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DEVELOPING VEHICLE LOCATIONS STRATEGY ON URBAN ROAD

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Various forecasting schemes have been proposed to manage urban road traffic data, which is collected by different sources such as, videos cameras, sensors and mobile phone services. However, these are not sufficient for the purpose because of their limited coverage and high costs of installation and maintenance.

This paper describes urban road congestion as a resource assignment problem in urban areas, in which vehicles are assigned to available sections of road. In order to accomplish this and reduce road congestion, an estimation of the vehicle location is needed. Different strategies for estimating location have been proposed, such as the use of Wi-Fi and cellular systems, and GPS/GNSS. In this process, accuracy plays an important role. Therefore, to increase the accuracy of the primary GNSS system, an augmentation system is considered.

Keywords: ITS, EMA, road traffic, speed adaptation

1. Introduction

To reduce the amount of traffic congestion in road networks, and its negative effects (i.e. delays, waiting time, driver stress, air and noise pollution, and the blocking of emergency vehicles), researchers have taken a road traffic data management approach to variations in traffic flow speed in real-time. This new form of management is based on personalized vehicle location and it improves transportation supply performance in time and space through real-time interventions. When the number of vehicles increases in a road network, high dynamics in traffic flow, and increases in travel time follow and traffic management becomes more complex (Adler *et al*., 2005); therefore, we have investigated a novel approach that integrates travel observations made by different sources and hybrid applications. Many ITS applications require real-time vehicle positioning data. The main task for a map-matching (MM) algorithm is to identify the correct road segment (Velaga *et al*., 2010). A navigation system that provides such positioning data consists of three components: a positioning system, such as a global positioning system (GPS) (Ramm and Schwieger, 2007); a geographic information system (GIS), based on road maps, and a map-matching (MM) algorithm (Quddus *et al*., 2007). Vehicle Positioning or vehicle location is a process to obtain the spatial position of a target. This paper aims to reduce the traffic congestion by finding the shortest path with low traffic load. To find the shortest path, an estimation of vehicle position and the travel on road are needed.

This paper is organized as follows: Section 2 formulates the problem as one of resource allocation in a system. Section 3 gives an overview of various strategies that are used to estimate vehicle location. Section 4 presents simulations and results. Finally, the conclusion summarizes the work and points to directions for future research.

2. Problem Formulation

In general, we assume that the resources in an urban area are distributed over *m* different roads and are to be allocated to *n activities*. Activity *j* corresponds to the car's request for a resource. Let R_j denote the total amount of the resource that activity *j* requires of the road network. Among R_j, let us assume that activity *j* requests $x_{i,j}$ amount of the resource from road *i*. $x_{i,j}$ represents activity *j*'s demand for the resource at road *i*. Since activity *j*'s total demand for the resource is R_j, the following equation holds:

$$\sum_{i=1}^{m} x_{i,j} = R_j , \quad (1 \le j \le n). \tag{1}$$

Let N_i denote the total amount of the resource at road i. Since the total demand at road i is smaller than N_i, the following equation holds:

$$\sum_{j=1}^{n} x_{i,j} \le N_i \quad (1 \le i \le m)\,. \tag{2}$$

In other words, we assume that resource requests are always granted, and that the requested amounts of the resource are always granted. In order to assign vehicles to available road sections with the aim of reducing road congestion, estimations of their locations are needed. The fee road sections considered the available resources that can be allocated by vehicle activities as illustrates Figure 1.

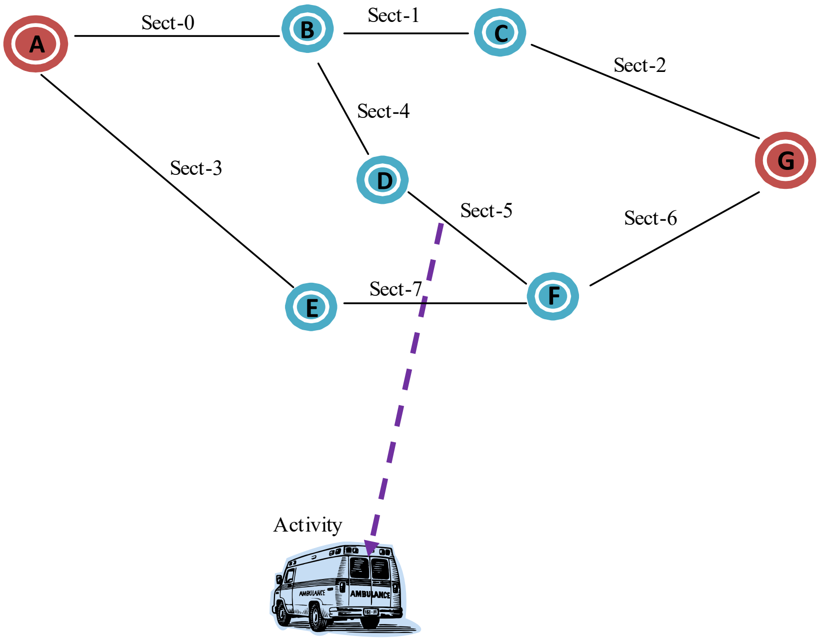

Figure 1. Resource allocation problem

3. Location Detection Schemes

Over the last few years, various geo-positioning technologies have been used to estimate the location of vehicles, such as satellite-positioning technologies (i.e., the GNSS and GPSs) (Hong *et al.*, 2014; Raiyn, 2017), Wi-Fi positioning systems, and cellular positioning systems. Some of the methods for collecting data on road traffic flow use fixed-point modes, with high costs and limited regional coverage, such as induction loop, radar and video techniques. In contrast to these fixed-point modes, we introduce floating data management based on a navigator map-matching algorithm. Map matching algorithms are used mostly to identify the correct road segment on which a car is moving. In general, these algorithms can be classified into four groups: geometric, analytical, topological, and probabilistic (Quddus *et al.*, 2007). The objective of this section is to propose a map-matching algorithm for floating data (car flow) in urban settings, based on short path searching. The proposed algorithm is used to identify a travel path between two edge positions. To find the correct segment a map-matching algorithm identifies a set of candidate segments based on -received longitude and latitude data, and then compares and analyzes them to determine the most likely segment. For the map matching process, we used a moving mode based on the previous and current positions of the vehicle located on a given segment, to proceed to the next step in map matching, which is based on the topology of the road networks.

3.1 Wi-Fi

Wi-Fi positioning uses terrestrial based Wi-Fi access points (APs) to determine a user's location. All of these APs repeatedly broadcast a signal announcing their existence to the surrounding area.

Typically, this signal covers a radius of several hundred meters in all directions. Various positioning algorithms have been developed for Wi-Fi positioning. These fall into the broad categories of geometric techniques, statistical techniques, fingerprinting and particle filtering (Zandberger, 2009). Fingerprinting is also referred to in the literature as radio mapping, database correlation, and pattern recognition. To collect data for a large area, a mobile device with a Wi-Fi receiver (typically a laptop) is hooked up to a GPS device, and the Wi-Fi signals and GPS coordinates are recorded as the device moves through the area (typically in a vehicle). In the positioning phase (or online phase) the observed Wi-Fi signals at an unknown location are compared to a database of previously recorded fingerprints to determine the closest match.

3.2 Cellular system

Cellular networks (Raiyn, 2013b) divide a geographical area into smaller regions, called cells. Each cell has a mobile service station and a number of mobile terminals, which we call hosts. To establish a communication session (or call), a mobile host sends a request to the mobile service station in its cell. The session is supported if a wireless channel can be allocated for the communication between the mobile host and the mobile service station. Since the frequency spectrum is limited, the frequency channels must be reused as much as possible in order to support a increasing demand for wireless communication. Propagation measurements in a mobile radio channel show that the average received signal strength at any point decays in keeping with the power law of the distance of separation between a transmitter and receiver. The average power P_r at a distance d from the transmitter antenna is approximated by

$$P_r = P_o\left(\frac{d}{d_0}\right)^{-n}, \qquad (3)$$

where P_0 is the power received at a close in reference point in the far filed region of the antenna at a small distance d_0 from the transmitting antenna and n is the path loss exponent.

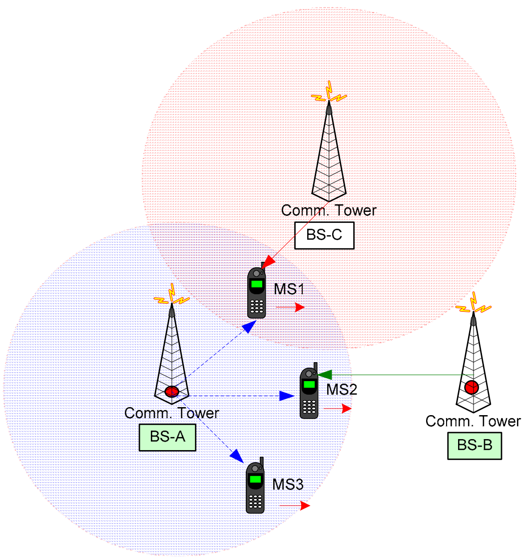

Figure 2. Estimation of user location

3.3 Matching map

Nowadays, navigation systems such as the GNSS and GPSs are used widely for vehicle position detection (Gong *et al.*, 2007; Raiyn, 2013a; Zheng and Liu, 2009). Navigation systems also provide travel information, destination directions, road maps, real-time road conditions, and vehicle speeds. Management of a heterogeneous road network requires locating vehicles within the network (Ronen *et al.*, 2001). To improve the detection of vehicle positions, a map- matching (MM) method has been proposed. Map-matching is often used to obtain the real-time positions of vehicles in a road network. It aims to identify the correct road segment and to determine the vehicle location on that segment. Various approaches have been proposed. Quddus *et al*. (2007) introduced a map-matching strategy based on distance and orientation, which does not involve any further knowledge about the movement besides the position samples. Civilis *et al.* (2005) introduced a map-matching algorithm based on edge distance and direction, like that of Quddus, for updating location by tracking the users of location-based services. Yin and Wolfson (2004) proposed an algorithm based on a weighted graph representation of the road network in which the weights of each edge represent the distance from the edge to the trajectory. The improved map-matching method proposed here uses an algorithm based on local path searching and enables better determination of vehicle position within a road network. There are three main form of geometric matching:

- **Point-to-point matching**

The simplest form of geometric matching is point to point matching. This matching strategy is used to find the true location based on the shape point that is closest to the raw GPS observation.

- **Point-to-curve matching**

Various algorithms have been developed calculate the distance between the GPS observation and the linear segments composing a curve (lines). As proposed by Andrada-Felix and Fernandez-Rodriguez (2008), using minimum norm projection, the distance to these segments can be computed and the closest one chosen as the true segment.

- **Curve-to-curve matching**

The curve-to-curve matching strategy is based on distances between curve segments. As in the above methods, the relevant nodes in the area surrounding the GPS fix and the set of arcs incident to these nodes are identified. Piece-wise linear segments are built from the GPS observations (*p*0... *pn*), requiring at least two consecutive GPS readings, where any previous fix acts as the start node with its follower representing the end node of the newly created line segment. The distance from this curve-segment to all the candidate segments in the area is measured, and the closest one is taken as the correct one, projecting the point onto it. The approach, when measuring the distance between the curve constructed by connecting the two GPS observations and the candidate road segment, as proposed in Andrada-Felix, and Fernandez-Rodriguez (2008), is to calculate the "subcurves" of equal length.

3.4 Global Positioning Systems (GPS)

Global positioning systems (GPS) have emerged as the leading technology for providing location information for these location based services (LBS). A GPS receiver provides accurate information on location, speed and time to a user, anywhere in the world and under any weather conditions.

Let s_i denote the distance between the device *j* and satellite *i*, t_i the time at which the signal is broadcast by the satellite, t_j the time at which the signal is received, and c the average speed of light in the air

$$s_t = c*\left(t_j - t_i\right). \tag{4}$$

where t_i - the time at which the signal is broadcast by the satellite, t_j - the time at which the signal is received, and c - the average speed of light in the air

However, equation 4 is applied only when the clock of the satellite and the receiver device are synchronized. The device's clocks are not as accurate as the satellite's clock, and these slight timing differences can lead to rather large errors in the distance measurements. Because of this, to compute the device's clock offset Δ_t

$$\rho_j = \sqrt{(x_j - x_u)^2 + (y_j - y_u)^2 + (z_j - z_u)^2} + c*\Delta_t , \tag{5}$$

where $\left(x_j, y_j, z_j\right)$ are the satellite positions and $\left(x_u, y_u, z_u\right)$- the user's coordinates. The user's position and Δ_t are unknown at the beginning, however, the position can be computed after least four different GPS signals have been received.

3.5 GNSS

Global navigation satellite system (GNSS) technology is a radio positioning technology with global coverage based on satellite infrastructure. The most well-known example of an existing system is the US NAVSTAR global positioning system (GPS). GNSS technology allows an unlimited number of users independent of satellite infrastructure. A GNSS consists of more than two dozen satellites orbiting the earth in a constellation such that four or more satellites are in view from any point on earth at any time. The positioning accuracy of GNSS systems is estimated to be within a few meters. However, in combination with an augmentation system, the positioning accuracy is within centimetre.

3.6 Augmented GNSS

Results indicate that assistant-GPS locations obtained using 3G mobile phones are much less accurate than those obtain from regular autonomous GPS units and Wi-Fi locations using 3G mobile phones are also much less accurate.

Nowadays, GNSS augmentation is used in civil aircraft landing systems. Augmentation systems provide additional data to users of GNSS equipment; improve accuracy, reliability and availability. GNSS augmentation systems can be divided into

- ground-based augmentation systems and
- satellite-/space-based augmentation systems.

An integrity monitoring solution uses GNSS signals to detect changes or anomalies in satellite signal characteristics that could affect the accuracy of the position calculated by the user's equipment. Integrity and correction data are generated based on measurements from a ground network and transmitted to geostationary satellites (GEO's), which then relay the information to the GNSS users.

4. Simulation Results and Discussion

To find the shortest path, the informed iterative approach computes and updates the forecasting model, which is based on vehicle location as illustrated in Figure 3. Figure 3 illustrates all of the path possibilities from start point *A* to end point *G*. The algorithm makes decisions regarding nodes *B, C, D, F, E,* and *G,* according to the vehicle speed forecasting scheme exponential moving average (EMA) for each path. The positioning of the nodes based on GPS coordinates is given in Table 1.

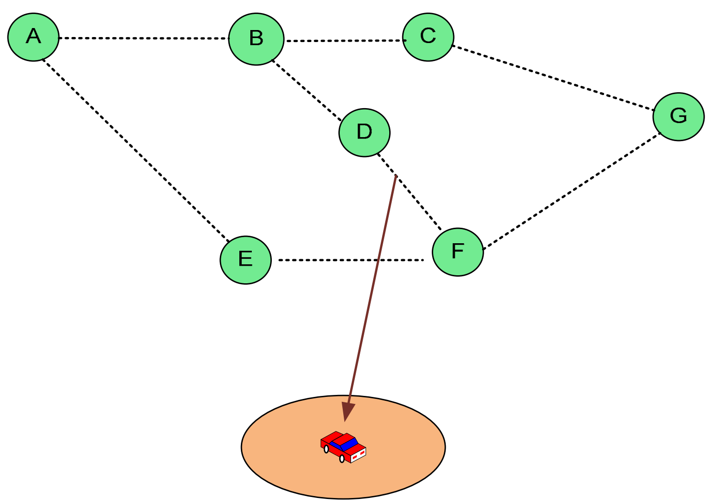

Figure 3. Road network scenario

- **Algorithm Description**

In the previous section, the informed iterative approach was used to estimate the movement of traffic in whole road networks. In order to reduce the complexity of processing time, we used an informed iterative approach based on vehicle location. Furthermore, the informed iterative location considered quality of experience (QoE) and driver behaviours by selecting the shortest path. The proposed algorithm process is a sort of informed iteration process as described in Figure 4.

Find the shortest path from start point A to end point E.

- Consider all routes from A to E
- Compute the cost for all paths
  - Estimate the speed for all paths
  - Estimate the capacity of all paths
- Compare the regular time to the updated time to get the destination t_{update}. If the time t_{update} is less than threshold time (regular time).
  - Select the shortest path
  - Otherwise selects the regular path
- Update
- For each edge call the function a new.
- *Find shortest path from point B to E*
- End

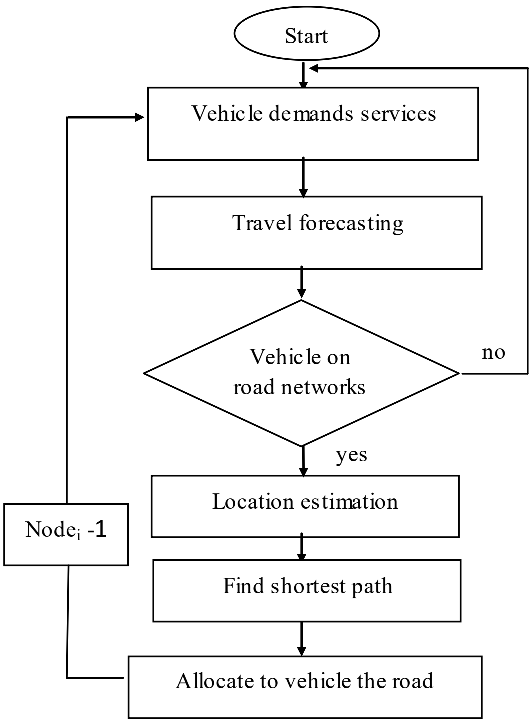

Figure 4. Personalized road traffic management

- **Road Traffic Management - Based QoE**

This section considered QoE in the management of urban road congestion. The term QoE relates to how end users perceive the quality of an application or service (Tang *et al.,* 2014). This phase aims to improve resource allocation under abnormal conditions based on mobile host behaviours. QoE monitoring includes monitoring urban road traffic, channel demand in base station, and drivers' experiences. To measure car drivers' (MCD) satisfaction with travel, we need to collect information. The most commonly used survey methods for data collections are focus groups, field surveys, in-vehicle surveys, driving simulators, and video surveys. Figure 5 illustrates three methods to measure divers' satisfaction, MCD based cellular system, MCD based prediction, and MCD based statistical techniques.

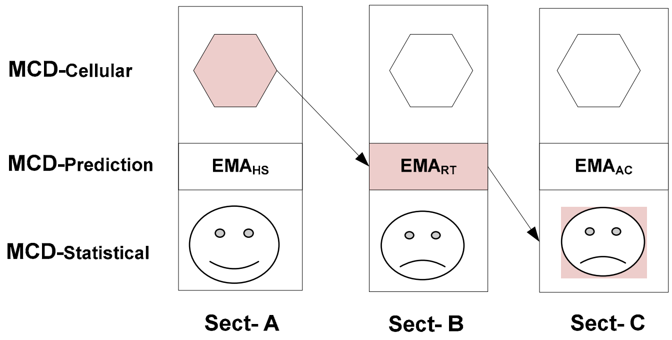

Figure 5. Drivers' satisfaction measurement

- **Vehicle Location Based on Google Map Data**

To find the shortest route, the informed iterative algorithm estimates the travel data for all paths. The forecasting scheme "informed iterative" that is based on exponential moving average (EMA) (Raiyn, 2016) considers the historical data (EMA^{H}), real time data (EMA^{R}), and accident data (EMA^{Acc}) as illustrated in Figure 6.

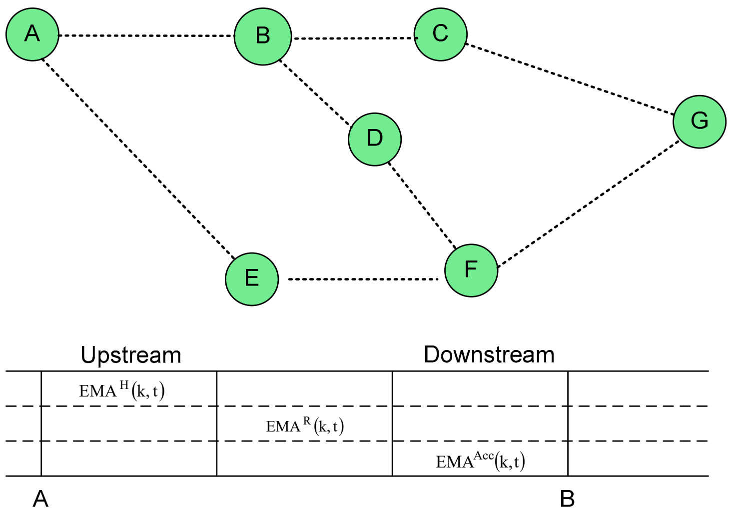

Figure 6. Paths in road networks

In the second phase, the informed iterative algorithm used the exponential moving average scheme to forecast the travel speed based according to vehicle location as illustrates Table 1. Hence the shortest path is calculated according to high speed average in each section as illustrated in Table 2 and Table 3. The informed iterative algorithm made a decision in the node *B* based on high speed average and it selected the next node *C* or *D*. The decision making included edge collapse, and some segments are eliminated.

Table 1. Location of nodes

Positioning	Longitude	Latitude	Velocity [km/h]
A	32.875902	35.187868	35.53
B	32.876271	35.191891	45.53
C	32.876866	35.197041	40.37
D	32.874280	35.197020	40.41
E	32.869117	35.200281	31.42
F	32.879540	35.203779	39.00
G	32.869838	35.207169	Destination

Table 2. Estimation of the shortest path from A to G based on historical data

Path	Average [km/h]
{A, E, G}	49.5
{A, B, C, G}	40
{A, B, C, D, F, G}	39.8
{A, B, D, F, G}	42
{A, B, D, F, E, G}	40.2

Table 3. Estimation of the shortest path based on vehicle location

Path	Real-time [km/h]
{A, E, G}	43.5
{A, E, F, G}	48.6
{A, B, C, G}	40
{A, B, C, D, F, G}	39.8
{A, B, D, F, G}	42
{A, B, D, F, E, G}	40.2

According to received real-time information that combines historical and abnormal conditions, the shortest path is selected as illustrated in Figure 7.

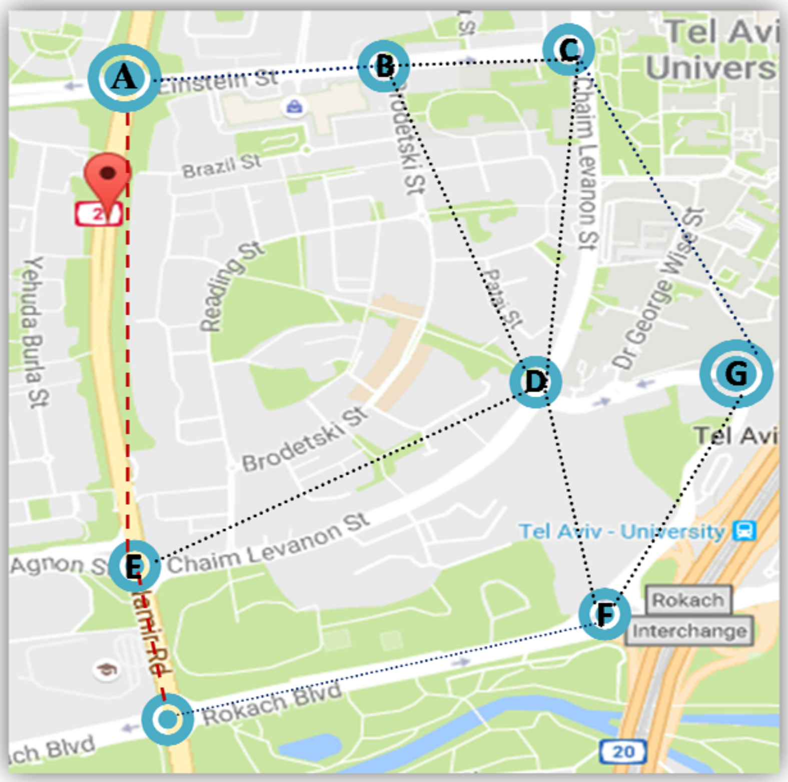

Figure 7. Urban road area

- **Cellular Data vs. Sensor Data**

We used the MATLAB environment to process the collected travel data. Figure 8 shows a comparison of travel data collected via mobile services with travel data collected by inductive-loop detectors (on-road sensors). The current system supports a data resolution of 2.5 minutes. The loops are embedded in roadways in a square formation that generates a magnetic field. The information is then transmitted to a counting device placed on the side of the road, which has a generally short life expectancy because it can be damaged by heavy vehicles. Accuracy depends heavily on the level of error related to vehicle positioning, which depends in turn on the technology used to calculate mobile phone locations. Obviously, any errors concerning phone locations could significantly affect the speed estimates. Speed data measured from inductive loops were compared with speed estimates provided by mobile phones. Globally, the results showed a good correlation between the two speed measurement methods, although they depended on the road section under consideration.

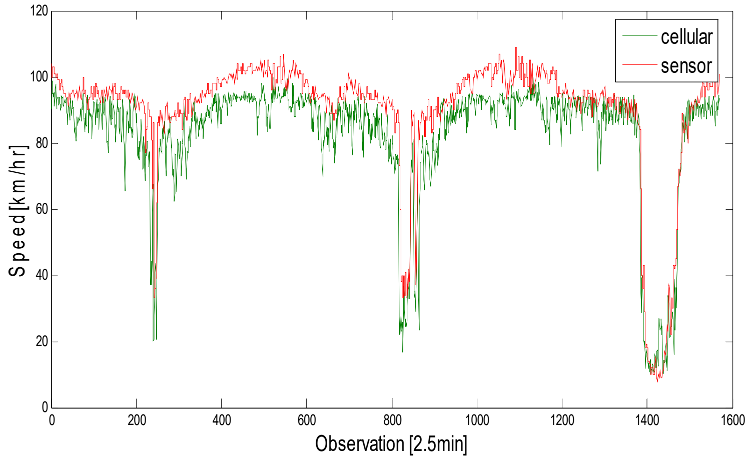

Figure 8. Cellular versus sensor travel data

In a cellular network, each cell is assigned a number of channels. Under a heavy traffic load, if a vacant channel is not found, the call is blocked. Figure 9 illustrates the channel demand in the base stations under accident condition. In some cells, the channel demand is high, which causes call blocking.

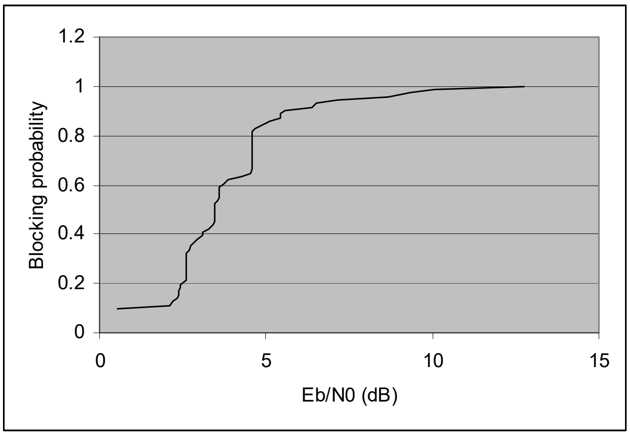

Figure 9. Blocking probability

5. Conclusion and Future Work

In this paper, several strategies for estimating vehicle location have been discussed. The data were collected using mobile services, Wi-Fi, GPSs, and the GNSS. Due to the lack of urban coverage by Wi-Fi, cellular systems, and the GNSS, a road management approach that aims to locate vehicles *route* is proposed.

To improve the detection of vehicle positions, a map-matching (MM) method has been proposed. Map-matching is often used to obtain the real-time positions of vehicles in a road network. It aims to identify the correct road segment and to determine the vehicle location on that segment. Highly accurate estimations of vehicle location are needed to find the shortest path and to assign vehicles to available roads. Several studies have that the most used strategy for vehicle location employs GPSs and the GNSS. However, to increase the accuracy of data based on satellite technology, augmentation to the system is needed to correct the satellite data. Furthermore, the informed iterative algorithm used also travel data and QoE to forecast the short time travel in the urban road. The road management scheme which is based on vehicle-road allocation strategy, has deceased the road congestion. In the future work, it is recommended to use hybrid tools to increase the accuracy of estimating the vehicle location.

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