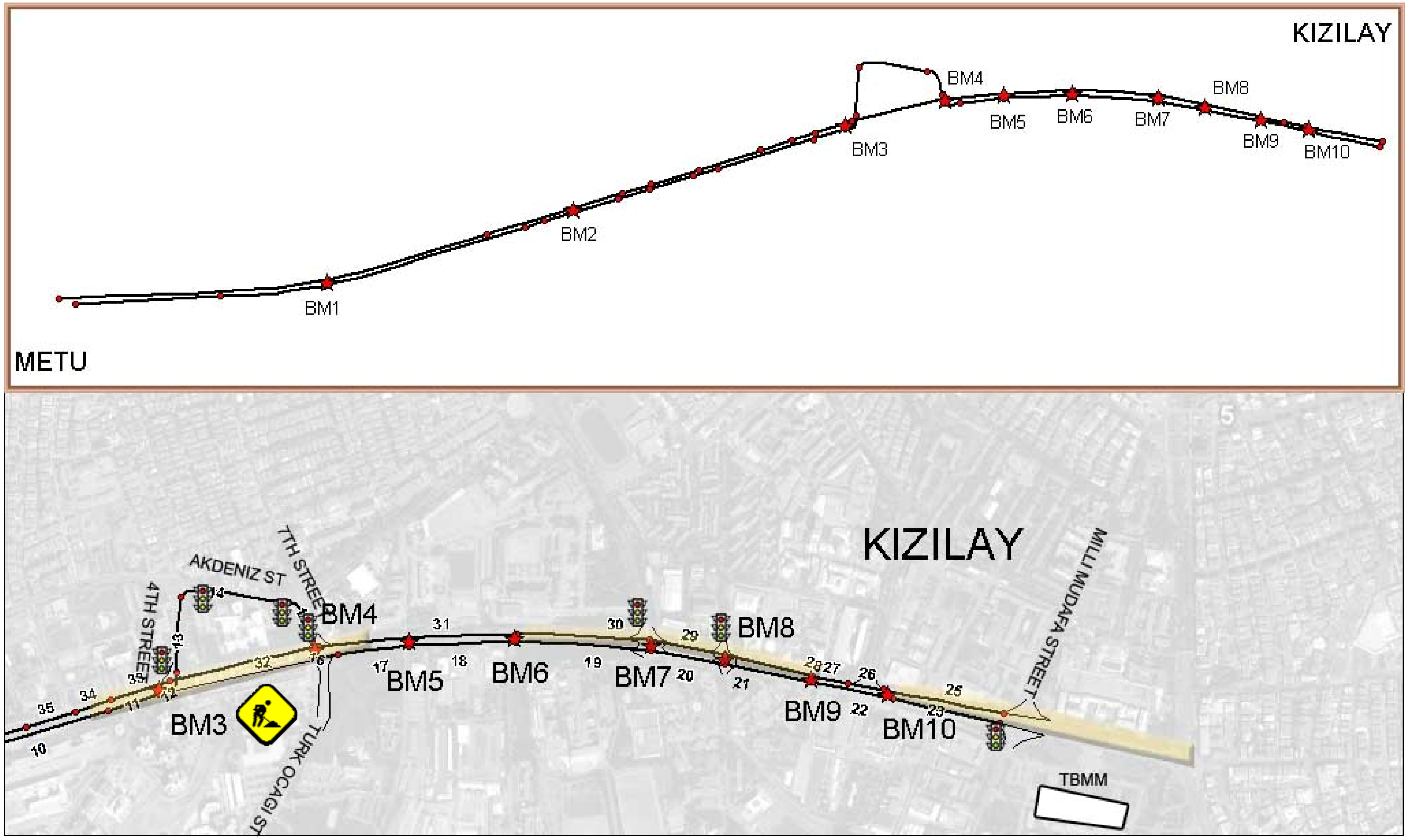

Figure 4.1b The Study Corridor from BM3 to Kizilay

The start point of the study corridor is selected as the start of the boulevard right after the interchange in front of the entrance of METU in inbound direction. The curved parts of the intersection is excluded for sake of simplicity and for cross analysis of inbound and outbound directions.

The map of the corridor includes selected benchmark (BM) points where bottlenecks, physical or operational changes exist on the road. The result of a parallel study on traffic safety showed that there is a black spot region between BM3 and BM2 in outbound direction. Therefore, at this location, segmentation is performed, as discussed in Chapter 3 and an additional link is created.

First benchmark point (BM1) is selected as the Söğütözü interchange where vehicles diverge to 48th Street and merge from Söğütözü Street via ramps. The second benchmark (BM2) is selected as the start of a cloverleaf interchange connecting the İnönü Boulevard and the Konya Road, which is a state highway carrying everyday commuter traffic as well as intercity freight and passenger traffic. Between BM1 and BM2, there are three attraction zones: Armada, which is a popular shopping mall in Ankara, Ulusoy and Varan, which are the hubs of two well-known intercity bus service companies in Turkey (see Figure 4.1a).

The third benchmark (BM3) is the intersection in Bahçelievler, a highly populated neighborhood with residential and business attractions, which connects 4th street to Inönü Boulevard. BM4 is another intersection connecting 7th street, Türk Ocağı Street and İnönü Boulevard. During the data collection, traffic was rerouted due to work zone at the link connecting BM3 and BM4 (see Appendix A, Figure A-1). Therefore, inbound traffic follows the links on 4th Street, Akdeniz Street, and 7th Street, which are all controlled by signalization, and it is longer than outbound direction between BM3 and BM4.

BM5, BM6, BM9, and BM10 are entrance and exit points of grade-separated intersections, one of which is shown in Figure 4.2. Since the special lanes for the grade-separated intersections are not used in this study, they are not shown on the traffic network. However, the locations of the special lanes are shown the figures on Figures 4.1a (with yellow color) and 4.1b. At BM7 and BM8, traffic is controlled by signalization.

Figure 4.2 Grade-separated intersection at Bahcelievler

4.2 Control Data Collection

Data collection is performed by two different probe vehicles during morning peak (at 08:30-09:30), noon off-peak (at 12:30-13:30) and evening peak (at 17:30-18:30) periods in three different days. To obtain simultaneous data in the inbound and the outbound directions, one of the vehicles start to collect data from METU in the inbound direction while the other from Kızılay in the outbound direction, at the same time. The probe vehicles completed three laps during off-peak period and two laps during peak periods on the corridor. During the three-day data collection period, no special case or incident was reported and resulting in developing base case traffic analysis with everyday traffic congestion. The probe vehicles are accessorized with Magellan GPS receivers (Explorer 400 and Explorer XL) connected to laptop computers providing track data with one-second epochs.

4.3 Corridor Analysis

While the GPS track data can be displayed in a network, it does not provide any traffic data unless it is associated with a traffic network. Thus, first the track data is matched to the traffic network of the corridor, using a software called Track Data Analyst (TDA) developed according to the methodology proposed by Unsal (2006). This software comprises four sub modules: the first module enables users to convert a digital map of a traffic network to a geographical database; the second module imports GPS track data to a database, the third module matches GPS track data to the traffic network and the last module reports statistical measures on the average link travel times.

First, a general corridor characterization is performed based on the average link speed values. Since the traffic patterns are very different for different time periods, the corridor speed profiles are developed for all three periods: morning peak, noon off-peak and evening peak periods. For every analysis, two graphs showing inbound and outbound traffic conditions are used to compare the effect of the demand at the same locations. Later, in addition to link speeds, slow regime and speed variation parameter are determined in a time-dependent fashion, as well. Later, all the derived traffic characteristics are used in the retrospective bottleneck detection algorithm, which is utilized in incident detection methodology. Some sensitivity analyses on selected decision parameters are provided as a part of these analyses as well.

4.3.1 Corridor Characterization

Before employing the incident management methodology, the corridor characteristics are compared against on-site observations to verify the collected data. To characterize the study corridor, first, average time-dependent link speeds for morning peak, noon off-peak and evening peak periods are analyzed (see Figures 4.3a and 4.3b).

Inbound Traffic Characteristics

In Figure 4.3a, it can be easily noticed that off-peak link speeds make an envelope over peak values which indicate effect of severe peak hour congestion for the inbound traffic.

- At the beginning of the corridor, the average speeds during these three periods keep almost constant. In all three graphs, before BM2, at about 1800 meters from the start, a major drop in speed (off-peak hour values drop from 65 kph to 50 kph, peak hour values drop from 50 kph to 40 kph) is observed, even though it is not depicted as benchmark. Thus, it is labeled as point of interest (POI1). The reason of this drop is most probably the capacity decrease after BM1 around Ulusoy (see Appendix A, Figure A-2).

- By BM2, the link speed reaches up back to nearly 60 kph after the ramp at that section and up to 70 kph showing an almost constant increase until about 2600 meters from the start, then, link speeds are decrease constantly as the vehicles approach the intersection at BM3.

- Between BM3 and BM4, there is a slow traffic regime with some fluctuations over small distances. This is due to work zone on İnönü Boulevard, which causes to traffic flow to be rerouted to low capacity streets which are controlled by traffic signals at three different points. (For the sake of simplicity in representation, we will use same lengths for inbound and outbound direction between these two points. However, in the calculations, original link lengths in inbound direction are used.)

- Between BM4 and BM5, at the end of the first link, where the traffic flow on a single lane, there is a relaxation and a drastic jump in average link speeds which suggests another point of interest (POI2) and indicates another bottleneck possibility on the upstream of the location.

- Between BM5 and BM6, average link speeds increase which might be a continuous acceleration after the potential bottleneck point between BM4 and BM5.

- Average link speeds decrease between BM6 and BM7, related to capacity decrease due to entrance of grade-separated intersection and traffic signals at BM7 (see Appendix A, Figure A-3).

- Between BM7 and BM8, link speeds continue to drop due to separated traffic lanes and another traffic signal at BM8. After BM8, link speeds increase until the end of BM10 , at the end of which drop to low speeds might result from multiple sources, such as due to cars trying to enter to grade-separated intersection, or long waiting times and queues due to traffic signals on the intersection in front of Türkiye Büyük Millet Meclisi (TBMM).

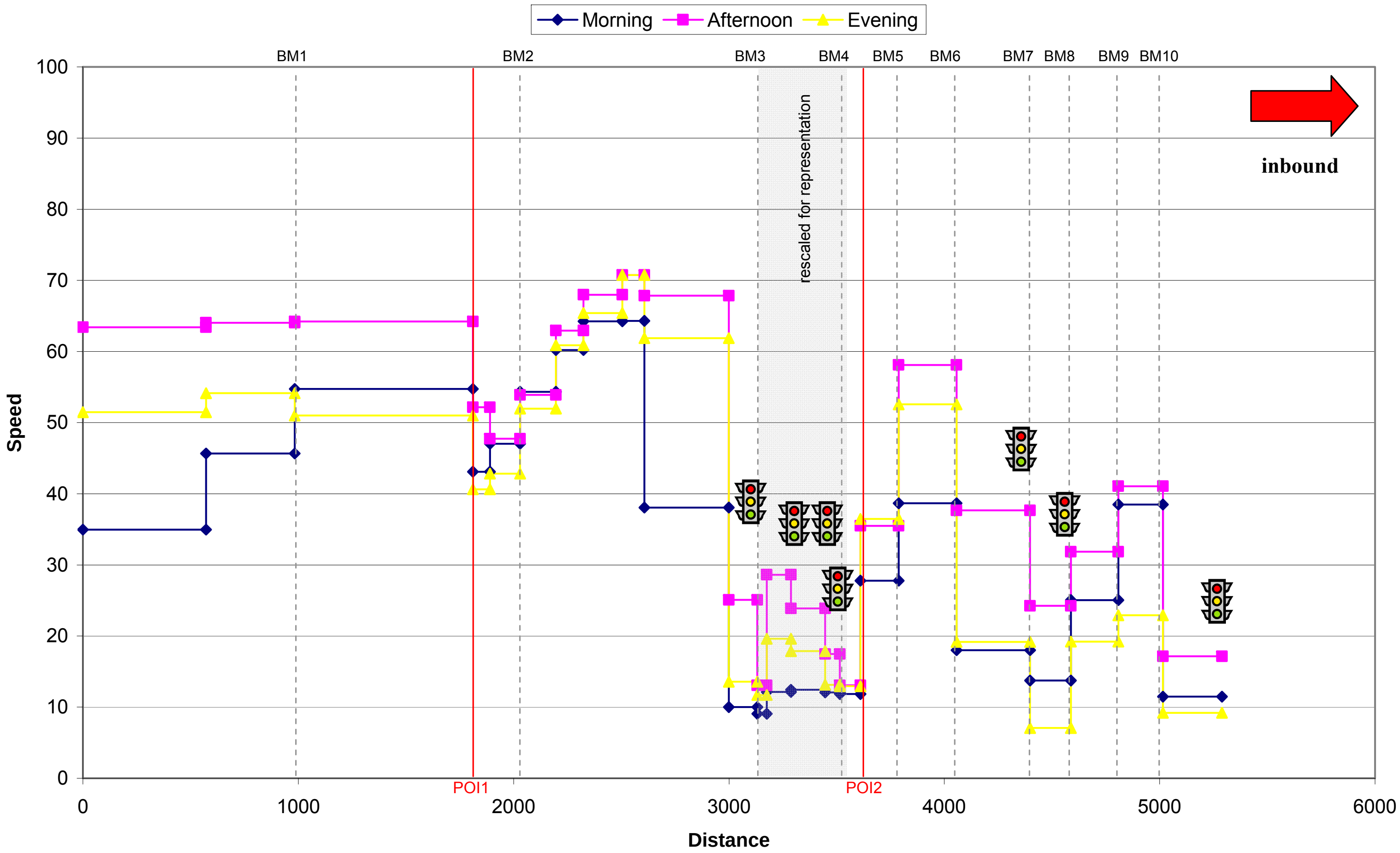

Figure 4.3a Overall 3-day link speeds averages in inbound direction

Outbound Traffic Characteristics

As in the inbound direction, in the outbound direction, again off-peak link speeds make an envelope over peak values, which is sign of peak hour congestion in outbound direction as well.

- First link outbound direction is the right after traffic signal in front of TBMM and vehicles increase their speeds until they join the traffic flow in the outbound direction of the corridor. Between BM10 and BM9, average peak hour link speeds are under 20 kph suggesting slow traffic regime (seeFigure 4.3b) This might be related to increase in demand due to vehicles joining to traffic flow from the exit of grade-separated intersection at BM10 or it might be caused by interaction between vehicles while they are trying to enter another grade-separated intersection at BM9.

- Between BM9 and BM8, off-peak and peak averages are under 30 kph and again peak hour averages are lower, most likely due to queue at the traffic signal at BM9.

- On the link connecting BM8 and BM7, there is a sudden drop in the link speeds in three time periods. Between BM8 and BM7, traffic is slower than the upstream, which might be effect of traffic lights at BM8, as vehicles generally waits at traffic signal at BM7 after traffic signal at BM8.

- After the traffic signal at BM7, there is a significant jump in average link speeds which suggest a release from a potential bottleneck at BM7.

- Between BM6 and BM4, the link speeds of all three periods tend to decrease significantly. This might be the combined effect of traffic lights and the entrance of grade separated intersection before BM4.

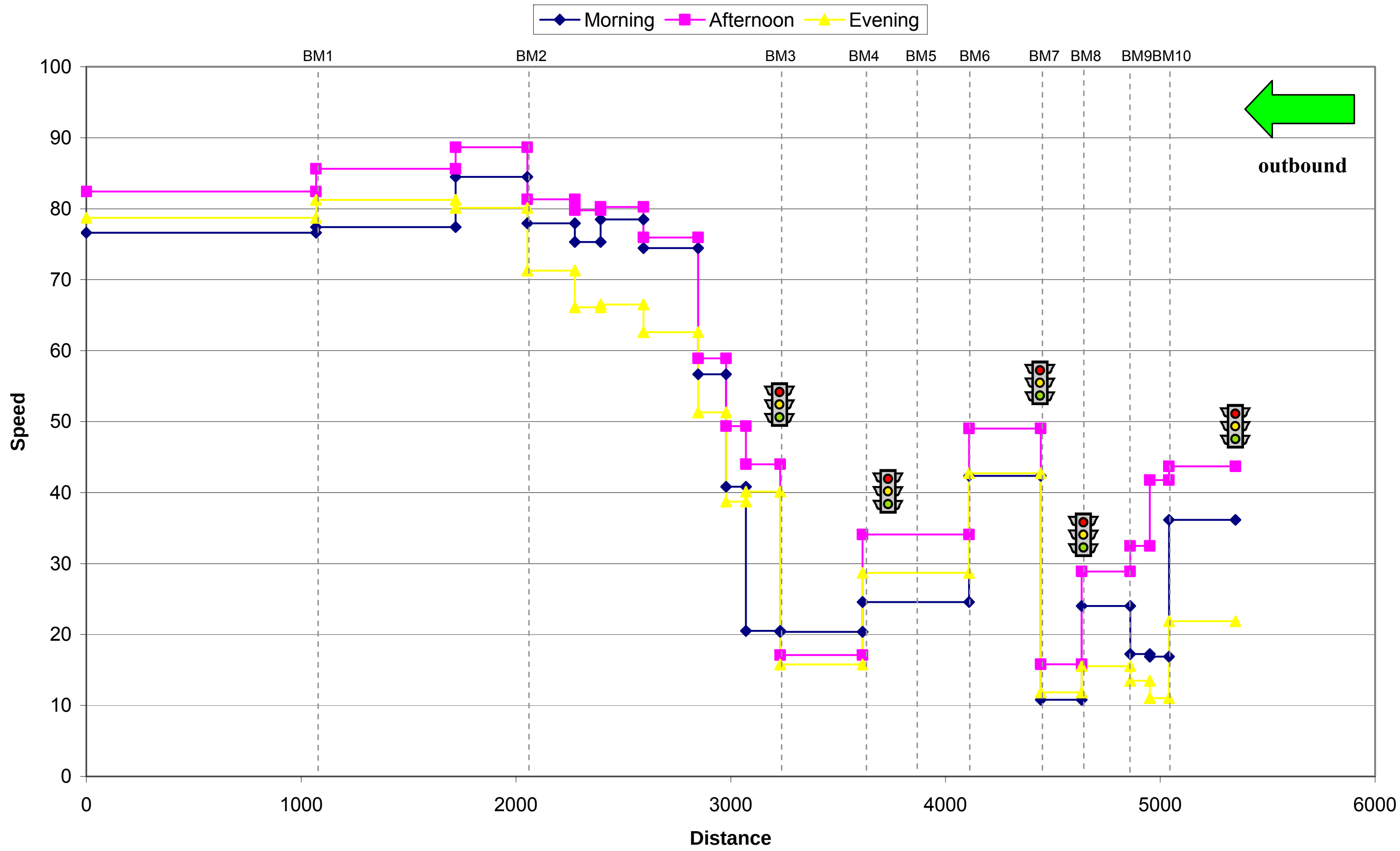

Figure 4.3b Overall 3-day link speeds averages in outbound direction

- The declining trend in average link speeds continues between BM4 and BM3. The reasons of this slow traffic regime (around 20 kph) on this link might be multiple transit vehicle stop points, and traffic signal at BM3.

- After slow regime on the link between BM4 and BM3, significant jump at first link between BM3 and BM2 suggests another bottleneck location at BM3.

- After BM3, average link speeds increase continuously and after BM2, traffic flows at 80 kph on the average and this can be assumed as free flow speed for the arterial since there is no sign of congestion in observations.

Comparison of Inbound and Outbound Traffic Characteristics

Comparison of Figure 4.3a and 4.3b clearly shows that the average link speeds in inbound direction are generally slower than outbound direction. Moreover, peak and off-peak averages in the outbound do not deviate as much as in the inbound direction. These two properties indicate that there is always high demand in the inbound direction while outbound demand is lower than that.

Another important finding, obtained from the comparative analysis of the inbound and outbound, is the opposite behavior between BM2 and BM3. Vehicles slowed down gradually in the inbound direction and speeded up gradually in the outbound direction, suggesting the existence of a “transition zone” from arterial to surface streets and vice versa, This behavior can be supported by the first signalized intersection at BM3, while there are only interchanges on corridor between the starting point of corridor and BM3.

Between BM3 and BM4, slow traffic regime is present in both directions. Although there are two traffic signals in outbound direction, due to rerouting in the inbound direction traffic flow is controlled by signalization at four different locations. There are multiple transit stops on the link between BM4 and BM3 in the outbound direction.

Between BM4 and BM6, there are two links in inbound direction, while there is one link in outbound direction. The average of two links is very close the average link speed in outbound link. Between BM6 and BM7, outbound traffic is faster than inbound traffic due to tendency of vehicles to accelerate after the traffic light at BM7. After BM7, inbound and outbound average link speeds are similar and slow traffic regime is present both directions, especially in the peak hours. The last link in inbound direction after BM10 is significantly slower than the first link in outbound direction before BM10. This might be explained by same behavior between BM6 and BM7, which is the delay at traffic signal in inbound direction and acceleration after the traffic signal in outbound direction.

4.3.2 Consistency of Link Speeds

In addition to benchmark locations, the points which are considered as potential bottleneck locations are tagged as POIs. These potential locations will be analyzed more in detail here, using graphs of daily link speeds from two probe vehicles, as some of the traffic characteristics might be lost due to averaging over multiple day data. Actually, to observe the different patterns in the traffic flow at different time windows, we analyzed the lap-based link speeds; however, for the sake of simplicity in representation, instead of displaying many lap-based speed profiles in a single graph, the data collection period averages (average of 2-3 lapses) are displayed while the lap-based values are used in the quantified speed variation parameters.

In the inbound direction, the average link speed graphs (see Figure 4.5a, 4.6a, and 4.7a) show that the links before BM1 are sometimes traveled with slow speeds in peak hours, which means that demand is high in the inbound direction during peak periods. However, this information cannot be generalized conclusively since link speeds on this link can be as high as 70 kph during the same period on different days.

After POI1, there is a drop in average link speeds without an exception in any periods of any day, which might be due to capacity decrease in the link after POI1 or due to attraction zones between BM1 and BM2. Between BM2 and BM3, there is a tendency to increase in average link speeds but with no distinct pattern regardless of time of day.

Between BM3 and BM4, traffic is diverted to low capacity streets and they are always congested due to this special case which make that section a chronicle bottleneck location even in off-peak hours.

After BM4, on the link which ends at POI2, there is a slow traffic regime. Therefore, this portion is considered as bottleneck Onsite observations show that this link is indeed a chronicle bottleneck location due to very low capacity.

When the Figure 4.4a, 4.5a, and 4.6a are analyzed at the same time, it can be seen that traffic patters are very similar between POI2 and BM6. However, after BM6, only traffic patterns of morning peak and noon off-peak, which is slow traffic regime most of the time, remain similar until the end of the corridor, while there is more deviation in average link speeds in evening peak values. The reason might be demand is higher at working hours in inbound direction but in the evening; the demand is high in the outbound direction as the return trips from work or attraction zone start.

In the outbound direction, between BM10 and BM7, the link speeds are very close in the morning peak and noon off-peak, while slow traffic regime is consistently present in evening peak. The jump after BM7 suggests a demand related bottleneck in this section activated in the evening peak hour (see Figures 4.4b, 4.5b and 4.6b).

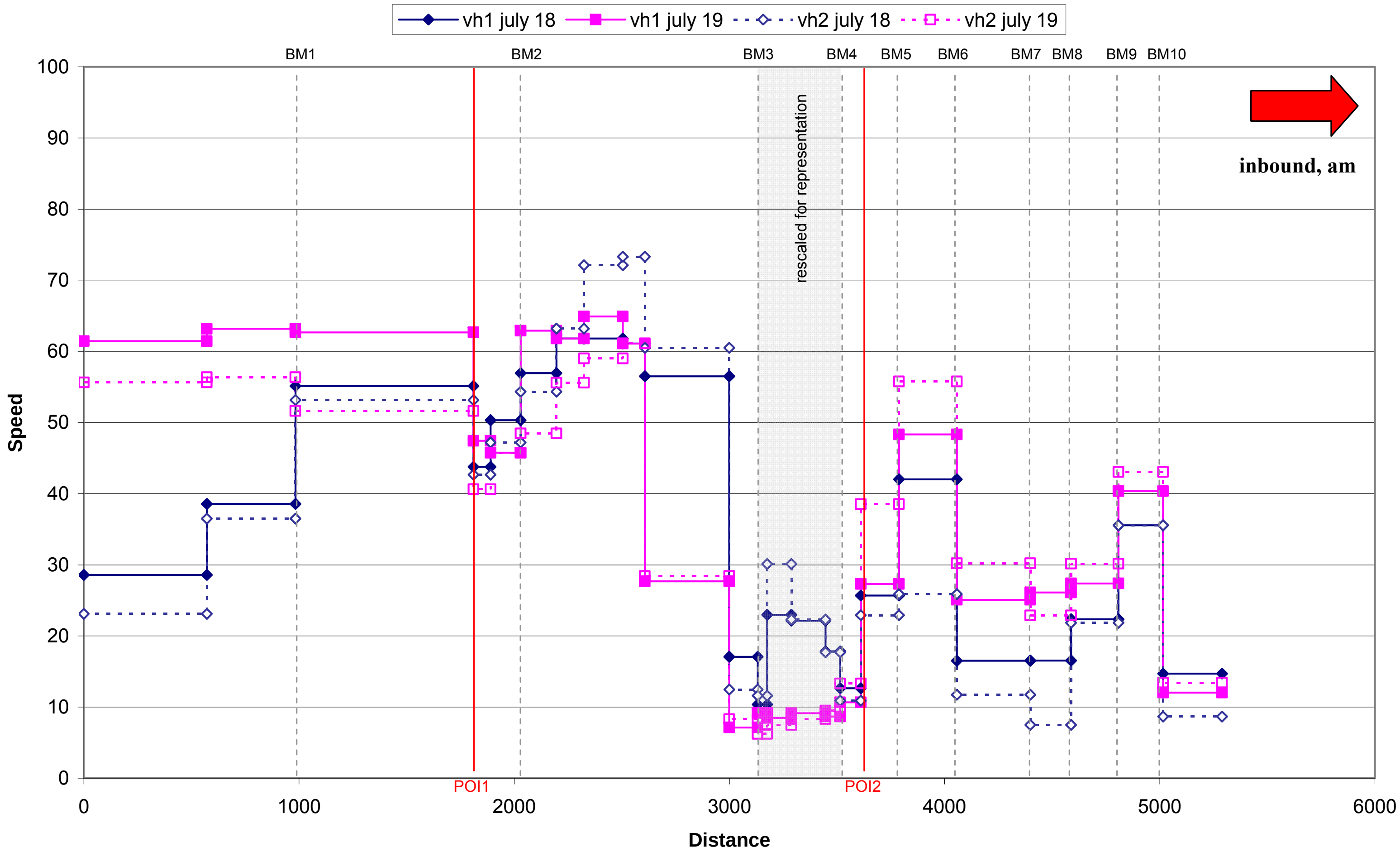

Figure 4.4a Link speed versus distance in inbound direction in the morning peak

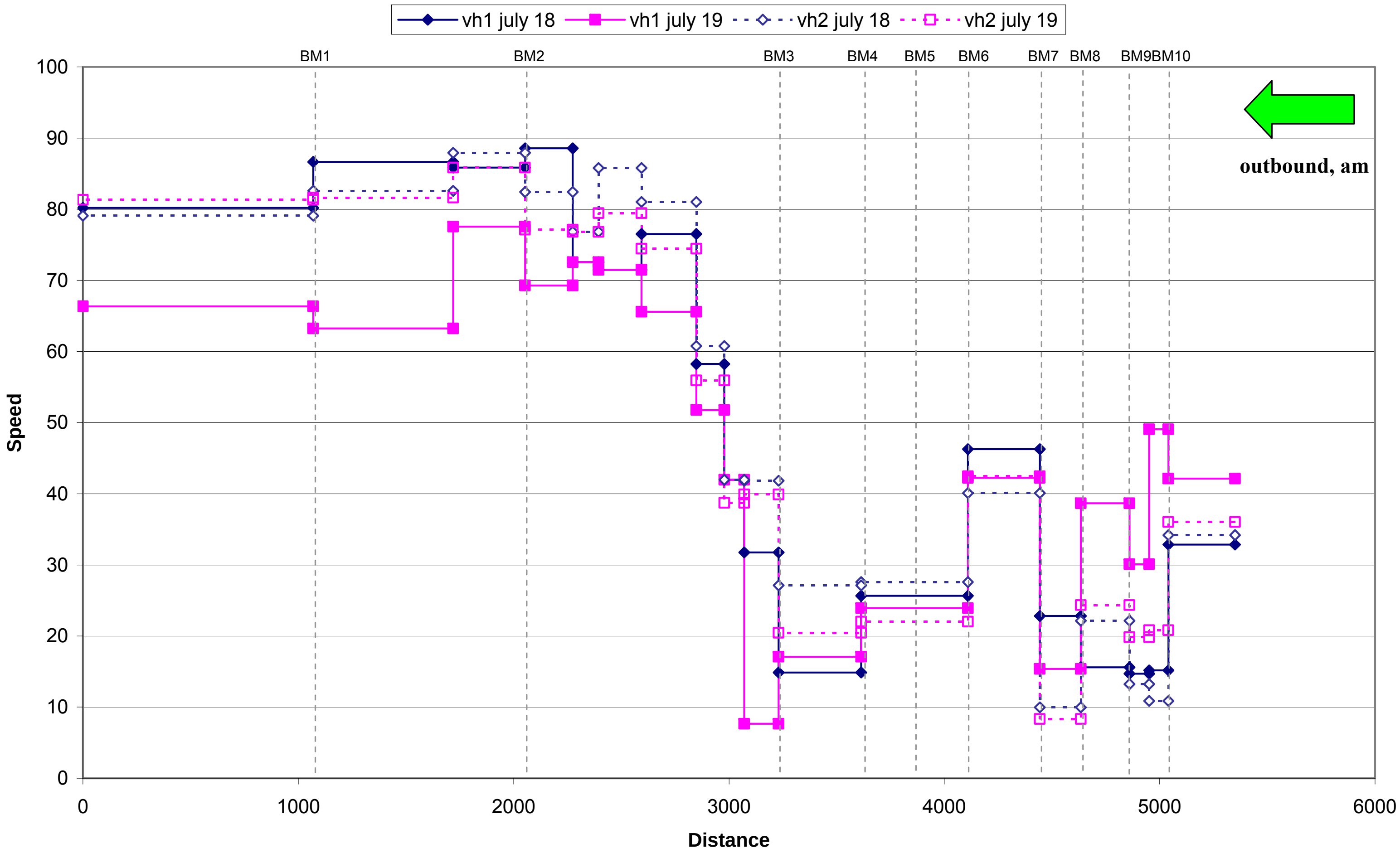

Figure 4.4b Link speed versus distance in outbound direction in the morning peak

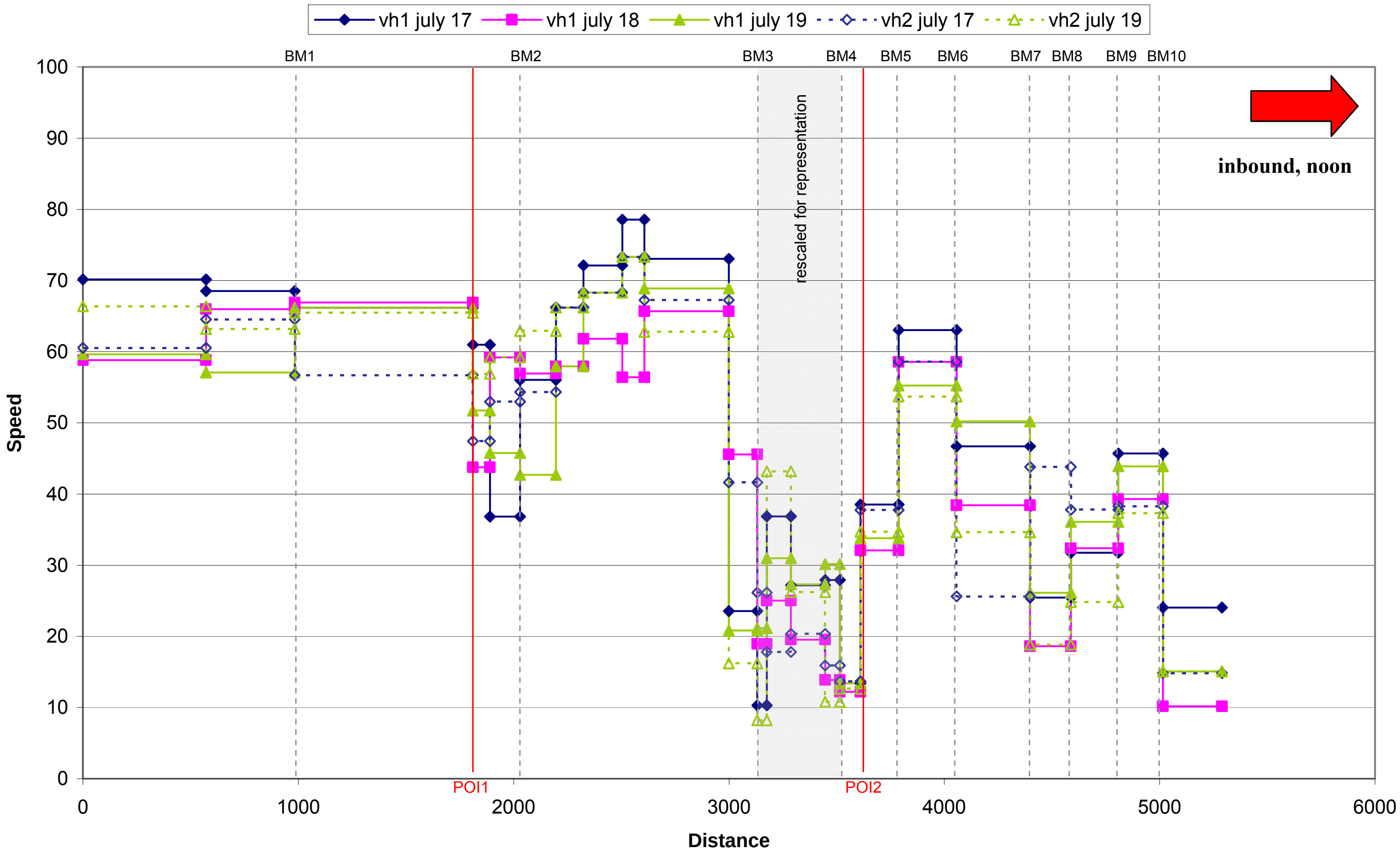

Figure 4.5a Link speed versus distance in inbound direction in noon off-peak

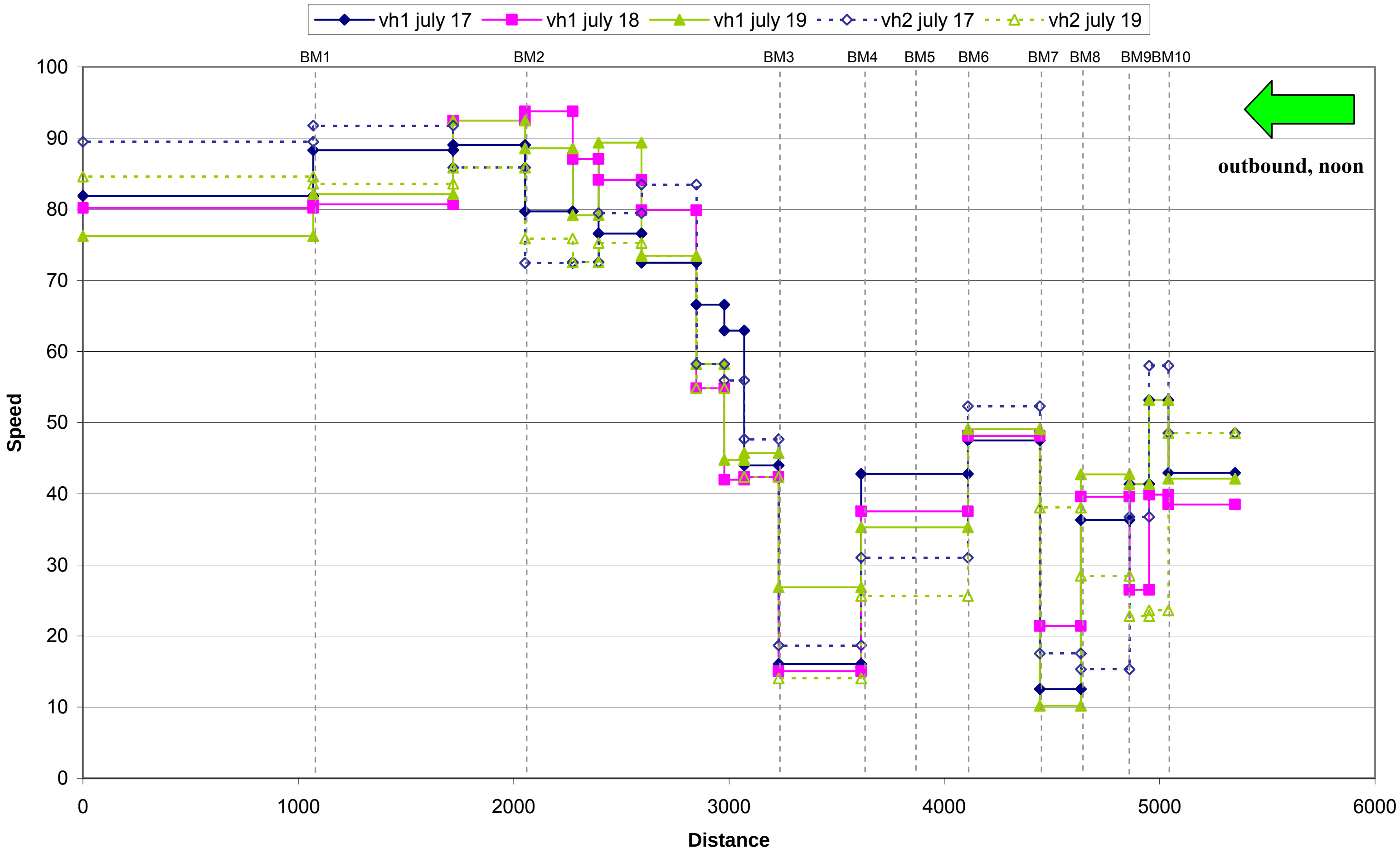

Figure 4.5b Link speed versus distance in outbound direction in noon off-peak

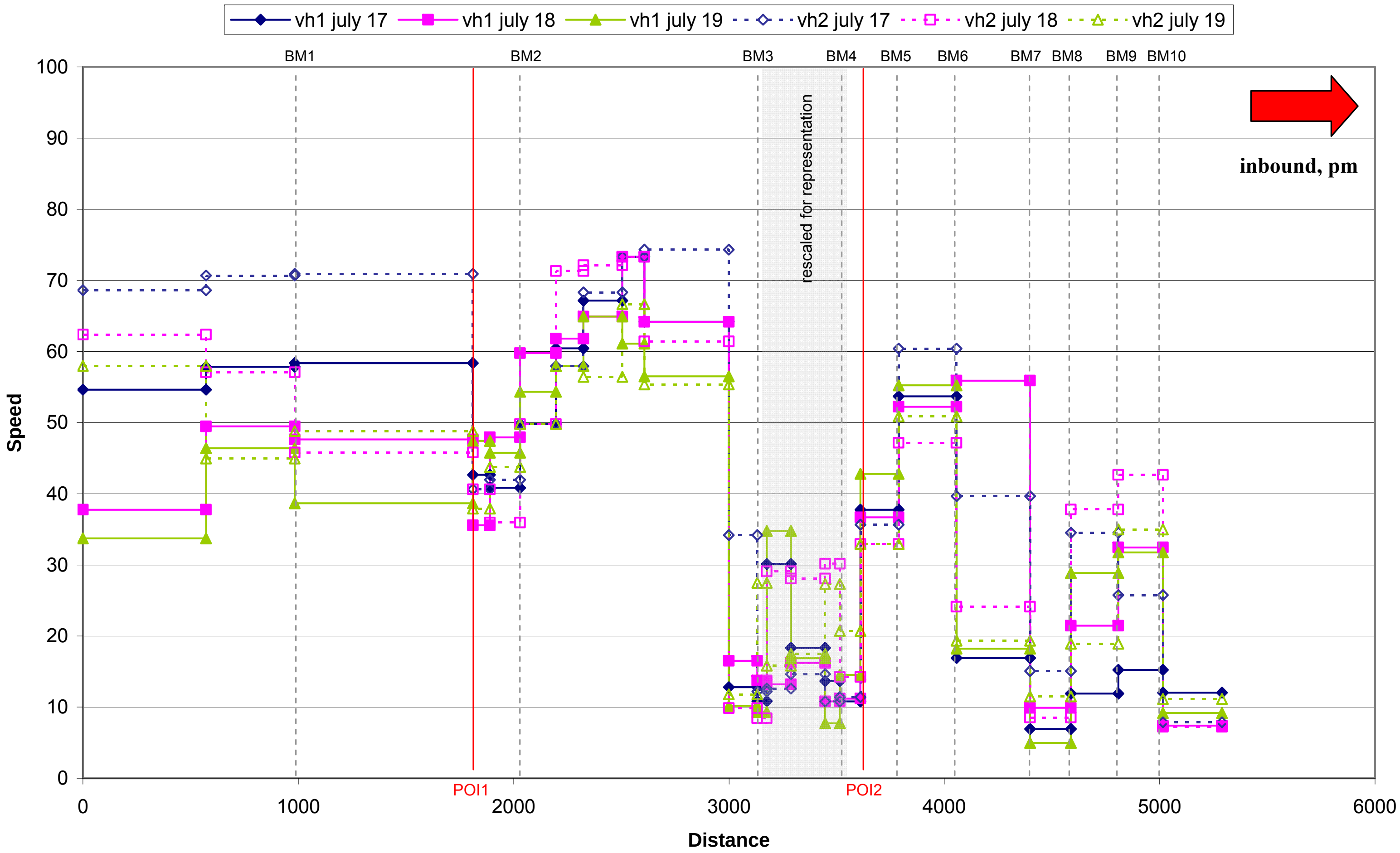

Figure 4.6a Link speed versus distance in inbound direction in the evening peak

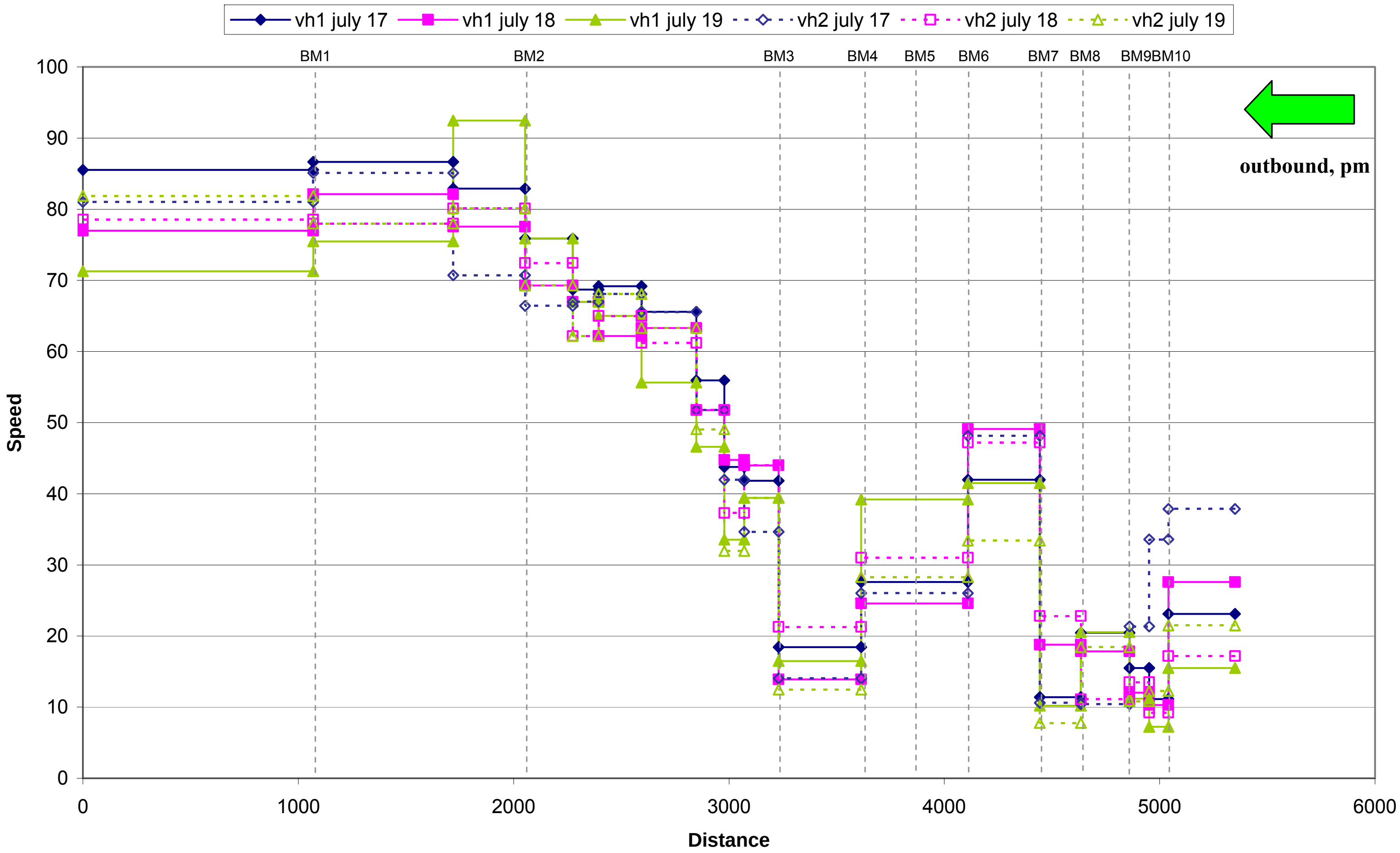

Figure 4.6b Link speed versus distance in outbound direction in the evening peak

Between BM6 and BM3, link speeds are similar and a gradual decrease is followed by a significant jump in link speed at BM3. Therefore, BM3 is regarded as another chronicle bottleneck location.

After BM3, link speeds increase consistently in all time windows until BM2. After that point link speeds are high and around 80 kph.

4.3.3 Probe Vehicle Biasedness

Since we have two probe vehicles traveling at the same time, biasedness of data due to possible driver pattern should be checked against daily averages in the inbound and the outbound direction. As an illustrative example, average period speeds during all three periods (morning peak, noon off-peak and evening peak) for Vehicle 1 and Vehicle 2, respectively, traveling in the inbound direction are shown in Figures 4.7a and 4.7b. In these figures, neither of the drivers shows a constant slow or fast driving pattern compared to the overall average speed values. This suggests that the data collection process was not biased due to driver patterns.

4.4 Time-dependent Corridor Characteristics Database

Due to its dynamic nature, traffic flow should be analyzed using time windows in which the traffic characteristics can be assumed homogenous. In this study, three time windows, morning peak (τ_1), noon off-peak (τ_2), and evening peak (τ_3), are chosen prior to the control data collection. After data collection, GPS data is processed using TDA and link travel times are calculated for each lap. Then using the link lengths from the digital map, average archival link speeds ${}_a\overline{v}_i^{\tau}$ are calculated for each link *i*, and each time window from Eq (3.1) and (3.2)

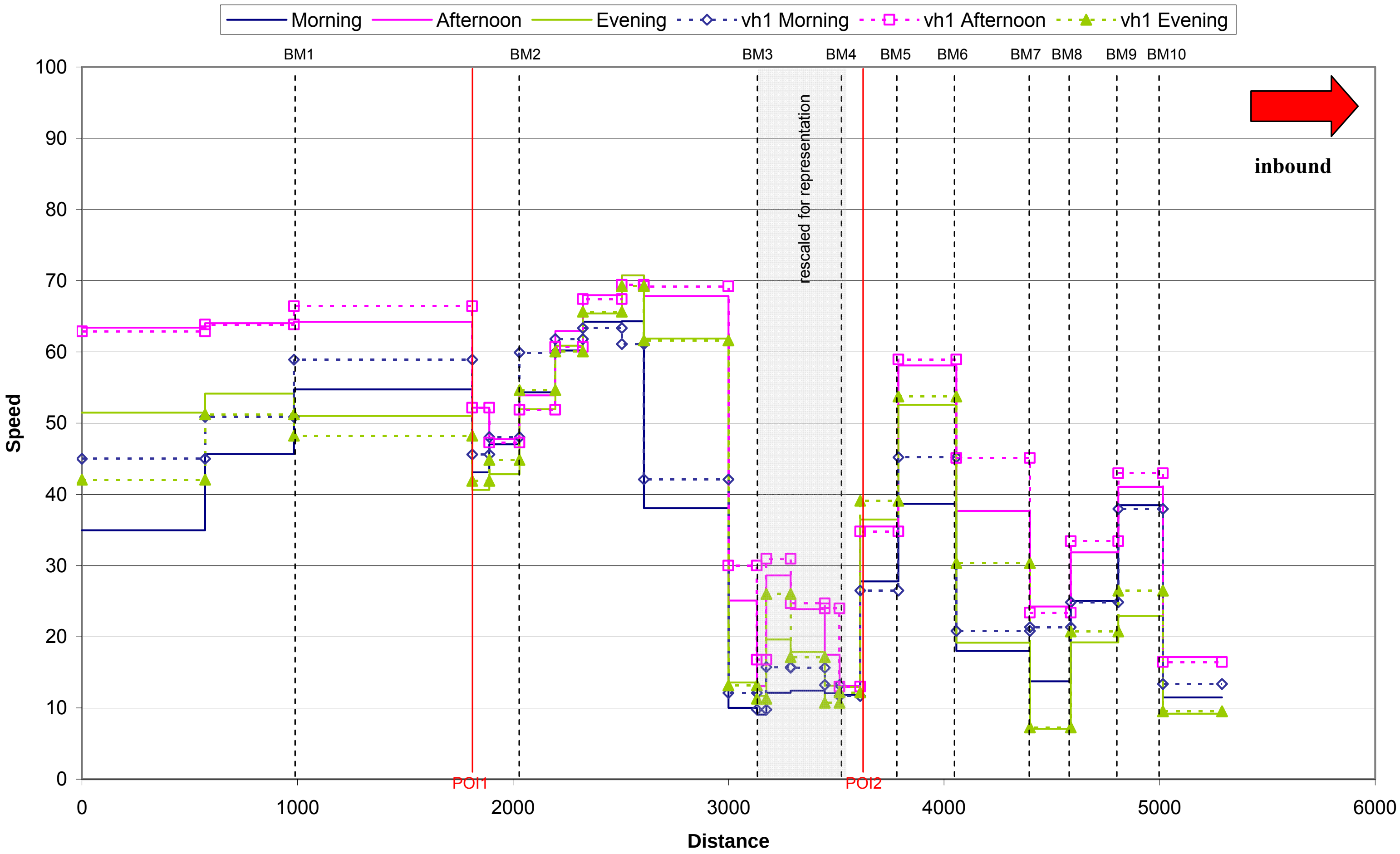

Figure 4.7a Overall link speeds versus average speed of Vehicle 1 for the three periods

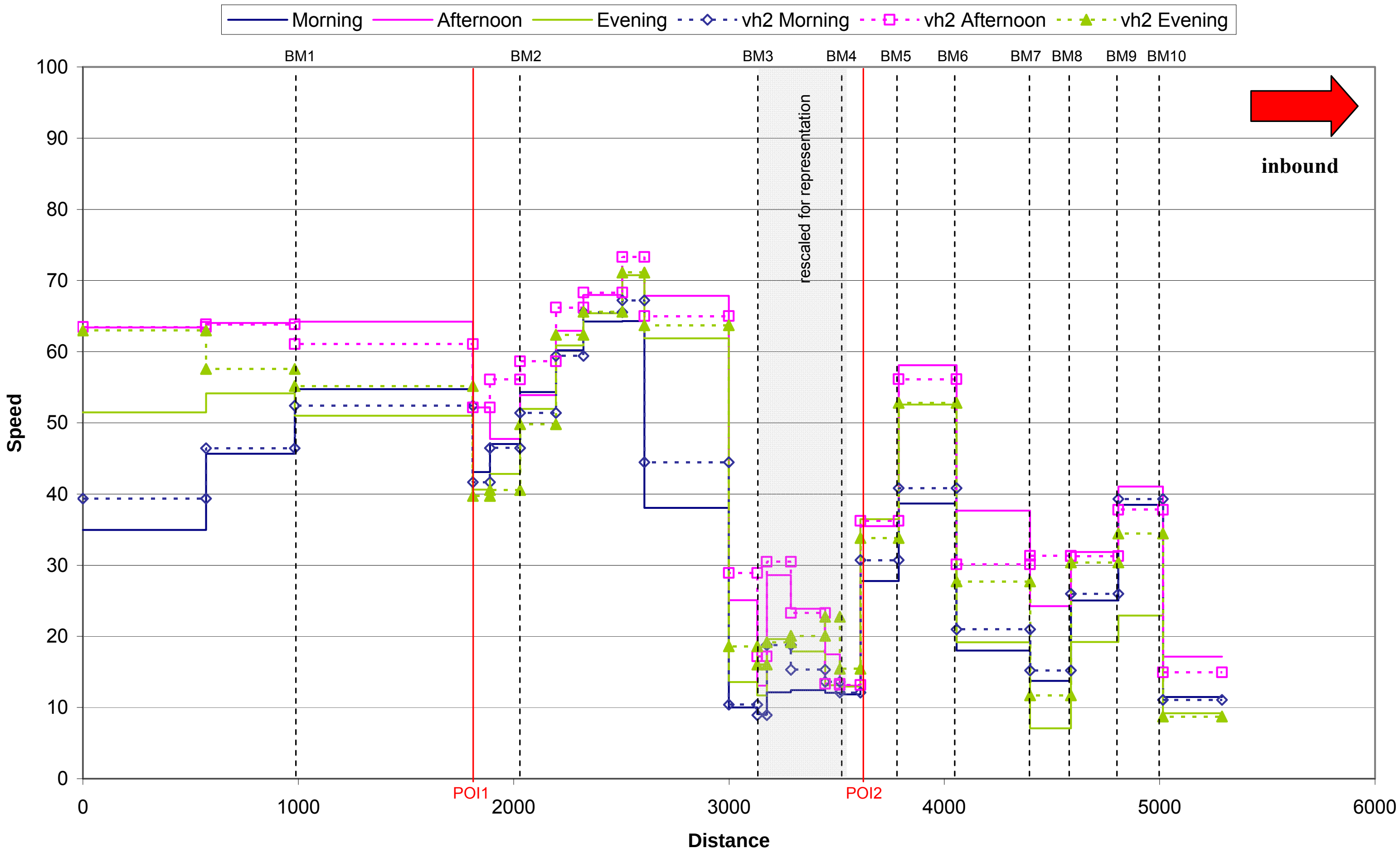

Figure 4.7b Overall link speeds versus average speed of Vehicle 2 for the three periods

In this study, sample size for link speeds is limited ($n < 20$), and both population mean μ and standard deviation σ are unknown. Therefore, *t*-distribution is assumed while estimating the population mean from the sample. Similarly, α-percent confidence interval for μ for each link i, which is needed for defining an acceptable lower limit for link speeds ${}_a\overline{v}_{i,l}^{\tau}$ in incident detection algorithm, is estimated from

$$\Pr\left(({}_a\overline{v}_i^{\tau})_n - t_{1-\alpha/2, n-1} \frac{{}_a(s_i)^{\tau}{}_n}{\sqrt{n}} < \mu_i^{\tau} < ({}_a\overline{v}_i^{\tau})_n + t_{1-\alpha/2, n-1} \frac{{}_a(s_i)^{\tau}{}_n}{\sqrt{n}} \right) = \alpha \qquad (4.1)$$

As an example, 95 percent confidence interval is chosen; however, the confidence interval in reality should be confirmed by on site observations.

Tables 4.1, 4.2 and 4.3 show mean values and standard deviation of link speeds and, upper and lower limits for 95-percent confidence interval. Although the probe vehicles continuously moved along the corridor, it might be noticed that the number of observations on some link might be differ from others. These are the locations where GPS is disconnected or the locations where TDA cannot match GPS track data on to links.

Table 4.1 Corridor characteristics in the morning peak (τ_1)

	Link Id	n	${}_a\overline{V}_i^{\tau_1}$ (kph)	${}_aS_i^{\tau_1}$ (kph)	95% Confidence Interval	
					*LL(kph)	*UL(kph)
INBOUND	1	10	43,29	17,74	30,6	55,98
	2	10	48,88	12,95	39,62	58,14
	3	10	56,66	10,69	49,01	64,31
	4	10	44,88	8,87	38,53	51,23
	5	10	48,28	8,19	42,42	54,14
	6	10	56,05	9,01	19,6	62,5
	7	10	60,91	6,57	56,21	65,61
	8	10	65,24	8,66	59,05	71,43
	9	10	65,47	8,87	59,12	71,82
	10	10	51,79	19,68	37,71	65,87
	11	10	12,25	6,37	7,69	16,81
	12	8	10,14	3,76	7	13,28
	13	10	21,50	13,50	11,84	31,16
	14	10	20,31	13,14	10,91	29,71
	15	10	16,20	11,76	7,79	24,61
	16	10	12,55	3,31	10,18	14,92
	17	10	31,27	9,25	24,65	37,89
	18	10	46,24	13,64	36,48	56
	19	10	23,31	12,94	14,05	32,57
	20	10	20,05	12,76	10,92	29,18
	21	10	28,10	10,94	20,27	35,93
	22	10	39,22	6,07	34,88	43,56
	23	10	15,99	12,45	7,08	24,9
OUTBOUND	25	9	37,00	6,05	32,35	41,65
	26	10	29,57	17,84	16,81	42,33
	27	10	21,85	10,57	14,29	29,41
	28	9	27,56	10,11	19,79	35,33
	29	9	13,06	7,39	7,38	18,74
	30	10	42,79	4,61	39,49	46,09
	31	10	27,88	10,96	20,04	35,72
	32	9	22,07	6,91	16,76	27,38
	33	9	36,78	13,93	26,07	47,49
	34	9	41,75	6,21	36,98	46,52
	35	9	57,16	5,43	52,99	61,33
	36	9	74,97	6,61	69,89	80,05
	37	9	79,22	8,27	72,86	85,58
	38	9	75,77	6,40	70,85	80,69
	39	9	78,57	7,31	72,95	84,19
	40	9	84,85	5,69	80,48	89,22
	41	9	78,62	9,71	71,16	86,08
	42	9	77,21	6,88	71,92	82,5
	43	8	61,05	5,61	56,36	65,74

(*) LL: lower limit
UL: upper limit

Table 4.2 Corridor characteristics in the noon off-peak (τ_2)

	Link Id	n	${}_a\overline{V}_i^{\tau_2}$ (kph)	${}_aS_i^{\tau_2}$ (kph)	95% Confidence Interval *LL(kph)	*UL(kph)
INBOUND	1	11	64,03	6,46	59,69	68,37
	2	11	64,65	6,47	60,3	69
	3	11	64,72	6,00	60,69	68,75
	4	11	55,39	15,88	44,72	66,06
	5	11	53,18	15,28	42,91	63,45
	6	10	54,63	9,47	47,86	61,4
	7	10	63,30	10,04	56,12	70,48
	8	10	67,73	7,76	62,18	73,28
	9	10	71,80	13,76	61,96	81,64
	10	10	67,68	7,34	62,43	72,93
	11	10	32,83	15,20	21,96	43,7
	12	10	16,44	7,63	10,98	21,9
	13	11	31,89	10,14	25,08	38,7
	14	11	25,23	5,85	21,3	29,16
	15	11	22,28	9,78	15,71	28,85
	16	9	13,40	2,15	11,75	15,05
	17	11	35,88	4,10	33,13	38,63
	18	11	58,44	4,83	55,2	61,68
	19	11	41,94	13,90	32,6	51,28
	20	11	29,75	12,59	21,29	38,21
	21	11	32,80	5,59	29,04	36,56
	22	11	41,70	5,68	37,88	45,52
	23	9	23,41	15,79	11,27	35,55
[redacted]						
OUTBOUND	25	11	44,20	4,88	40,92	47,48
	26	11	48,66	13,69	39,46	57,86
	27	11	37,27	11,56	29,5	45,04
	28	11	33,56	10,92	26,22	40,9
	29	11	21,97	14,14	12,47	31,47
	30	11	49,34	4,22	46,5	52,18
	31	11	37,29	11,68	29,44	45,14
	32	11	19,34	10,20	12,49	26,19
	33	10	44,33	4,01	41,46	47,2
	34	10	51,45	10,89	43,66	59,24
	35	11	59,63	6,59	55,2	64,06
	36	11	76,86	8,22	71,34	82,38
	37	11	81,42	9,52	75,02	87,82
	38	11	81,12	11,62	73,31	88,93
	39	10	82,32	9,72	75,37	89,27
	40	9	89,10	6,61	84,02	94,18
	41	9	86,01	6,38	81,11	90,91
	42	10	82,83	6,23	78,37	87,29
	43	11	61,49	9,14	55,35	67,63

(*) LL: lower limit
UL: upper limit

Table 4.3 Corridor characteristics in the evening peak (τ_3)

	Link Id	n	$_a\overline{V}_i^{\tau_3}$ (kph)	$_aS_i^{\tau_3}$ (kph)	95% Confidence Interval	
					*LL(kph)	*UL(kph)
	1	10	55,57	13,78	45,71	65,43
	2	10	56,84	13,15	47,43	66,25
	3	8	53,85	12,77	43,17	64,53
	4	9	43,02	10,14	35,23	50,81
	5	10	43,89	7,13	38,79	48,99
	6	10	52,28	4,28	49,22	55,34
	7	11	61,61	7,20	56,77	66,45
	8	11	65,93	6,00	61,9	69,96
I	9	9	71,66	8,68	64,99	78,33
N	10	9	62,52	6,75	57,33	67,71
B	11	10	21,42	15,04	10,66	32,18
O	12	11	14,82	8,48	9,12	20,52
U	13	11	24,94	11,51	17,21	32,67
N	14	11	20,59	8,03	15,2	25,98
D	15	11	17,58	9,78	11,01	24,15
	16	11	13,83	4,37	10,89	16,77
	17	11	36,87	4,11	34,11	39,63
	18	11	52,97	4,58	49,89	56,05
	19	11	28,55	17,60	16,73	40,37
	20	11	10,17	6,21	6	14,34
	21	11	23,63	10,37	16,66	30,6
	22	11	31,38	13,85	22,08	40,68
	23	9	9,95	3,11	7,56	12,34
	25	11	26,83	10,96	19,47	34,19
	26	11	15,70	10,97	8,33	23,07
	27	11	15,06	6,99	10,36	19,76
	28	11	20,05	9,79	13,47	26,63
	29	11	14,97	6,80	10,4	19,54
O	30	11	43,81	6,38	39,52	48,1
U	31	11	30,41	7,33	25,49	35,33
T	32	11	17,80	8,13	12,34	23,26
B	33	10	41,16	7,09	36,09	46,23
O	34	10	39,62	6,24	35,16	44,08
U	35	10	52,20	7,22	47,04	57,36
N	36	10	63,76	8,57	57,63	69,89
D	37	10	67,41	8,29	61,48	73,34
	38	10	67,27	9,37	60,57	73,97
	39	9	71,82	7,00	66,44	77,2
	40	9	81,49	11,34	72,77	90,21
	41	8	81,90	7,44	75,68	88,12
	42	8	79,57	8,70	72,3	86,84

(*) LL: lower limit
UL: upper limit

4.5 Bottleneck Location Detection

One of the objectives of this study is to detect potential bottleneck locations with an intelligent search algorithm. At this part, the results of proposed bottleneck algorithm will be checked against the observed bottleneck locations in data analysis part for validation.

For this step, time-dependent average speeds for consecutive links from Tables 4.1-4.3 used to search for speed variation according to difference function θ_i^τ, given in Eq.(3.4). The significant change in speed parameter ψ, is defined as 5 kph for this study, meaning that changes within ±5 kph in average link speed are disregarded surpassing small temporal irregularities in traffic. ψ can be assumed a greater value, if the variation between consecutive links is expected larger. ϕ_i^τ values are calculated for every lap of probe vehicles for every link in every τ period, providing relative frequencies of jump or drop in speed, or constant speed. From these relative frequencies, the speed variation parameter δ_i^τ, which carries directional information is derived for each link by finding the mean of change where jump is represented by "1", constant speed by "0" and drop by "-1". Then, the slow traffic regime parameter γ_i^τ is generated for each link on the study corridor for each time window.

After detecting bottleneck locations by δ_i^τ, the algorithm carried out the search for extent of impact zone by looking at consecutive upstream links. The upstream links are added to bottleneck impact zone, if slow traffic regime ($\gamma_i^\tau = 1$) is on them without interruption and bottleneck possibility index ϕ_i^τ at these links are set to "1". Tables 4.4-4.6 show the detected bottlenecks and their impact zones for the three time periods separately. In these tables, while dark shaded links show the bottleneck release points at the start of the link, light shaded links show the bottleneck impact zones and also the links which are tagged as potential locations due to speed variation are shaded in the tables. The detected bottleneck and their impact zones are shown on the map in Figures 4.8-4.10.

In the morning peak period, start of Link 17 is detected as bottleneck release and it is impact zone includes Links 16-11 (see Table 4.4 and Figure 4.8). Also the start node of Link 30 is identified as bottleneck release and its impact zone is Link 29. These two bottleneck locations can be validated by the observed bottleneck locations at BM3 in inbound direction and BM7 in outbound direction in section 4.3.

In the noon off-peak period, , the impact zone of the bottleneck at the upstream of Link 17 shortens to Links 16 and 15, which is probably due to lower demand at off-peak time (see Table 4.5 and Figure 4.9). The bottleneck release at Link 30 and its impact zone is again detected in this period. Furthermore, a bottleneck release at Link 33 is located and with impact zone extending to Link 32. This bottleneck was also observed at BM3 in section 4.3

In the evening peak period, the same bottleneck locations are detected as in noon off-peak (see Table 4.7 and Figure 4.10). However, the impact zones of bottleneck at Link 17 and at Link 30 are extended to Links 16-11 and to Link 29-26, respectively, which might be related to heavy evening peak traffic in both directions on the corridor. The results can also be seen on the map of the study corridor.

Table 4.4 Bottleneck locations and their impact zones in the morning peak

	Link Id	Speed variation relative frequencies $v_i > v_{i-1}$	$v_i < v_{i-1}$	$v_i \approx v_{i-1}$	δ_i^τ	${}_a\overline{v}_i^{\tau_3}$ (kph)	γ_i^τ	ϕ_i^τ
INBOUND	**1**	*	*	*	*	43,29	0	**0**
	2	0,50	0,00	0,50	0,50	48,88	0	**0**
	3	0,70	0,10	0,20	0,60	56,66	0	**0**
	4	0,00	0,90	0,10	-0,90	44,88	0	**0**
	5	0,40	0,00	0,60	0,40	48,28	0	**0**
	6	0,50	0,00	0,50	0,50	56,05	0	**0**
	7	0,60	0,00	0,40	0,60	60,91	0	**0**
	8	0,60	0,20	0,20	0,40	65,24	0	**0**
	9	0,10	0,20	0,70	-0,10	65,47	0	**0**
	10	0,00	0,70	0,30	-0,70	51,79	0	**0**
	11	0,00	1,00	0,00	-1,00	12,25	1	**1**
	12	0,13	0,25	0,63	-0,13	10,14	1	**1**
	13	0,75	0,00	0,25	0,75	21,50	1	**1**
	14	0,20	0,30	0,50	-0,10	20,31	1	**1**
	15	0,20	0,40	0,40	-0,20	16,20	1	**1**
	16	0,10	0,30	0,60	-0,20	12,55	1	**1**
	17	1,00	0,00	0,00	1,00	31,27	0	**0**
	18	0,90	0,00	0,10	0,90	46,24	0	**0**
	19	0,00	0,90	0,10	-0,90	23,31	1	**0**
	20	0,20	0,40	0,40	-0,20	20,05	1	**0**
	21	0,70	0,10	0,20	0,60	28,10	0	**0**
	22	0,70	0,00	0,30	0,70	39,22	0	**0**
	23	0,00	0,80	0,20	-0,80	15,99	1	**0**
OUTBOUND	**25**	*	*	*	*	37,00	0	**0**
	26	0,22	0,44	0,33	-0,22	29,57	0	**0**
	27	0,10	0,50	0,40	-0,40	21,85	1	**0**
	28	0,44	0,22	0,33	0,22	27,56	0	**0**
	29	0,11	0,89	0,00	-0,78	13,06	1	**1**
	30	1,00	0,00	0,00	1,00	42,79	0	**0**
	31	0,10	0,70	0,20	-0,60	27,88	0	**0**
	32	0,22	0,33	0,44	-0,11	22,07	1	**0**
	33	0,89	0,11	0,00	0,78	36,78	0	**0**
	34	0,44	0,22	0,33	0,22	41,75	0	**0**
	35	0,89	0,00	0,11	0,89	57,16	0	**0**
	36	1,00	0,00	0,00	1,00	74,97	0	**0**
	37	0,56	0,11	0,33	0,44	79,22	0	**0**
	38	0,22	0,44	0,33	-0,22	75,77	0	**0**
	39	0,44	0,22	0,33	0,22	78,57	0	**0**
	40	0,67	0,00	0,33	0,67	84,85	0	**0**
	41	0,00	0,67	0,33	-0,67	78,62	0	**0**
	42	0,11	0,33	0,56	-0,22	77,21	0	**0**

(*) Difference function is calculated starting from second link in each direction

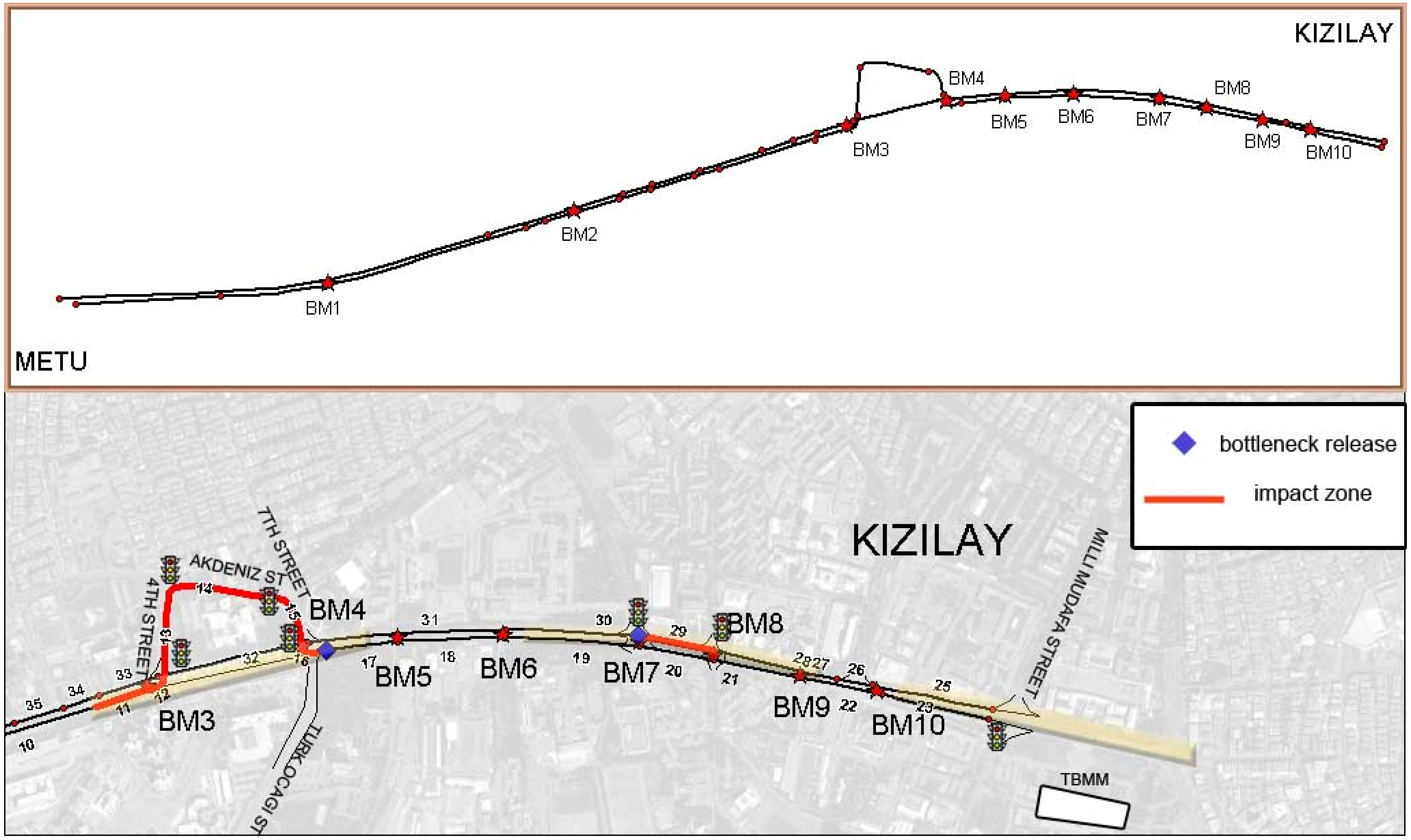

Figure 4.8 Bottlenecks and their possible impact zones in the morning peak

Table 4.5 Bottleneck locations and their impact zones in the noon off-peak

	Link Id	Speed variation relative frequencies			δ_i^τ	${}_a\overline{V}_i^{\tau_3}$ (kph)	γ_i^τ	ϕ_i^τ
		$v_i>v_{i-1}$	$v_i<v_{i-1}$	$v_i\approx v_{i-1}$				
	1	*	*	*	*	64,03	0	**0**
	2	0,09	0,09	0,82	0,00	64,65	0	**0**
	3	0,18	0,18	0,64	0,00	64,72	0	**0**
	4	0,09	0,82	0,09	-0,73	55,39	0	**0**
	5	0,27	0,36	0,36	-0,09	53,18	0	**0**
	6	0,30	0,20	0,50	0,10	54,63	0	**0**
	7	0,70	0,00	0,30	0,70	63,30	0	**0**
	8	0,60	0,30	0,10	0,30	67,73	0	**0**
I	**9**	0,40	0,10	0,50	0,30	71,80	0	**0**
N	**10**	0,30	0,40	0,30	-0,10	67,68	0	**0**
B	**11**	0,00	1,00	0,00	-1,00	32,83	0	**0**
O	**12**	0,00	0,89	0,11	-0,89	16,44	1	**0**
U	**13**	0,70	0,20	0,10	0,50	31,89	0	**0**
N	**14**	0,09	0,45	0,45	-0,36	25,23	0	**0**
D	**15**	0,18	0,45	0,36	-0,27	22,28	1	**1**
	16	0,00	0,67	0,33	-0,67	13,40	1	**1**
	17	1,00	0,00	0,00	1,00	35,88	0	**0**
	18	1,00	0,00	0,00	1,00	58,44	0	**0**
	19	0,09	0,73	0,18	-0,64	41,94	0	**0**
	20	0,27	0,64	0,09	-0,36	29,75	0	**0**
	21	0,45	0,27	0,27	0,18	32,80	0	**0**
	22	0,73	0,00	0,27	0,73	41,70	0	**0**
	23	0,11	0,67	0,22	-0,56	23,41	1	**0**
	25	*	*	*	*	44,20	0	**0**
	26	0,45	0,09	0,45	0,36	48,66	0	**0**
	27	0,00	0,73	0,27	-0,73	37,27	0	**0**
	28	0,82	0,45	-0,27	0,36	33,56	0	**0**
	29	0,18	0,64	0,18	-0,45	21,97	1	**1**
O	**30**	1,00	0,00	0,00	1,00	49,34	0	**0**
U	**31**	0,18	0,64	0,18	-0,45	37,29	0	**0**
T	**32**	0,00	0,91	0,09	-0,91	19,34	1	**1**
B	**33**	0,90	0,00	0,10	0,90	44,33	0	**0**
O	**34**	0,50	0,10	0,40	0,40	51,45	0	**0**
U	**35**	0,50	0,00	0,50	0,50	59,63	0	**0**
N	**36**	0,91	0,09	0,00	0,82	76,86	0	**0**
D	**37**	0,45	0,00	0,55	0,45	81,42	0	**0**
	38	0,00	0,36	0,64	-0,36	81,12	0	**0**
	39	0,30	0,00	0,70	0,30	82,32	0	**0**
	40	0,67	0,00	0,33	0,67	89,10	0	**0**
	41	0,11	0,44	0,44	-0,33	86,01	0	**0**
	42	0,00	0,44	0,56	-0,44	82,83	0	**0**

(*) Difference function is calculated starting from second link in each direction

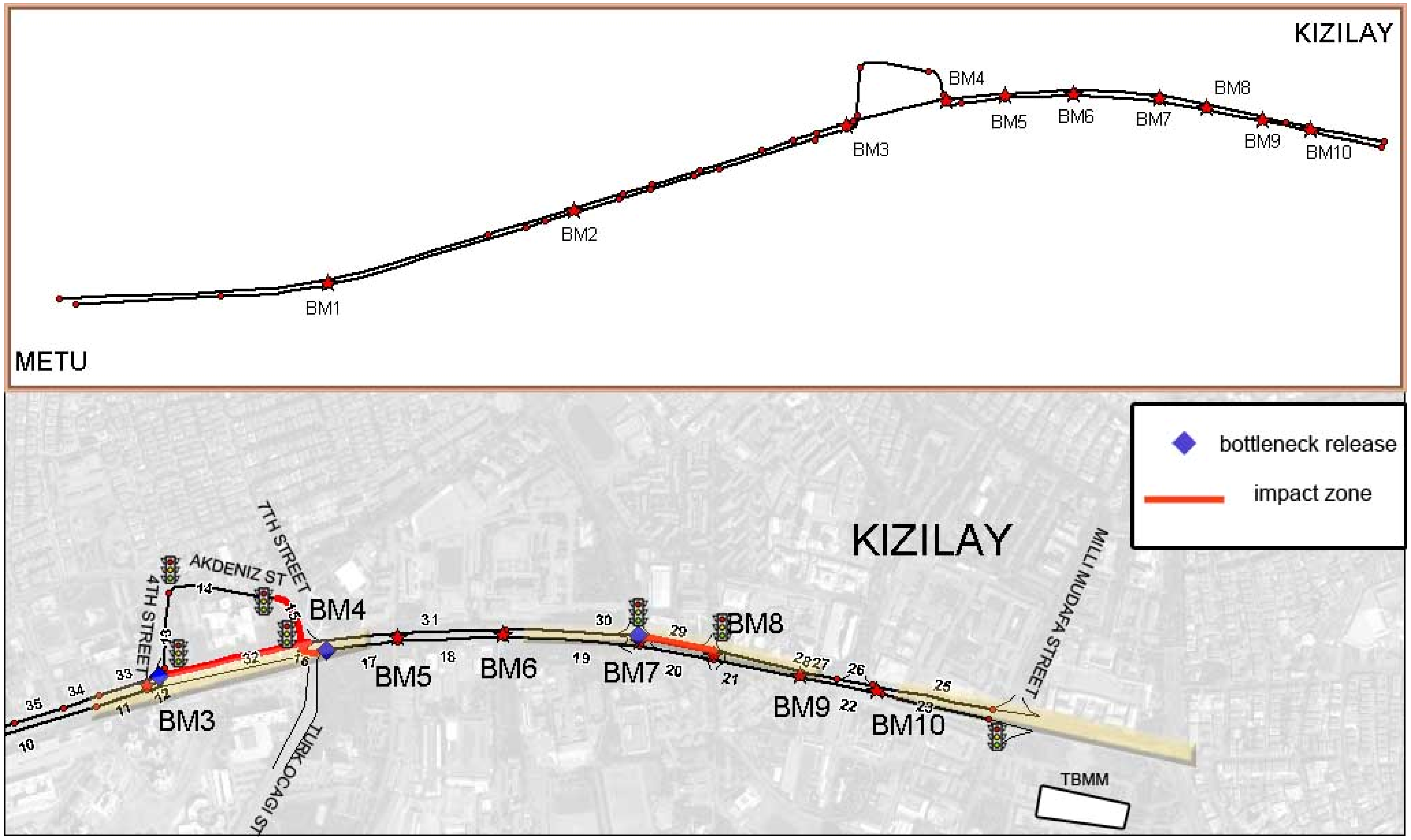

Figure 4.9 Bottlenecks and their possible impact zones in the noon off-peak

Table 4.6 Bottleneck locations and their impact zones in the evening peak

	Link Id	Speed variation relative frequencies			δ_i^{τ}	${}_a\bar{v}_i^{\tau_3}$ (kph)	γ_i^{τ}	ϕ_i^{τ}
		$v_{i+1}-v_i>5$	$v_{i+1}-v_i<-5$	$5>v_{i+1}-v_i>-5$				
	1	*	*	*	*	55,57	0	**0**
	2	0,25	0,33	0,42	-0,08	56,84	0	**0**
	3	0,30	0,30	0,40	0,00	53,85	0	**0**
	4	0,10	0,90	0,00	-0,80	43,02	0	**0**
	5	0,27	0,09	0,64	0,18	43,89	0	**0**
	6	0,75	0,08	0,17	0,67	52,28	0	**0**
	7	0,50	0,00	0,50	0,50	61,61	0	**0**
	8	0,75	0,17	0,08	0,58	65,93	0	**0**
I	**9**	0,45	0,09	0,45	0,36	71,66	0	**0**
N	**10**	0,00	0,64	0,36	-0,64	62,52	0	**0**
B	**11**	0,00	0,91	0,09	-0,91	21,42	1	**1**
O	**12**	0,08	0,42	0,50	-0,33	14,82	1	**1**
U	**13**	0,62	0,15	0,23	0,46	24,94	1	**1**
N	**14**	0,23	0,46	0,31	-0,23	20,59	1	**1**
D	**15**	0,15	0,46	0,38	-0,31	17,58	1	**1**
	16	0,08	0,38	0,54	-0,31	13,83	1	**1**
	17	1,00	0,00	0,00	1,00	36,87	0	**0**
	18	1,00	0,00	0,00	1,00	52,97	0	**0**
	19	0,08	0,77	0,15	-0,69	28,55	0	**0**
	20	0,08	0,77	0,15	-0,69	10,17	1	**0**
	21	0,77	0,08	0,15	0,69	23,63	1	**0**
	22	0,54	0,08	0,38	0,46	31,38	0	**0**
	23	0,00	0,91	0,09	-0,91	9,95	1	**0**
	25	*	*	*	*	26,83	0	**0**
	26	0,00	0,77	0,23	-0,77	15,70	1	**1**
	27	0,23	0,23	0,54	0,00	15,06	1	**1**
	28	0,38	0,15	0,46	0,23	20,05	1	**1**
	29	0,15	0,54	0,31	-0,38	14,97	1	**1**
O	**30**	1,00	0,00	0,00	1,00	43,81	0	**0**
U	**31**	0,08	0,77	0,15	-0,69	30,41	0	**0**
T	**32**	0,08	0,69	0,23	-0,62	17,80	1	**1**
B	**33**	1,00	0,00	0,00	1,00	41,16	0	**0**
O	**34**	0,17	0,33	0,50	-0,17	39,62	0	**0**
U	**35**	0,75	0,00	0,25	0,75	52,20	0	**0**
N	**36**	0,92	0,00	0,08	0,92	63,76	0	**0**
D	**37**	0,33	0,17	0,50	0,17	67,41	0	**0**
	38	0,25	0,25	0,50	0,00	67,27	0	**0**
	39	0,45	0,18	0,36	0,27	71,82	0	**0**
	40	0,73	0,09	0,18	0,64	81,49	0	**0**
	41	0,30	0,30	0,40	0,00	81,90	0	**0**
	42	0,00	0,40	0,60	-0,40	79,57	0	**0**

(*) Difference function is calculated starting from second link in each direction

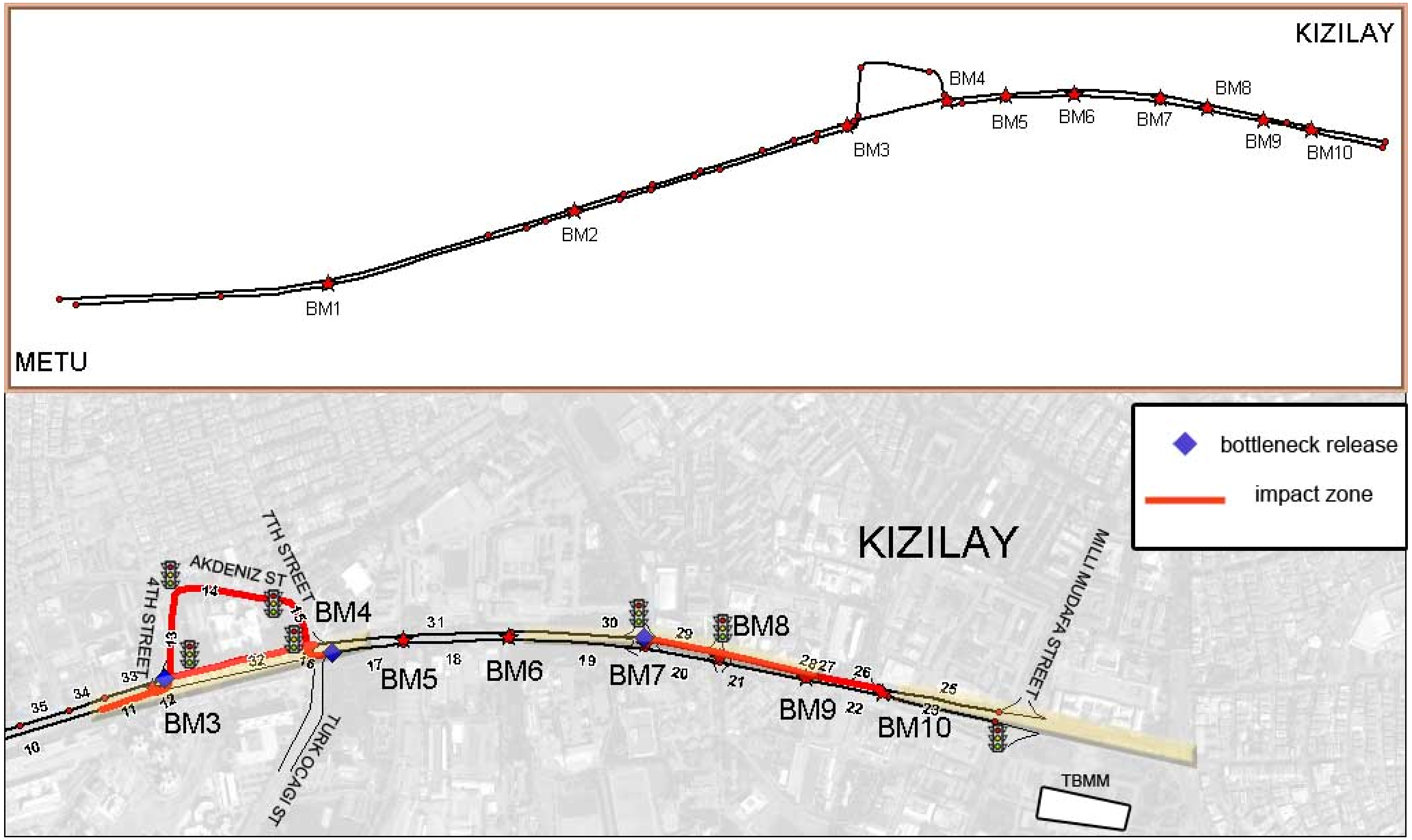

Figure 4.10 Bottlenecks and their possible impact zones in the evening peak

The location which is labeled as POI1 in the Section 4.3, is not detected by the algorithm. Because, although, average link speeds drop at this section, the speed jump at a bottleneck release is not identified after POI1 suggesting congestion due to effect of in city traffic.

4.6 Sensitivity Analysis for Speed Variation and Slow Regime Parameters

While identifying potential bottleneck locations and their impact zones, the speed variation and slow regime parameters are assigned cut-off values of 0,9 and 25 kph, respectively, based on prior knowledge on the corridor. However, the sensitivity of the algorithm for these threshold values must be checked. For this purpose, different threshold values for both parameters are selected as $\lambda_1 = 30$ kph and $\lambda_1 = 25$ kph for slow regime parameter γ; and $\delta_1 = 0,7$ and $\delta_2 = 0,9$ for the speed variation parameter. The scenario analysis for two sets of parameters yield in 4 different bottleneck searches for each time window, $\phi^{\tau}_{0.7,25}$, $\phi^{\tau}_{0.7,30}$, $\phi^{\tau}_{0.9,25}$, $\phi^{\tau}_{0.9,30}$, where the two subscripts represent the selected value of δ^{τ}_i and γ^{τ}_i, respectively.

Using a lower cut-off limit for speed variation such as 0.70 leads to 4 more possible bottleneck release points (Links 13 and 22 in the inbound and Links 33 and 35 in the outbound direction) in the morning peak period (see Table 4.7). At the Link 33, the bottleneck is confirmed for both 25 kph or 30 kph for slow regime limit; with an impact zone of Link 32 for the former case, and impact zone of Links 32 and 31 for the latter. At Link 22, a bottleneck release is confirmed with slow regime limit of 30 kph, suggesting that even if Link 22 is a possible bottleneck location, the upstream conditions are not as severe as the other bottleneck situations and detected only when the slow regime threshold is extended. On Link 13, while a possible bottleneck is

Table 4.7 Sensitivity of the threshold value of speed variation and slow regime parameter in the morning peak

	Link Id	$\delta_i^\tau = 0,7$	$\delta_i^\tau = 0,9$	$\gamma_i^\tau = 25$	$\gamma_i^\tau = 30$	$\phi_{0.7,25}^\tau$	$\phi_{0.7,30}^\tau$	$\phi_{0.9,25}^\tau$	$\phi_{0.9,30}^\tau$
	1	*	*	0	0	*	*	*	*
	2	0,50	0,50	0	0	0	0	0	0
	3	0,60	0,60	0	0	0	0	0	0
	4	-0,90	-0,90	0	0	0	0	0	0
	5	0,40	0,40	0	0	0	0	0	0
	6	0,50	0,50	0	0	0	0	0	0
	7	0,60	0,60	0	0	0	0	0	0
	8	0,40	0,40	0	0	0	0	0	0
I	9	-0,10	-0,10	0	0	0	0	0	0
N	10	-0,70	-0,70	0	0	0	0	0	0
B	11	-1,00	-1,00	1	1	1	1	1	1
O	12	-0,13	-0,13	1	1	1	1	1	1
U	13	0,75	0,75	1	1	1	1	1	1
N	14	-0,10	-0,10	1	1	1	1	1	1
D	15	-0,20	-0,20	1	1	1	1	1	1
	16	-0,20	-0,20	1	1	1	1	1	1
	17	1,00	1,00	0	0	0	0	0	0
	18	0,90	0,90	0	0	0	0	0	0
	19	-0,90	-0,90	1	1	0	0	0	0
	20	-0,20	-0,20	1	1	0	0	0	0
	21	0,60	0,60	0	1	0	0	0	0
	22	0,70	0,70	0	0	0	0	0	0
	23	-0,80	-0,80	1	1	0	0	0	0
	25	*	*	0	0	*	*	*	*
	26	-0,22	-0,22	0	1	0	1	0	1
	27	-0,40	-0,40	1	1	0	1	0	1
	28	0,22	0,22	0	1	0	1	0	1
	29	-0,78	-0,78	1	1	1	1	1	1
O	30	1,00	1,00	0	0	0	0	0	0
U	31	-0,60	-0,60	0	1	0	1	0	0
T	32	-0,11	-0,11	1	1	1	1	0	0
B	33	0,78	0,78	0	0	0	0	0	0
O	34	0,22	0,22	0	0	0	0	0	0
U	35	0,89	0,89	0	0	0	0	0	0
N	36	1,00	1,00	0	0	0	0	0	0
D	37	0,44	0,44	0	0	0	0	0	0
	38	-0,22	-0,22	0	0	0	0	0	0
	39	0,22	0,22	0	0	0	0	0	0
	40	0,67	0,67	0	0	0	0	0	0
	41	-0,67	-0,67	0	0	0	0	0	0
	42	-0,22	-0,22	0	0	0	0	0	0

(*) Difference function is calculated starting from second link in each direction

Table 4.8 Sensitivity of the threshold value of speed variation and slow regime parameter in the noon off-peak

	Link Id	$\delta_i^\tau = 0,7$	$\delta_i^\tau = 0,9$	$\gamma_i^\tau = 25$	$\gamma_i^\tau = 30$	$\phi_{0.7,25}^\tau$	$\phi_{0.7,30}^\tau$	$\phi_{0.9,25}^\tau$	$\phi_{0.9,30}^\tau$
INBOUND	1	*	*	0	0	0	0	0	0
	2	0,00	0,00	0	0	0	0	0	0
	3	0,00	0,00	0	0	0	0	0	0
	4	-0,73	-0,73	0	0	0	0	0	0
	5	-0,09	-0,09	0	0	0	0	0	0
	6	0,10	0,10	0	0	0	0	0	0
	7	0,70	0,70	0	0	0	0	0	0
	8	0,30	0,30	0	0	0	0	0	0
	9	0,30	0,30	0	0	0	0	0	0
	10	-0,10	-0,10	0	0	0	0	0	0
	11	-1,00	-1,00	0	0	0	0	0	0
	12	-0,89	-0,89	1	1	0	0	0	0
	13	0,50	0,50	0	0	0	0	0	0
	14	-0,36	-0,36	0	0	0	0	0	0
	15	-0,27	-0,27	1	1	1	1	1	1
	16	-0,67	-0,67	1	1	1	1	1	1
	17	1,00	1,00	0	0	0	0	0	0
	18	1,00	1,00	0	0	0	0	0	0
	19	-0,64	-0,64	0	0	0	0	0	0
	20	-0,36	-0,36	0	1	0	0	0	0
	21	0,18	0,18	0	0	0	0	0	0
	22	0,73	0,73	0	0	0	0	0	0
	23	-0,56	-0,56	1	1	0	0	0	0
OUTBOUND	25	*	*	0	0	0	0	0	0
	26	0,36	0,36	0	0	0	0	0	0
	27	-0,73	-0,73	0	0	0	0	0	0
	28	0,36	0,36	0	0	0	0	0	0
	29	-0,45	-0,45	1	1	1	1	1	1
	30	1,00	1,00	0	0	0	0	0	0
	31	-0,45	-0,45	0	0	0	0	0	0
	32	-0,91	-0,91	1	1	1	1	1	1
	33	0,90	0,90	0	0	0	0	0	0
	34	0,40	0,40	0	0	0	0	0	0
	35	0,50	0,50	0	0	0	0	0	0
	36	0,82	0,82	0	0	0	0	0	0
	37	0,45	0,45	0	0	0	0	0	0
	38	-0,36	-0,36	0	0	0	0	0	0
	39	0,30	0,30	0	0	0	0	0	0
	40	0,67	0,67	0	0	0	0	0	0
	41	-0,33	-0,33	0	0	0	0	0	0
	42	-0,44	-0,44	0	0	0	0	0	0

(*) Difference function is calculated starting from second link in each direction

Table 4.9 Sensitivity of the threshold value of speed variation and slow regime parameter in the evening peak

	Link Id	$\delta_i^\tau = 0,7$	$\delta_i^\tau = 0,9$	$\gamma_i^\tau = 25$	$\gamma_i^\tau = 30$	$\phi^\tau_{0.7,25}$	$\phi^\tau_{0.7,30}$	$\phi^\tau_{0.9,25}$	$\phi^\tau_{0.9,30}$
	1	*	*	0	0	0	0	0	0
	2	-0,08	-0,08	0	0	0	0	0	0
	3	0,00	0,00	0	0	0	0	0	0
	4	-0,80	-0,80	0	0	0	0	0	0
	5	0,18	0,18	0	0	0	0	0	0
	6	0,67	0,67	0	0	0	0	0	0
	7	0,50	0,50	0	0	0	0	0	0
	8	0,58	0,58	0	0	0	0	0	0
I	9	0,36	0,36	0	0	0	0	0	0
N	10	-0,64	-0,64	0	0	0	0	0	0
B	11	-0,91	-0,91	1	1	1	1	1	1
O	12	-0,33	-0,33	1	1	1	1	1	1
U	13	0,46	0,46	1	1	1	1	1	1
N	14	-0,23	-0,23	1	1	1	1	1	1
D	15	-0,31	-0,31	1	1	1	1	1	1
	16	-0,31	-0,31	1	1	1	1	1	1
	17	1,00	1,00	0	0	0	0	0	0
	18	1,00	1,00	0	0	0	0	0	0
	19	-0,69	-0,69	0	1	0	0	0	0
	20	-0,69	-0,69	1	1	0	0	0	0
	21	0,69	0,69	1	1	0	0	0	0
	22	0,46	0,46	0	0	0	0	0	0
	23	-0,91	-0,91	1	1	0	0	0	0
	25	*	*	0	1	0	1	0	1
	26	-0,77	-0,77	1	1	1	1	1	1
	27	0,00	0,00	1	1	1	1	1	1
	28	0,23	0,23	1	1	1	1	1	1
	29	-0,38	-0,38	1	1	1	1	1	1
O	30	1,00	1,00	0	0	0	0	0	0
U	31	-0,69	-0,69	0	0	0	0	0	0
T	32	-0,62	-0,62	1	1	1	1	1	1
B	33	1,00	1,00	0	0	0	0	0	0
O	34	-0,17	-0,17	0	0	0	0	0	0
U	35	0,75	0,75	0	0	0	0	0	0
N	36	0,92	0,92	0	0	0	0	0	0
D	37	0,17	0,17	0	0	0	0	0	0
	38	0,00	0,00	0	0	0	0	0	0
	39	0,27	0,27	0	0	0	0	0	0
	40	0,64	0,64	0	0	0	0	0	0
	41	0,00	0,00	0	0	0	0	0	0
	42	-0,40	-0,40	0	0	0	0	0	0

(*) Difference function is calculated starting from second link in each direction

confirmed, it can be also seen that this is a part of a bottleneck queue starting from Link 16. The other possible location (Link 35) can not be confirmed as bottlenecks as the upstream conditions do not suggest severe limits.

Similar analysis for the noon off-peak and evening peak periods presents a) two additional possible bottleneck locations for the former (Links 36, 22 and 7) and b) one additional location for the latter (Link 35). However, none of these locations was confirmed as bottlenecks as the upstream conditions were not detected as slow regimes with either of the limits, 25 kph or 30 kph (see Tables 4.8 and 4.9).

Among the four combinations, definitely $\delta = 0,9$ and $\gamma = 25$ is the most conservative case while $\delta = 0,7$ and $\gamma = 30$ is the least conservative one. Even the most conservative case does not detect bottleneck locations very different than the others or inconsistent with on-site observations, suggesting that on the İnönü Boulevard corridor, slow regime can be chosen as either limit, 25 kph or 30 kph. This also suggests that the bottlenecks on this corridor are chronic situations that are not defined by some mathematical limits only.

Looking at the number of possible bottleneck locations and their impacts as a function of the threshold values for slow regime and speed variation parameters, it can be concluded that a) a lower cut-off limit for speed variation results in detection of more bottleneck releases and b) a higher value for slow traffic regime parameter results in detection of longer impact zones of bottlenecks or confirmation of more bottleneck locations.

4.7 Incident Detection from Control Data

Since incidents are generally random events, it is very difficult to encounter an incident while collecting traffic control data. Luckily, in a previous data collection attempt (on the May 30th, 2007) in the selected corridor using same time periods, unannounced road maintenance resulting in a lane blocking incident at Link 42 was observed (see Figure 4.11). The incident caused a capacity loss of approximately 2 lanes and 1 lane during the morning peak and noon off-peak periods, respectively. By the evening peak data collection time, the maintenance was finished. This non-recurrent event can be used as an exercise to test the proposed incident detection algorithm. Unfortunately, the data collection routes for the incident day and incident free days had minor differences at the start and end points; such that the former route goes straight through the METU intersection, while the latter merges on to the Anadolu Boulevard to loop. The impact of these different movements in the link speed calculations is expected to be negligible, if there is any. Link 43 is added to the network (see Figure 4.11) to represent this part of the corridor that was previously discarded to study the inbound and outbound segment comparatively.

The incident detection algorithm compares the real-time link speed values against pre-defined archival link speeds and lower limits to foresee an incident. In this control example, the incident day link speeds can be treated as the "real time" values retrospectively and checked against archival link values from incident free days (see Figure 4.12 -4.14).

The archival link speeds suggest an almost constant travel speed through Links 41 and 42 (around 75-80 kph) followed by drop in speed at Link 43 down to close to 60 kph (possibly due a merge movement at the end of the data collection route). This travel pattern is observed persistently through all three time periods. Based on the calculated link speeds, the 95-percent confidence intervals for the link speeds are calculated proving a lower limit (LL) for each link (see Table 4.8). ϕ_i^τ values show that historically these 3 links are not expected to be in a bottleneck impact zone.

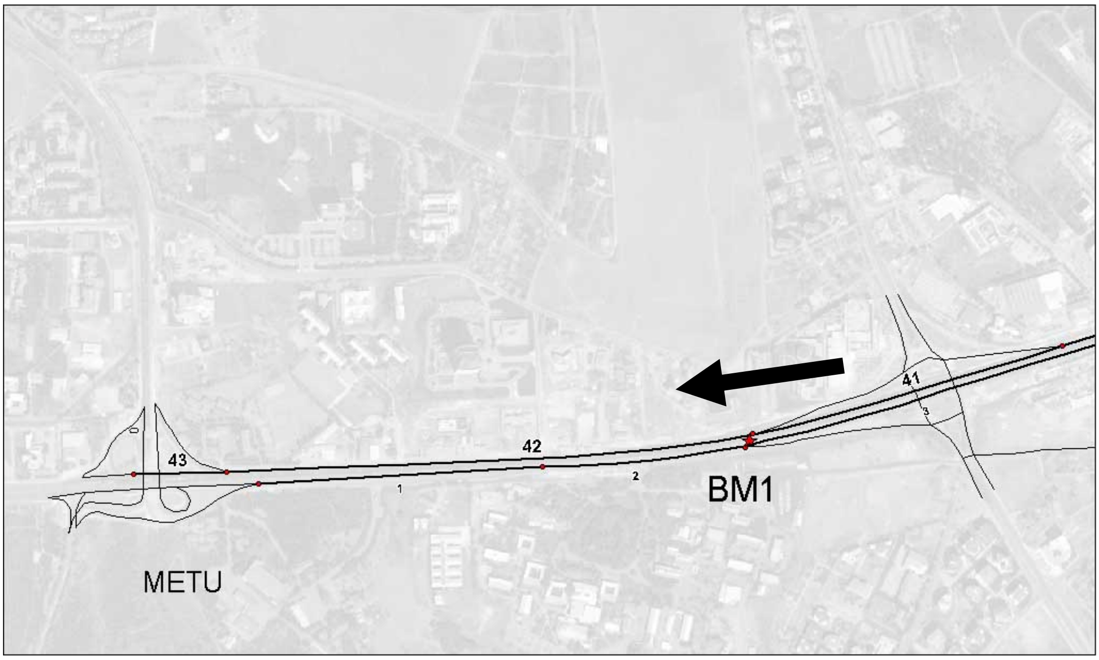

Figure 4.11 Links used in incident detection

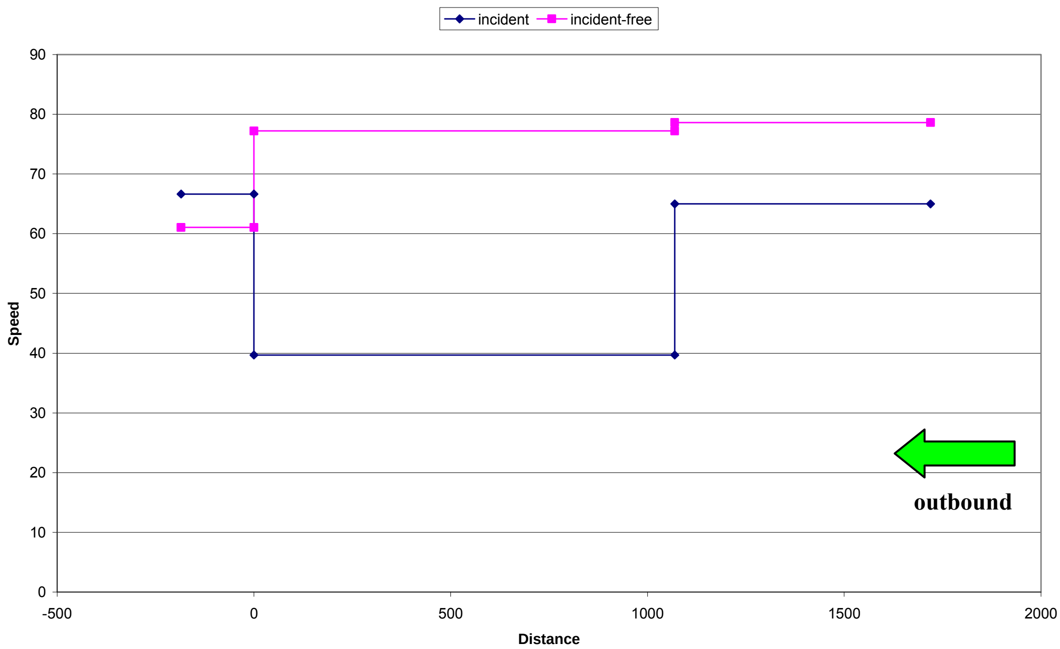

Figure 4.12 Link speeds in the morning peak period on the day of incident versus archival values (incident-free days)

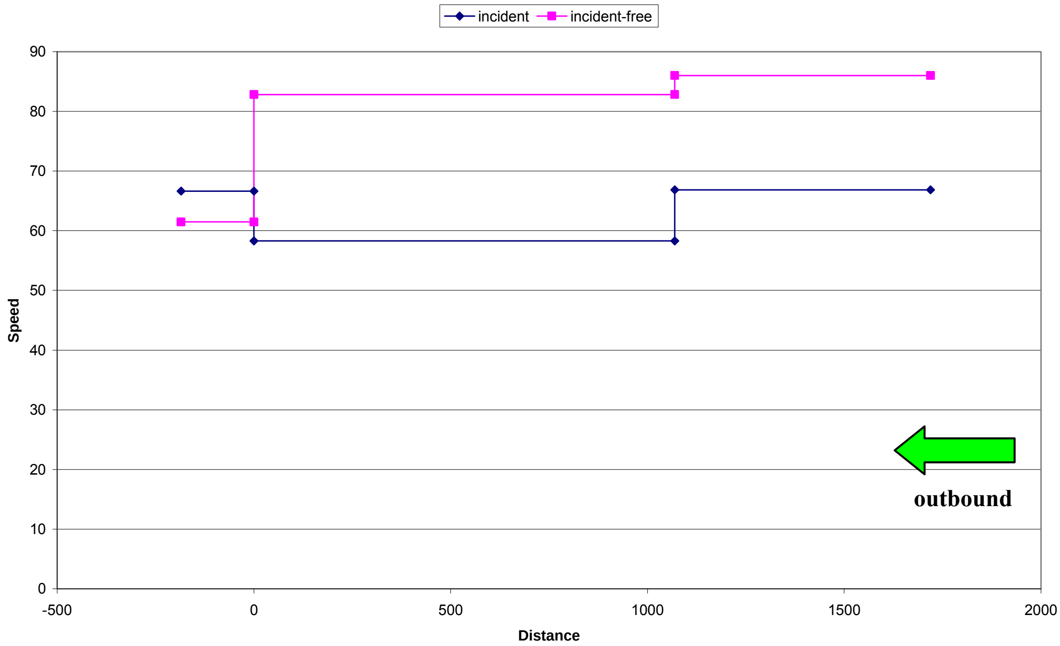

Figure 4.13 Link speeds in the noon off-peak period on the day of incident versus archival values (incident-free days)

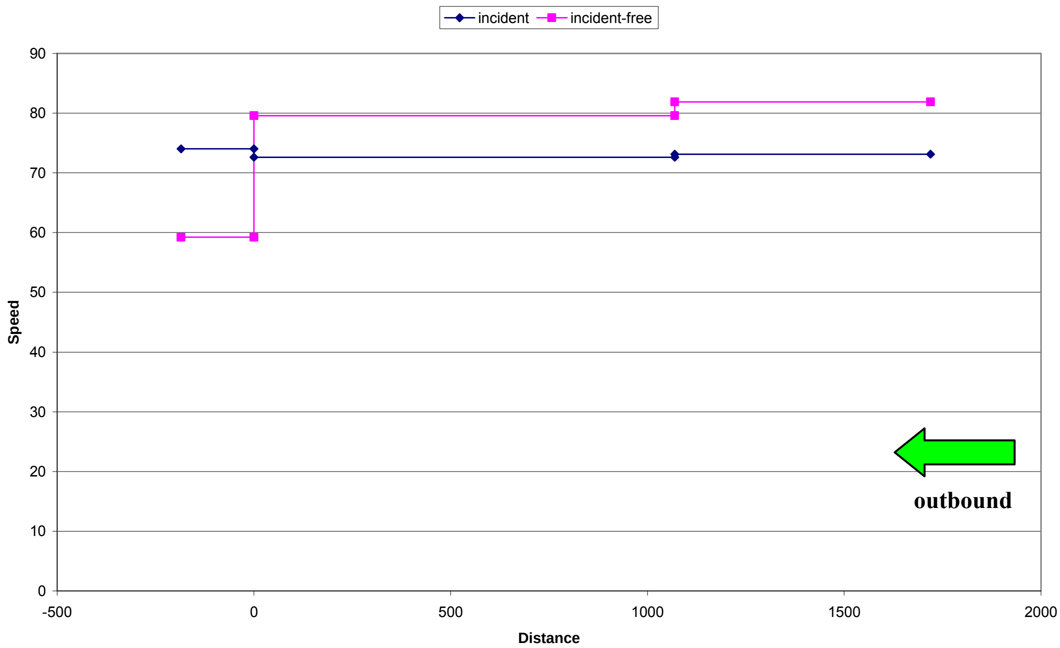

Figure 4.14 Link speeds in the evening peak period on the day of incident versus archival values (incident-free days)

When the two lanes were blocked by the incident the morning, the speed at link 42 is the least and the behavior in the traffic can be recognized at the link, which is drop in speed at the link entrance and jump in speed at the end of the link (see Figure 4.12). Then, the effect of work zone lessens when a single is blocked; however, drop and jump in speed is still distinctive (see Figure 4.13).

As stated before, the impact of the incident was cleared by the evening peak period, where the incident day and archival link speed values would represent the uncertainty in the traffic conditions except for incidents. Supporting this, in Figure 4.14, the speeds for Links 41 and 42, for the incident day and the archival values, are almost constant at around 70 kph and 80 kph, respectively. This approximately 10 kph difference may be due to seasonal change in demand between spring and summer. Later, on Link 43, the difference in the speed for the day of the incident and the archival value can be explained by the different movements of the routes in the link as explained before (thru versus diverge to off-ramp).

<u>Tracing and Evaluation of the Proposed Incident Detection Algorithm</u>

As proposed in Section 3.3, to detect an incident in the network along the followed route for a given time period, the real-time traffic measures are used in association with the archival values and information. This algorithm is employed for the 3-link corridor for the three time periods. The results are shown in Table 4.9.

In the morning peak, real-time link speed is less than the lower limit; therefore incident detection algorithm is executed. First, bottleneck possibility index is checked at the link. Since the bottleneck possibility index is “0”, the algorithm set incident possibility index as “1”.At Link 42, the link speed is again less than acceptable lower limit; therefore, bottleneck possibility is checked and incident possibility index is set to “1”. The link speed exceeds the lower limit at Link 43 so the location of incident is reported as Link 42 and Link 41 is considered as impact zone then procedure is terminated. The incident is detected by the algorithm in approximately 181 seconds.

In the afternoon, the real-time link speed of Link 41 is again less than the lower limit, therefore algorithm checked bottleneck possibility index and incident possibility index is set to “1” The speed at Link 42 is also less than lower limit so bottleneck possibility index is checked and incident possibility index is set to “1” for this link. At Link 43, the real-time speed is higher than the lower limit for the link so the location of incident is reported as Link 42 and Link 41 is considered as impact zone then procedure is terminated. The incident is detected in 99 seconds.

Table 4.10 The parameters used in the algorithm at different time periods

Morning				
Link Id	v_i^τ	${}_a v_{i,l}^\tau$ *	ϕ_i^τ	η_i^τ
41	65,00	71,16	0	1
42	39,68	71,92	0	1
43	66,64	56,36	0	0
Noon				
Link Id	v_i^τ	${}_a v_{i,l}^\tau$ *	ϕ_i^τ	η_i^τ
41	66,86	81,11	0	1
42	58,31	78,37	0	1
43	66,64	55,35	0	0
Evening				
Link Id	v_i^τ	${}_a v_{i,l}^\tau$ *	ϕ_i^τ	η_i^τ
41	73,13	75,68	0	1
42	72,61	72,30	0	0
43	74,04	55,52	0	0

(*) lower limit for 95-percent confidence interval

In the evening, since the real-time link speed is slightly less than the lower limit, bottleneck possibility index is checked at the link and then incident possibility index is set to “1”. The speed at Link 42 is slightly higher than lower limit. Therefore, the algorithm falsely detects the location of incident as Link 41.

CHAPTER 5

CONCLUSION

In this study a comprehensive methodology for incident detection with GPS equipped vehicles is developed. This methodology depends mainly on detection of certain link speed patterns along a corridor, such as sudden jumps in the speeds of consecutive links after a slow regime, suggesting a queue formation. However, it is also important to distinguish the causing phenomenon behind a possible queue, as it can be due to a recurrent congestion such as a chronic bottleneck case, as well as an incident. Since the probe-based detection technologies are not always capable of collecting data on both the upstream and downstream condition of a location (especially in a single probe vehicle case), archival values for certain traffic measures can be used as a guideline to make this distinction. For either case, the queues will be time-dependent as a result of a) time-dependent demand characteristics in recurrent congestions or b) time-dependent capacity loss in case of incidents. Thus, the proposed methodology has to be a time-dependent analysis inherently.

In this study, the proposed incident detection methodology using GPS-equipped probe vehicles pre-requires development of

- a time-dependent corridor characteristics database (TCCD)
- a retrospective bottleneck analysis
- an incident detection algorithm

which are individually developed. These sub modules use selected traffic measures such as average link speeds and probabilistic distributions, speed variations between two consecutive links, slow regime characteristics, and produce bottleneck and incident detection possibility measures for every link in any time window in the corridor. Comparative analysis of these two measures along consecutive links also yield information on the possible location and impact zones of bottlenecks or incidents. The methodology and individual modules are tested over a selected study corridor in the City of Ankara with control GPS data. The highlights of the study is given in the next section while further improvement and research possibilities are discussed in the last section of this chapter.

5.1 Conclusions

In the development of the methodology, the major issues addressed can be summarized as follows:

- The methodology proposed foresees use of GPS track data to calculate link speeds. Thus, network representation of the study region has to comply with the data format and precision of GPS devices used. As the GPS track data will be mapped on the traffic network, the more precise representation of the geometric features of the network will contribute to the success of the whole methodology.
- On a corridor, where demand characteristics vary significantly over a day, this must be stored in the archival values properly. Thus, the time-dependent nature of the conditions must be represented by as many time windows, as need (such as morning peak, noon off-peak, evening peak, nighttime or even hourly) to avoid any loss of traffic characteristics due to unnecessary averaging. If there are significant changes between different days, or periods of the year, such as weekdays versus weekends or seasonal changes, the TCCD has to provide appropriate dimensions for the selected measure
- The threshold values for decision parameters (such as lower limits for links speeds, cut-off limits on speed variation parameter for bottleneck detection, slow traffic regime limit, etc.) have to be selected and calibrated by on-site

observations, as these values are products of many features of the flow and infrastructure characteristic.

- Even though, the numeric analysis in the case study here is based on very limited control data, it includes a real life incident data as well as data collections on incident-free days, which enables us to test the developed algorithm numerically.
- However, to produce more generalizable results and more reliable decision criteria, a larger TCCD is necessary. Also, the more mature the TCCD of a network, the more conclusive statistical analyses in the methodology will be.

The major findings of the case study of a major arterial in Ankara, İnönü Boulevard, suggest the following conclusions:

- The selected corridor serves different demand levels not only in the inbound and outbound directions but also during different time windows of the day. This can be seen in average link speed graphs shown in Figures 4.3a and 4.3b
- In the analysis of the corridor, the link definitions are made based on geometric and operational features as well as some level of segmentation due to traffic safety measures such as observed “black spots”. Major traffic pattern changes are denoted by either benchmark points (BM) as foreseen a priori and by additional Point-of Interest (POIs), as the link speed data suggested.
- The derived average link speed patterns were able to capture correctly different roadway classes, such as surface streets versus arterial, as the corridor includes both.
- The retrospective bottleneck analysis detected different bottleneck locations for different time windows, consistent with on-site observations and road capacities. The calculated impact zones for these bottlenecks rely on very limited data, which can not be conclusively defended statistically, although the do not conflict with on-site observations.

- Using the traffic measurements from a day with an actual incident encountered in comparison with TCCD values with incident-free data, the proposed incident detection algorithm is tested numerically. While the incident possibility during morning peak and noon off-period periods are consistent with the observations, the forecasted incident possibility during the evening peak is a false alarm, probably caused by seasonal differences in the demand patterns on the day of the incident and days of control data collection for the TCCD. This false alarm case can be avoided with the use of more precise measures and checks of more complex queue formation patterns.

5.2 Recommendations for Future Research

There are some limitations of the proposed methodology. This methodology is applicable to non-transit vehicles as the dwelling times that may occur on the route of transit vehicles such as at bus stops cannot be detected. If it is intended to use transit vehicles as probe vehicles, a proper dwelling time algorithm that calculates time spend at the stops separately is needed. Moreover, by using GPS equipped transit vehicles, a huge data warehouse can be created easily so that statistical significance in analyses will increase.

Another concern might be the applicability of this methodology to highways. On highways, entrance and exits are very limited and hence the link lengths are very long. On such links, link based approach most probably will become inadequate. Therefore, by further developing the segmentation step, a methodological approach can be generated to divide links to small segments. This will enable to calculate the average speed on smaller distances so the variation on long highway links would be better represented.

Although the incident detection algorithm in the proposed methodology successfully detected a real-life incident and its impact zone, this part is needed to be verified by more incidents. This might be possible if the incident are reported and checked with the GPS data while creating a data warehouse on a corridor. A simulation study might be another alternative for the verification of incident detection algorithm. In this study, only one observed incident is detected but with help of a simulation, severity, duration and location of an incident can be altered so that in those cases, detection rate and false alarm rate parameters can be calculated for incident detection algorithm.

REFERENCES

1. Abdulhai, B. and Ritchie, S.G. (1999). Enhancing the universality and transferability of freeway incident detection using a Bayesian-based neural network. *Transportation Research Part C*, Vol. 7, No. 5, pp. 261-280.

2. Adeli, H. and Samant, A. (2000). An adaptive conjugate gradient neural network-wavelet model for traffic incident detection. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 15, No.4, pp. 251.260.

3. Ahmet S. A. and Cook A.R. (1980) Time Series Models for Freeway Incident Detection. *Journal of Transportation Engineering* Vol.106(6), ASCE, 731-745.

4. Bachman, L. R. and Preziotti, G. R. (2001). Automated Collision Notification (ACN) Field Operational Test (FOT): Evaluation Report. Last accessed from http://www.itsdocs.fhwa.dot.gov//JPODOCS/REPTS_TE//13830.html Last accessed on August 21, 2007

5. Basnayake, C. (2004) *Automated Traffic Incident Detection Using GPS Based Transit Probe Vehicles*, Doctoral Dissertation, University of Calgary

6. Bhandari, N., Koppelman, F.S., Schofer, J.L., Sethi, V. and Ivan, J.N. (1995). Arterial incident detection integrating data from multiple sources. *Transportation Research Record*, No. 1510, TRB, National Research Council, pp. 60-69.

7. Black, J. and Sreedevi, I. (2001). "Automatic incident detection algorithms." http://www.calccit.org/itsdecision/serv_and_tech/Incident_management/Incident_detection/detection_algorithms/detection_algorithms_report.html Last accessed on August 02, 2007

8. Cambridge Systematics (1990). *Incident Management*. Trucking Research Institute, Alexandria, VA.

9. Cassidy, M. J. and Bertini, R. L. (1999). Some Traffic Features at Freeway Bottlenecks. *Transportation Research Part B* 33 25-42.

10. D'Este, G. M., Zito, R., and Taylor, M. A. P. (1999). Using GPS to Measure Traffic System Performance. *Computer-Aided Civil and Infrastructure Engineering* Vol.14 pp255-265.

11. Dia, H. and Rose, G. (1997). Development and evaluation of neural network freeway incident detection models using field data. *Transportation Research Part C*, Vol. 5, No. 5, pp. 313-331.

12. Dudek, C.L., Messer, C.J. and Nuckles, N.B. (1974). Incident detection on urban freeway. *Transportation Research Record*, No. 495, TRB, National Research Council, pp. 12-24.

13. Forbes, G.J. and Hall, F.L. (1990). "The applicability of Catastrophe theory in modeling freeway traffic operations." *Transportation Research Part A*, Vol. 24, No. 5, pp. 335-344.

14. Guo, F., Ji, Y., and Hu, G. (2000). Methods for Improving the Accuracy and Reliability of Vehicle-borne GPS Intelligence Navigation. Last accessed from

http://www.gisdevelopment.net/application/utility/transport/utilitytr0022.htm
Last accessed on April 19, 2007

15. Hall R. W. and Y. Mehta, 1998 *Incident Management Process Analysis and Improvement Phase 1 Review of Procedures*. California PATH Working Paper, UCB-ITS-PWP-98-31

16. Han, L. D., and May, A. D. (1989). *Automatic Detection of Traffic Operational Problems on Urban Arterials*. Research Report UCB-ITS-RR-89-15. Institute of Transportation Studies, University of California at Berkeley, CA

17. Hellinga, B. and Knapp, G. (2000). AVI Based freeway incident detection. *the 79th TRB Annual Meeting*, Transportation Research Board, National Research Council

18. Khan, S.I. and Ritchie, S.G. (1998). Statistical and neural classifiers to detect traffic operational problems on urban arterials. *Transportation Research Part C*, Vol. 6, No. 3, pp. 291-314.

19. Lee, Y.-I. and Hwang, J.-H. (2001). "Development of a logit-based incident detection algorithm for urban streets." *the 80th TRB Annual Meeting*, Transportation Research Board, National Research Council, Washington D.C.

20. Lee, S., Krammes, R.A. and Yen, J. (1998). Fuzzy-logic-based incident detection for signalized diamond interchanges. *Transportation Research Part C*, Vol. 6, No. 3, pp. 359-377.

21. Levin, M. and Krause, G.M. (1978). Incident detection: a Bayesian approach. *Transportation Research Record*, No. 682, TRB, National Research Council, pp. 52-58.

22. Li, Y. (2004). *Journey Time Estimation and Incident Detection Using GPS Equipped Probe Vehicle*, Doctoral Dissertation, University of Southampton

23. Mouskos, K.C., Niver, E., Lee, S., Batz, T. and Dwyer, P. (1999). TRANSMIT: Evaluation of the Incident Detection System*. the 78th TRB Annual Meeting*, Transportation Research Board, National Research Council, Washington D.C.

24. Mussa, R. N. and Upchurch, J. E. (1999). Simulation Assessment of Incident Detection by Cellular Phone Call-in Programs. *Transportation* 26: 399-416

25. Ochieng W. Y. and Sauer K. (2002). Urban Road Transport Navigation: Performance of the Global Positioning System after Selective Availability. *Transportation Research Part C*, Vol. 10, pp. 171-187.

26. Ozbay, K., Hobeika, A. G., and Zhang, Y. (1997). Estimation of Duration of Incidents in Northern Virginia. *TRB Annual Conference*, Washington

27. Ozbay, Kaan and Kachroo P. (1999) *Incident Management in Intelligent Transportation Systems* Artech House

28. Ozbay, K., and Bartin B. (2003). Incident Management Simulation. *SIMULATION* Vol.79, Issue 2 pp. 69-82.

29. PB Farradyne (2000). *Traffic Incident Management Handbook*. Federal Highway Administration, Office of Travel Management, Washington, DC

30. Parkany, E., & Xie, C. (2005). *A Complete Review of Incident Detection Algorithms & Their Deployment: What Works and What Doesn't*. Report No. NETCR37

31. Petty, K. F. (1997). *Incidents on the Freeway: Detection and Management* Doctoral Dissertation, University of California

32. Quiroga, C. A. (1997). *An Integrated GPS-GIS Methodology for Conducting Travel Time Studies*, Doctoral Dissertation, Louisiana State University

33. Quiroga, C. A. and Bullock, D. (1998). Travel Time Studies with Global Positioning and Geographic Information Systems: An Integrated Methodology. *Transportation Researh Part C* 6 101-127.

34. Quiroga, C., & Bullock, D. (1999). Travel Time Information Using Gps And Dynamic Segmentation Techniques, *the 78th TRB Annual Meeting*, Transportation Research Board, National Research Council, Washington D.C.

35. Raub, R. A. and Schofer, J. L. (1998). Managing Incidents on Urban Arterial Roadways. *Transportation Research Record*, No.1603, National Research Council, pp 12-19.

36. Ritchie, S.G. and Cheu, R.L. (1993). Simulation of freeway incident detection using artificial neural networks. *Transportation Research Part C*, Vol. 1, No. 3, pp. 203-217.

37. Samant, A. and Adeli, H. (2000). Feature extraction for traffic incident detection using wavelet transform and linear discriminant analysis. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 15, No. 4, pp. 241-250.

38. Sawaya, O. B., Ziliaskopoulos, A. K., Mouskos, K. C., and Kamaryiannis, D. (2005). A Methodology for Computing Time-Dependent Alternate Routes around Freeway Incidents. *Journal of Intelligent Transportation Systems* 9(3) pp.123-132.

39. Skabardonis, A., Chavala, T. C., and Rydzewski, D. (1998). *The I-880 Field Experiment: Effectiveness of Incident Detection Using Cellular Phones* PATH Research Report, UCB-ITS-PRR-98-1, Institute of Transportation Studies, University of California at Berkeley, CA

40. Stephanedes, Y.J. and Chassiakos, A.P. (1993). Application of filtering techniques for incident detection. *Journal of Transportation Engineering*, Vol. 119, No. 1, ASCE, pp. 13-26.

41. Sullivan, E. (1997). New Model for Predicting freeway Incidents and Incident Delays. *Journal of Transportation Engineering* 123(4) pp.267-275.

42. Taylor, M. A. P., Woolley, J. E., and Zito, R. (2000). Integration of the Global Positioning System and Geographical Information Systems for Traffic Congestion Systems. Transportation Research Part C Vol.8 pp257-285

43. Taylor, G., Uff, J., and Hamadani, A. (2001). GPS positioning using map-matching algorithms, drive restriction information and road network connectivity. GIS Research in the UK: *Proceedings of GIS Research UK* 2001 9th Annual Conference. Glamorgan, pp.114–119.

44. Tavana, H., Mahmassani, H. S., and Haas, C.C. (1999). Effectiveness of Wireless Phones in Incident Detection: A Probabilistic Approach. *TRB Annual Conference*, Washington, DC

45. Thill, J. C. (2000). Geographic Information Systems for Transportation in Perspective. *Transportation Research Part C* Vol.8 No.1 pp.3-12.

46. U.S. Department of Transportation (1997). *Freeway Management Handbook*. Report No. FHWA-SA-97-064

47. U.S. Department of Transportation (1990). *Traffic Detector Handbook Second Edition.* Report No. FHWA-IP-90-002

48. Unsal, A. D. (2006). *Estimation of Time-dependent Link Costs Using GPS Track Data.* Master Thesis, Middle East Technical University, Ankara

49. Wang, Y., and Sisiopiku, V.P. (1998). Review and Evaluation of Incident Detection Methods. *Proceedings of the 5th World Congress on Intelligent Transport Systems*, Seoul, Korea

50. Weil, R., Wootton, J. and Garcia-Ortiz, A. (1998). Traffic incident detection: sensors and algorithms. *Mathematical and Computer Modeling*, Vol. 27, No. 9-11, pp. 257-291.

51. Willsky, A.S., Chow, E.Y., Gershwin, S.B., Greene, C.S., Houpt, P. and Kurkjian, A.L. (1980). Dynamic model-based techniques for the detection of incidents on freeways. *IEEE Transactions on Automatic Control*, Vol. 25, No. 3, pp. 347-360.

52. Yokota, T. (2004). Innovative Approaches to the Application of ITS in Developing Countries. *ITS Technical Note for Developing Countries*, World Bank

53. Zou, L., Xu, J., and Zhu, L. (2005). Arterial Speed Studies with Taxi Equipped with Global Positioning Receivers as Probe Vehicle. *Proceedings of 2005 International Conference on Wireless Communications, Networking and Mobile Computing*, IEEE, Vol.2 pp.1343-1347.

APPENDIX

CRITICAL LOCATIONS ON THE CORRIDOR

Figure A-1 Work zone on the corridor

Figure A-2 Capacity decrease around Ulusoy

Figure A-3 Capacity decrease due to entrance of grade-separated intersection

Figure A-2 Traffic queue due traffic light on Akdeniz Street