ASSESSMENT OF TRAFFIC DETECTION IN A HIGHWAY NETWORK

Tian Jiang, Ph.D.. Student, University of Tokyo, Institute of Industrial Science, 4-6-1 Komaba, Meguro-ku, 153-8505 Tokyo, Japan

Marc Miska, Project Lecturer, University of Tokyo, Institute of Industrial Science, 4-6-1 Komaba, Meguro-ku, 153-8505 Tokyo, Japan

Masao Kuwahara, Professor, University of Tokyo, Institute of Industrial Science, 4-6-1 Komaba, Meguro-ku, 153-8505 Tokyo, Japan

Shinji Tanaka, Lecturer, University of Tokyo, Institute of Industrial Science, 4-6-1 Komaba, Meguro-ku, 153-8505 Tokyo, Japan

ABSTRACT

The mobility demand of our society increased rapidly in the last decades. To ensure accessibility the traffic infrastructure needs to be used more efficiently. One way to achieve this is dynamic traffic management (DTM). Vital for the DTM cycle is traffic data collection to enable the feedback loop to traffic operations. Roadside detection is nowadays the most common way of traffic data collection, but probe vehicle data, GSM data and vehicle to infrastructure communication are getting more and more momentum. With the new variety in data collection methods, research on data fusion, to combine different data sources to better traffic state information, it is important to have a detection plan, which is cost efficient and designed to serve the policy of the road authority. To analyse the detection efficiency of a network or to develop guidelines for detection placement planning, several aspects have to be taken into account. The costs of the detection equipment are vital, and should include not only the purchase costs, but also the maintenance costs and equipment life-cycle. With the budget for detection equipment installation and maintenance being usually the limiting factor, an evaluation should indicate an area specific level of detection (LOD) that is possible inside this budget. The LOD is representing the overall coverage of the network, but especially the area wide data availability for reliable incident detection, travel time estimation, traffic control and traveller information systems. Such data availability and also reliability depends on the detection equipment. In this paper we propose a framework that introduces demand and supply functions for traffic information throughout a network, which allow an objective assessment of the detection system and can be used to optimise the detection plan for the network. To check feasibility of the proposed framework we provide case studies on road stretches in Japan, the United States and the Netherlands with data from the International Traffic Database (ITDb)

Keywords: detection, optimisation, assessment, highway

INTRODUCTION

The mobility demand of our society increased rapidly in the last decades. To ensure accessibility the traffic infrastructure needs to be used more efficiently. One way to achieve this is the introduction of dynamic traffic management (DTM). DTM monitors the traffic situation and tries to optimise it by applying different control measures like speed limits, route guidance, lane closure, ramp metering, intersection control or others to the traffic network. In its ideal form it is a continuous cycle that gets evaluated by checking the effects of the taken measures to the traffic situation, although in practice the measures are often predefined and not tuned to the detailed actual traffic situation. Traffic models are used to support traffic engineers with the optimisation task by predicting the effect of different measures before applying them to the real network. Vital for the DTM cycle is traffic data collection to enable the feedback loop to traffic operations. Roadside detection is nowadays the most common way of traffic data collection, but probe vehicle data, GSM data and vehicle to infrastructure communication are getting more and more momentum. With the new variety in data collection methods, research on data fusion, to combine different data sources to better traffic state information increases.

Publications dealing with the different sensor technologies, their operation and cost can be found in Klein (2001), FHWA (2006), Mimbela (2007), but the detector placement problem is a less explored research topic in transportation. Relevant research includes the work done in transportation planning for obtaining accurate origin-destination trip matrices, see Yang 1998). Some researchers have conducted simulation based research to identify the relationship between detector location and travel characteristics on arterial roads. Examples can be found in Sisiopiku (1994), Thomas (1999), and Oh (2003). Very limited research to date has been focused on the detector placement problem for freeways with respect to travel time estimation, such as Edara (2008). A Virginia Transportation Research council report (Edara, 2008) found that the placement of detectors for the development of accurate travel time estimates will vary by location based on specific conditions. Arbitrary, evenly spaced detectors do not necessarily result in accurate travel time estimates. With carefully placed detectors that are well maintained, travel time estimates can be derived with an acceptable level of accuracy from point detection, under incident-free travel conditions. This stays in contrast to most detection installations with constant spacing, mostly resulting from budget constraints.

In this paper we will describe a framework for detection installation assessment on highway networks, taking into account the infrastructure, demand and authority policies. In a first step we will present algorithms to automatically detect points of interest in the network that require more dense detection as a starting point for practitioners to define the policy based level of information they require for the network. The level of information can be defined by adjusting data demand functions resulting from the analysis. Placed detectors in the network are represented with data supply functions based on the sensor technology and measurement entity. A comparison of both functions for each link in the entire network will result in a level of detection (LOD) that can be used to assess detection installation objectively. Based on these functions, an optimisation, based on genetic algorithms, will determine optimal sensors and spacing for given demand, find optimal spacing for existing equipment, and select additional sensor to fill gaps based on a given sensor pool.

To check the feasibility of the proposed framework we provide case studies on road stretches of the Tokyo Metropolitan Expressway, Japan, Route 101 in San Francisco, United States and the motorway A13 in the Netherlands. The analysis is done with data from the International Traffic Database, see Miska et. al. (2010).

NETWORK ANALYSIS

Detector placement and its assessment depends strongly on the traffic network, its load and control installations. This means, that the first step of our efforts is a network analysis based on the available information. First, we will classify and simplify the network to reduce computational demand for the further analysis, which includes network robustness (weak links need more detection), waypoint detection (to determine route choice), bottleneck detection (for possible control measures), and a risk analysis, since road safety is commonly a major concern. In this paragraph we will briefly discuss the network analysis and for further details we refer to Jiang et. al. (2010).
In a first step in our analysis we detect if the given network has a special structure, such as grid networks, radial networks or star networks, which allows in the further network simplification to adjust algorithms for a better performance. To detect the network structure, pattern matching algorithms are searching for grid and radial patterns. Then the network gets simplified to its essential nodes. Essential nodes include on ramp start points, off ramp end points, merging nodes and diverging nodes. To determine the essential nodes of a network we follow the links of a network from all entry points until arriving at a node that has more than one exit link or another entry link. Reached this node we delete all visited links and replace it with an equivalent link from the starting position to the actual position. Afterwards we repeat the process until all node of the network have been visited. To give an indication of the node and link reduction, we found that for the network description of the Tokyo Metropolitan Expressway we could eliminate about 48% of the nodes. All further structural analysis is based on the simplified network, and includes:

- *Network Robustness* (determining the vulnerable links of the network, which when combined with high traffic volumes require a more dense detection)
- *Waypoint detection* (discover waypoints that are basis for route choice)
- *Bottleneck detection*(look for structural hints of a bottleneck and afterwards consult historical data - if available - to investigate the area of interest around the bottleneck)
- *Risk analysis* (accident records, weather records, geometry, buildings)

With the knowledge of this analysis, the data demand functions for each link is created. In the following section, speed data demand for travel time estimation has been chosen to explain how to formulate demand functions based on network analysis. Since bottleneck detection is crucial to estimate travel time, a case study for detecting active bottlenecks has been done to figure out feasible speed data demand function.

Through the International Traffic Database (http://www.trafficdata.info), we have chosen speed data recorded during morning peak hours on Freeway 80, San Francisco, United States of America as shown in Figure 1.

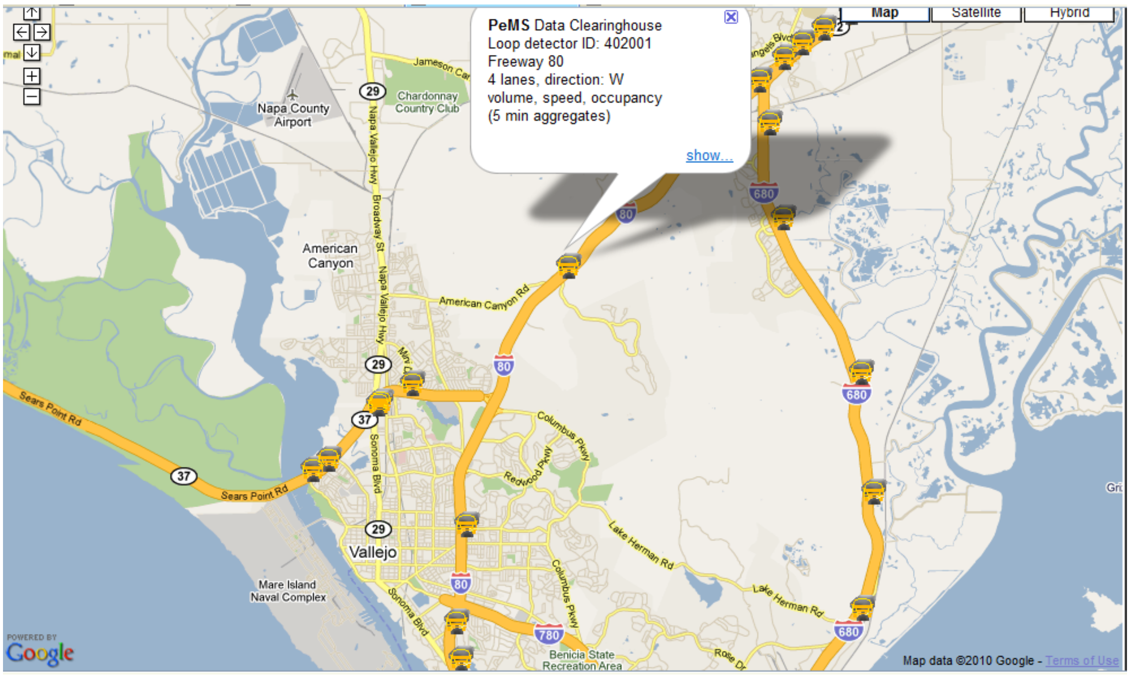

Figure 1. Area of the case study (International Traffic Database)

We analysis speed data which is collected by five neighbour loop detectors. Detector 1, 2 and 3 are installed along the upstream road section and Detector 3 is close to a bottleneck, a highway merging area. Detector 4 is located at downstream 0.8 km away from the bottleneck. Five-minute aggregated speed data recorded by the five detectors are shown in Figure 2.

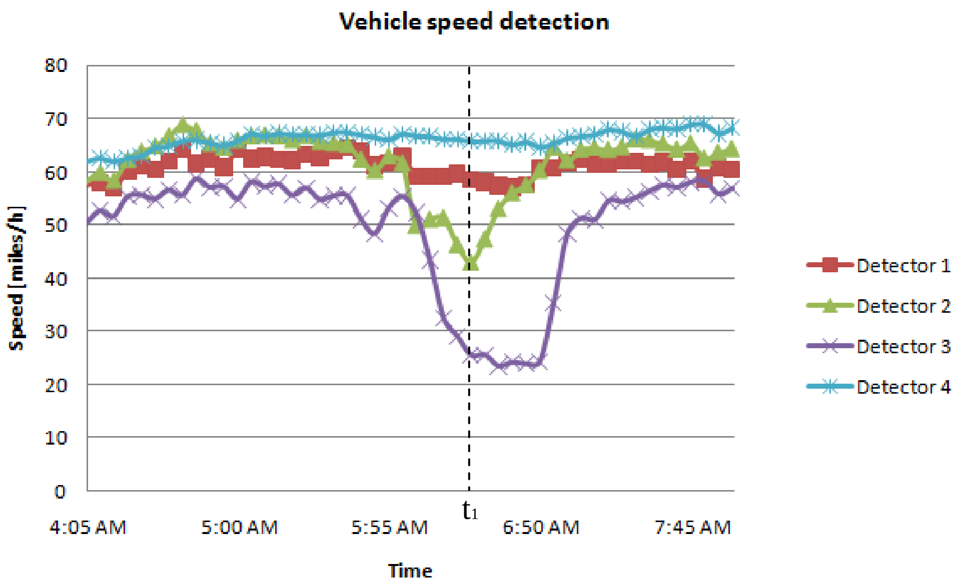

Figure 2. Speed data analysis for bottleneck detection

When the bottleneck is active, vehicle speed at Detector 3 location decreases quickly and a queue starts to grow to upstream. The queue almost reaches Detector 3 Location at Time t_1 (see Figure.2), therefore the maximum queue is form the bottleneck to a location close to Detector 2. Based on the data recorded from Detector 1, basically vehicle speed is not affected by the active bottleneck. However since traffic demand varies with time, from detector 2 to detector 1 could be a potential queuing section. Speed data recorded from Detector 4 reflects vehicles can keep free flow speed after passing the bottleneck which means the vehicle speed in downstream is quite stable. Based on this bottleneck analysis, data demand function for travel time estimation is introduced in the following section.

DATA DEMAND FUNCTIONS

Demand functions, that are set by the network analysis and can be adjusted manually by the traffic engineers to incorporate their extensive knowledge of the traffic network, are reflecting the network structure and demand distribution to identify areas of special interest for traffic management. For a fixed route, DTM measure, data type and control policy, the data demand is a function of position along the link with three parameters. It is defined as:

$$\chi_{i,\eta,\tau,\gamma} = g_{\rho,\beta}(x)$$

where:
χ: data demand function [%]
x: position [m]
i: route i
η: DTM measures
τ: data type
γ: control policy
ρ: vulnerable location
β: queue length [m]

For our prototype we have chosen the example of travel time provision to create a data demand function. To estimated travel times, we need to ensure to have information about bottlenecks along the route. This includes the head of the bottleneck to detect if the bottleneck is active and further upstream detection to determine the tail of the queue. As prototype we have chosen the following formulation with its visualisation in Figure 3.

$$\chi_{i,\eta,\tau,\gamma} = \begin{cases} \dfrac{\sin\left[\frac{\pi}{\beta_2}(x-\rho_n+\beta_1)+\frac{\pi}{2}\right]+1}{2} & , \ \rho_n-\beta_1-\beta_2 \le x \le \rho_n-\beta_1 \\ 1 & , \ \rho_n-\beta_1 < x \le \rho_n \end{cases}$$

where:
ρ: bottleneck location [m]
β1: length of high potential queuing section [m]
β2: length of low potential queuing section [m]

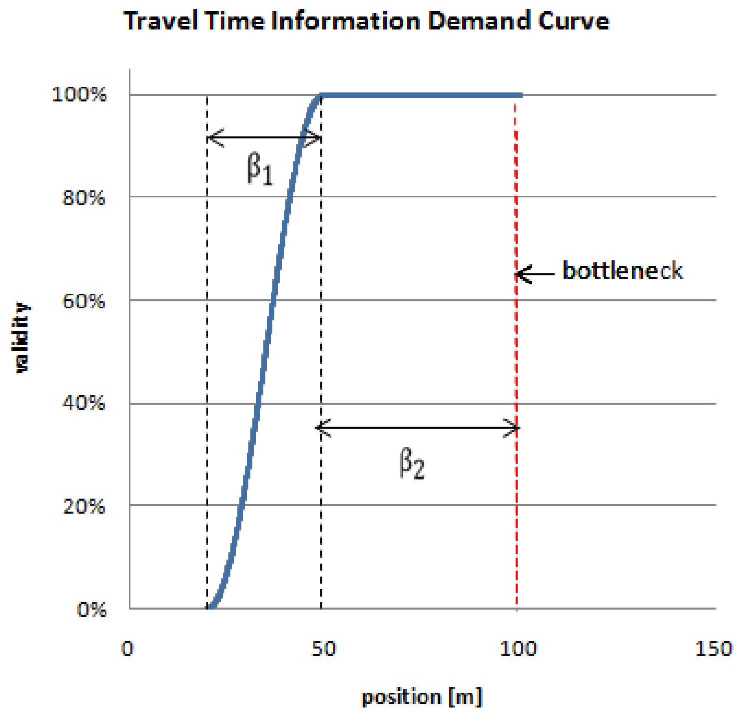

Figure 3. Prototype data demand function for travel time information provision

DATA SUPPLY FUNCTIONS

Data supply functions are created for different sensor technologies. For a comprehensive list refer to Miska (2007). The function depends on:

- sensor response time
- sensor reliability
- data collected
- data aggregation
- data lifecycle (availability of historical data)
- data time line throughout the network
- missing data
- outliers / unrealistic measurements

For mobile sensors additionally:

- mobile sensor penetration
- mobile sensor effectiveness (information span)

For a fixed route, data type and detector type, the data supply is a function of position along the link with four parameters. Based on that information we create a data supply function:

$$\psi_{i,\delta,\iota} = f_{\alpha,\omega,\mu,\lambda,}(x)$$

where:
ψ: data supply function [%]
x: position [m]
i: route i
δ: detector type
τ: data type
α: first detector location [m]
ω: sensor technology parameter [m]
μ: detector number (1,2,3 …)
λ: distance between two detectors [m]

In the following the prototype definitions of the supply function for inductive loop detectors, video camera installations and probe vehicles for speed measurements.

Inductive Loop detectors

Inductive loop sensors are measuring speeds on a single location, however, taken into account vehicle dynamics, it can be assumed that the data is valid in a wider area, the so called valid range of the sensor. This results in the following expression, which is visualised in Figure 4.

$$\psi_{i,\delta,\tau} = \frac{\sin\left\{\frac{2\pi}{\omega}[x-(\alpha+\mu\cdot\lambda)]+\frac{\pi}{2}\right\}+1}{2} \qquad \alpha+\mu\cdot\lambda-\frac{\omega}{2} \le x \le \alpha+\mu\cdot\lambda+\frac{\omega}{2}$$

where:
δ: loop detector
τ: speed measures
ω: valid range of each individual detector [m]

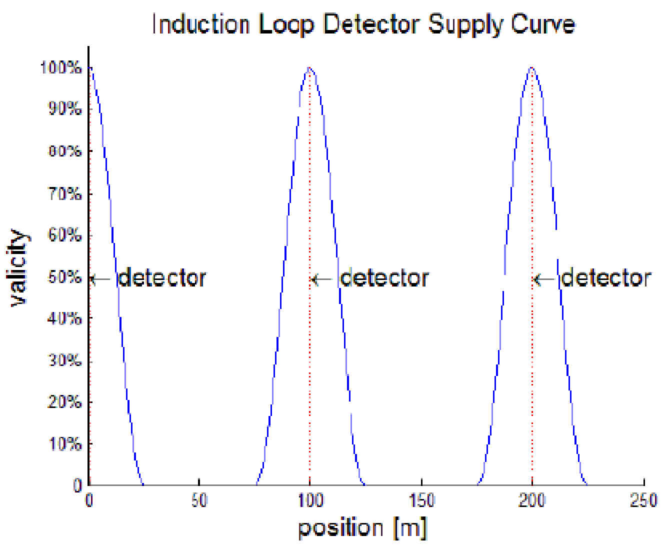

Figure 4. Prototype data supply function for loop detectors

Video detection installation

Camera installations are similar to loop detectors, however, the span in which they can perform accurate measurements (theoretically) is wider. This leads to the following function that is visualised in Figure 5.

$$\psi_{i,\delta,\tau} = \begin{cases} \dfrac{\sin\left\{\frac{2\pi}{\omega_1}[x-(\alpha+\mu\cdot\lambda)-\omega_2]+\frac{\pi}{2}\right\}+1}{2}, & \alpha+\mu\cdot\lambda+\omega_2 \leq x \leq \alpha+\mu\cdot\lambda+\frac{\omega}{2}+\omega_2 \\ \dfrac{\sin\left\{\frac{2\pi}{\omega_1}[x-(\alpha+\mu\cdot\lambda)]+\frac{\pi}{2}\right\}+1}{2} & ,\alpha+\mu\cdot\lambda-\frac{\omega_1}{2} \leq x \leq \alpha+\mu\cdot\lambda \\ 1 & ,\ \alpha+\mu\cdot\lambda < x < \alpha+\mu\cdot\lambda+\omega_2 \end{cases}$$

where:
δ: video cameras
ω1: valid range of each individual detector [m]
ω2: camera working range [m]

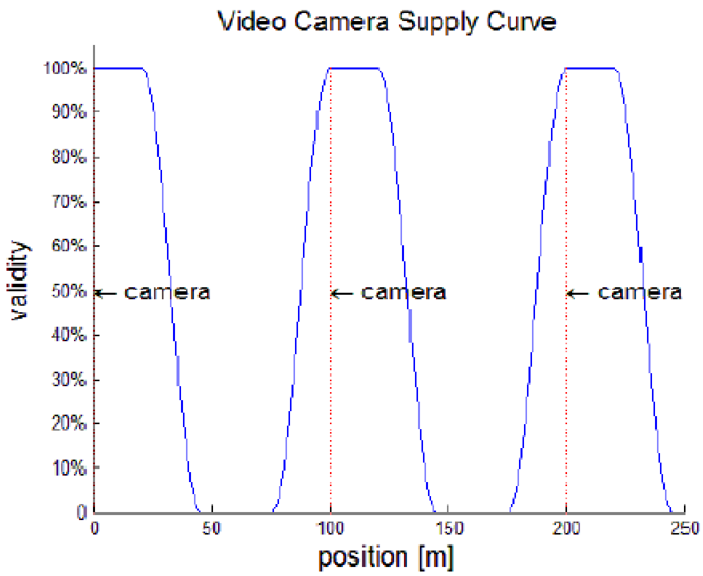

Figure 5. Prototype data supply function for video camera detection

Probe vehicles

As a last example we have chosen the probe vehicle data collection to cover the mobile sensors. Since validity of recorded data depends on probe vehicle penetration, as ratio of probe vehicles to total number of vehicles increase, the speed data validity grows gradually visualised in Figure 6. If the penetration of probe vehicles in a road section is constant, the validity of information is stable as shown in Figure 7.

$$\psi_{i,\delta,\tau} = \lg(5p+5)$$

where:

p : *penetration of probe vehicle*

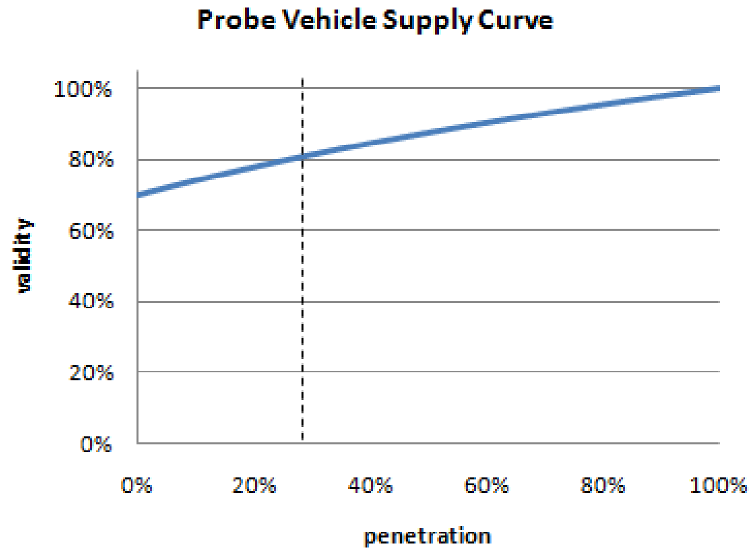

Figure 6. Probe vehicle data validity varies with penetration

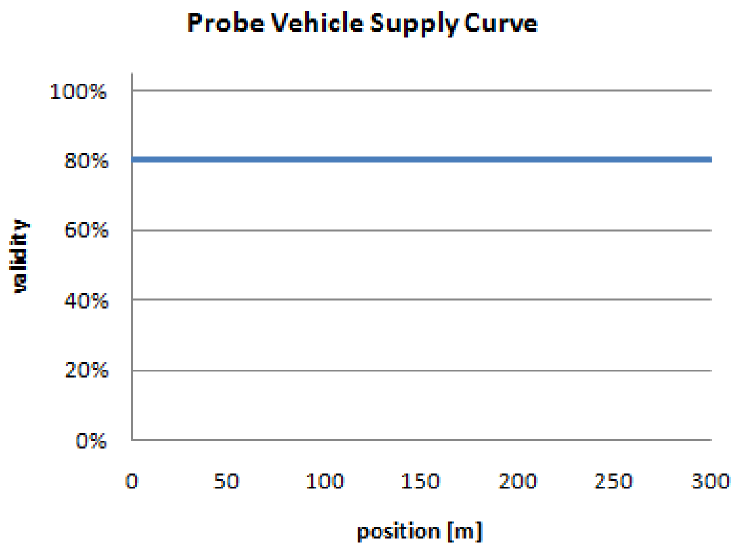

Figure 7. Prototype data supply function for probe vehicle

LEVEL OF DETECTION

With having defined the demand and supply functions, the level of detection is then determined as follows:

$$\varphi_{i,\tau} = 1 - \frac{\sum_0^{\theta}\{\max[g_{\rho,\beta}(x)] - \max[f_{\alpha,\omega,\mu,\lambda,}(x)]\}}{\sum_0^{\theta}\{\max[g_{\rho,\beta}(x)]\}}$$

where:
φ: level of detection on link i

The value indicates how many percent of the data demand can be supplied by the sensors placed. This value is objective and a good indicator for planning or changing detection installation plans. While it is possible to compute the level of detection for networks link by link, the optimisation of these functions is difficult. In the following we will discuss a simplification of the problem we use to perform the optimisation.

OPTIMISATION

To optimise the detection of the road we have to maximise the level of detection. Since data supply and demand function can grow rather complicated when overlapping, we describe the functions in a grid. Figure 8 show the simplified version of the supply function of a loop detector. Depending on the chosen grid size the approximation of the function varies, and can be adjusted depending on the requirements.

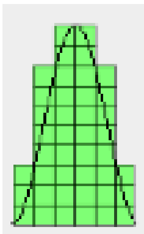

Figure 8. Approximation of the data supply function for inductive loop detectors

The same simplification we apply for the data demand function along the road stretch. Figure 9 visualises a road stretch including its demand and different sensor shapes.

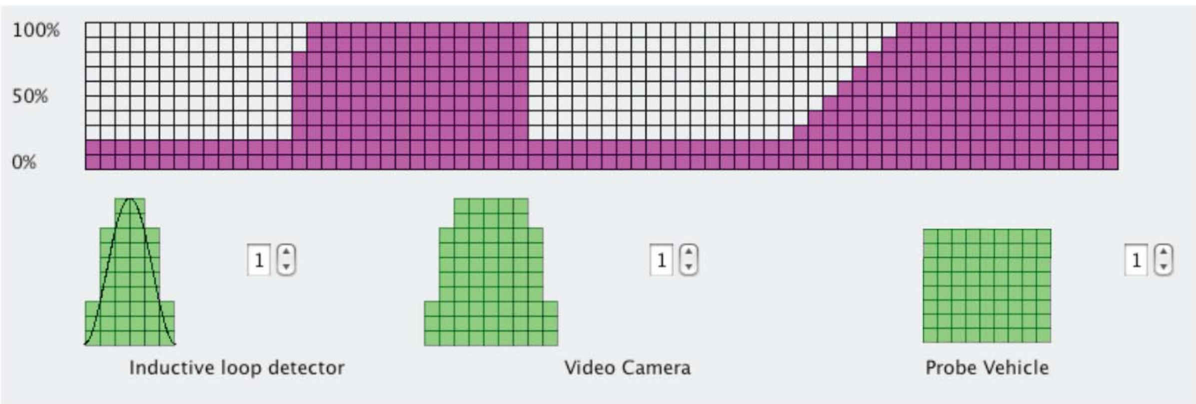

Figure 9. Approximation of data demand along a link and shapes of different sensors

Given the grid and the simplified functions, optimisation becomes now a matter of pattern matching. We know the shape of our supply functions and we know the shape of the demand function. Therefore, we can overlay supply function shapes with the demand shape and evaluate the grid due to over detection (data available without demand) and insufficient detection (no data available for area with demand). The following utility function is used to evaluate a grid. Given a pool of sensors, we test different arrangements so to minimise the utility function.

$$\epsilon_{i,\tau} = \kappa_{i,\tau} + \zeta_{i,\tau}$$

where:
ε = bad detection utility
i = route i
τ = data type
κ = units of over detection
ζ = units of insufficient detection

To avoid over detection, meaning that we have a high redundancy in traffic data we further calculate the over detection ratio and include it in the evaluation:

$$\Delta = \frac{\kappa}{\Gamma}$$

where:
Δ= over detection ratio
Γ = units of unnecessary detection

Since the problem can differ significantly from network to network, we have to utilise a solution that is able to adapt. Genetic algorithms are adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetic. The basic concept of GAs is designed to simulate processes in natural system necessary for evolution, specifically those that follow the principles first laid down by Charles Darwin of survival of the fittest. As such they represent an intelligent exploitation of a random search within a defined search space to solve a problem. GAs were invented by John Holland in the 1960s and were developed by Holland and his students and colleagues at the University of Michigan in the 1960s and the 1970s. the goal was not to solve specific problems, but rather to formally study the phenomenon of adaptation as it occurs in nature and to develop ways in which the mechanisms of natural adaptation might be imported into computer systems (Mitchell, 1996). That is why we use GA for this task of image comparison and pattern recognition. GA have been applied to practically every step of image processing and pattern recognition. References of GA used in fuzzy systems and pattern recognition can be found e.g. in the bibliographies of Alander (1995; 2002), respectively. Tao et al. (2003) have optimised membership functions to attain three-level segmentation with maximum fuzzy entropy using GA. Han et al. (2001) used GA for stereo vision matching. They took the advantage of GAs in multi- criteria optimisation and optimised simultaneously similarity matching and disparity smoothness. Yokoo et al. (1996) developed an algorithm to detect faces based on edges and ellipse matching: Binary edge map is smoothed to a multi-level image and the GA generated ellipses are matched using pixel-wise similarity metric.

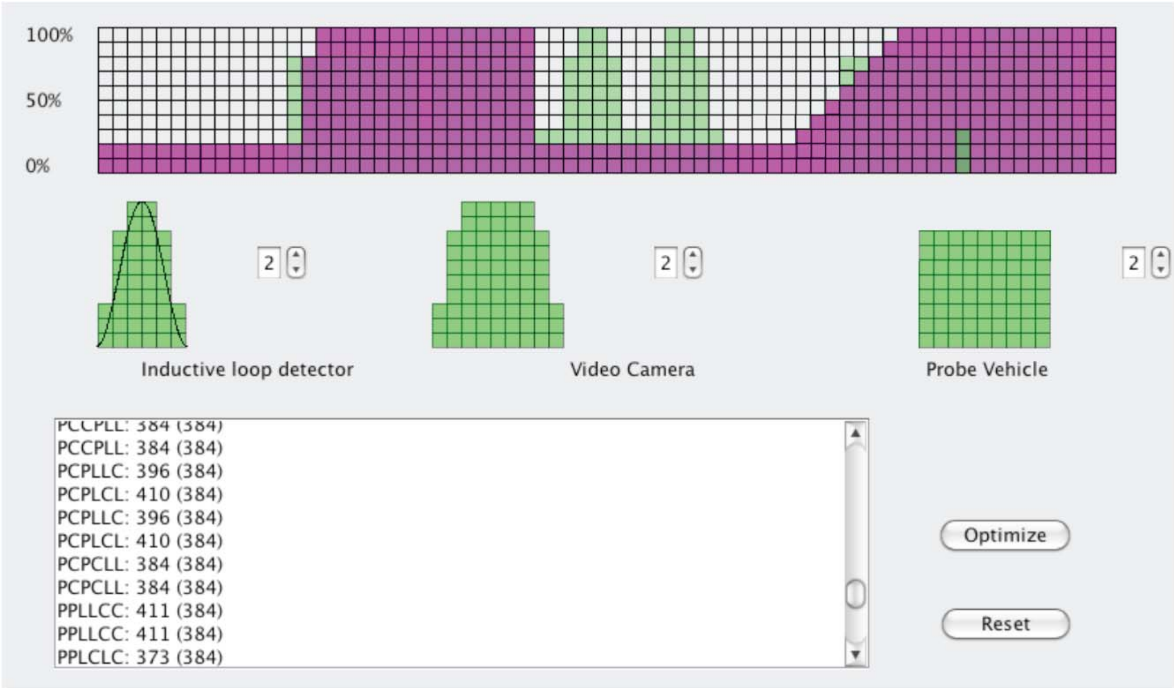

Figure 10. GA for detector placement

In our case we are placing a given sensor pool, step by step and evaluate the grid. Since the placement of a single sensor depends on the already placed sensors, we have to check all permutations of the sensor pool. Then the remaining shape of the demand is analysed, additional sensors accordingly selected and placed so that the desired level of detection is reached. In a last check, the new sensor pool gets allocated with all its permutations for the final result. Figure 10 shows a tool for a link optimisation.

After the optimisation we calculate the level of detection based on the grid according to the following equation:

$$\varphi^*_{i,\tau} = 1 - \frac{\sum_0^{\Theta} \{\max[g^*_{\rho,\beta}(x)] - \max[f^*_{\alpha,\omega,\mu,\lambda,}(x)]\}}{\sum_0^{\Theta} \{\max[g^*_{\rho,\beta}(x)]\}}$$

$\max[g^*_{\rho,\beta}(x)] > \max[f^*_{\alpha,\omega,\mu,\lambda,}(x)]$
$\varphi^*_{i,\tau} =$ Approximate LOD
$g^*_{\rho,\beta}(x)$ = units of data demand
$f^*_{\alpha,\omega,\mu,\lambda,}(x) =$ units of data supply

The difference is that we are using units for data demand and supply, instead of the continuous functions. The grid size should be chosen so to satisfy the desired accuracy.

CASE STUDIES

To test the framework under real world conditions we have chosen three areas around the world for case studies. Since the implementation is still in a prototype state, we limit the case studies to road stretches instead of whole networks. In the following we have examples from the motorway A13, close to the City of Delft in the Netherlands, the Route 101 in San Francisco, USA and the Route 4 of the Tokyo Metropolitan Expressway in Tokyo, Japan. We have chosen these areas due to the data availability through the International Traffic Database (http://www.trafficdata.info).

Motorway A13, Delft, The Netherlands

The motorway A13, located close to the City of Delft in the Netherlands, connects the capital The Hague with the port city of Rotterdam. The motorway carries a huge amount of traffic and is highly congested during the rush hours. The data on the International Traffic Database (ITDb) is provided by the Regiolab Delft, a research project carried out by the Delft University of Technology. The area of our case study is shown in Figure 11, as a screenshot of ITDb.

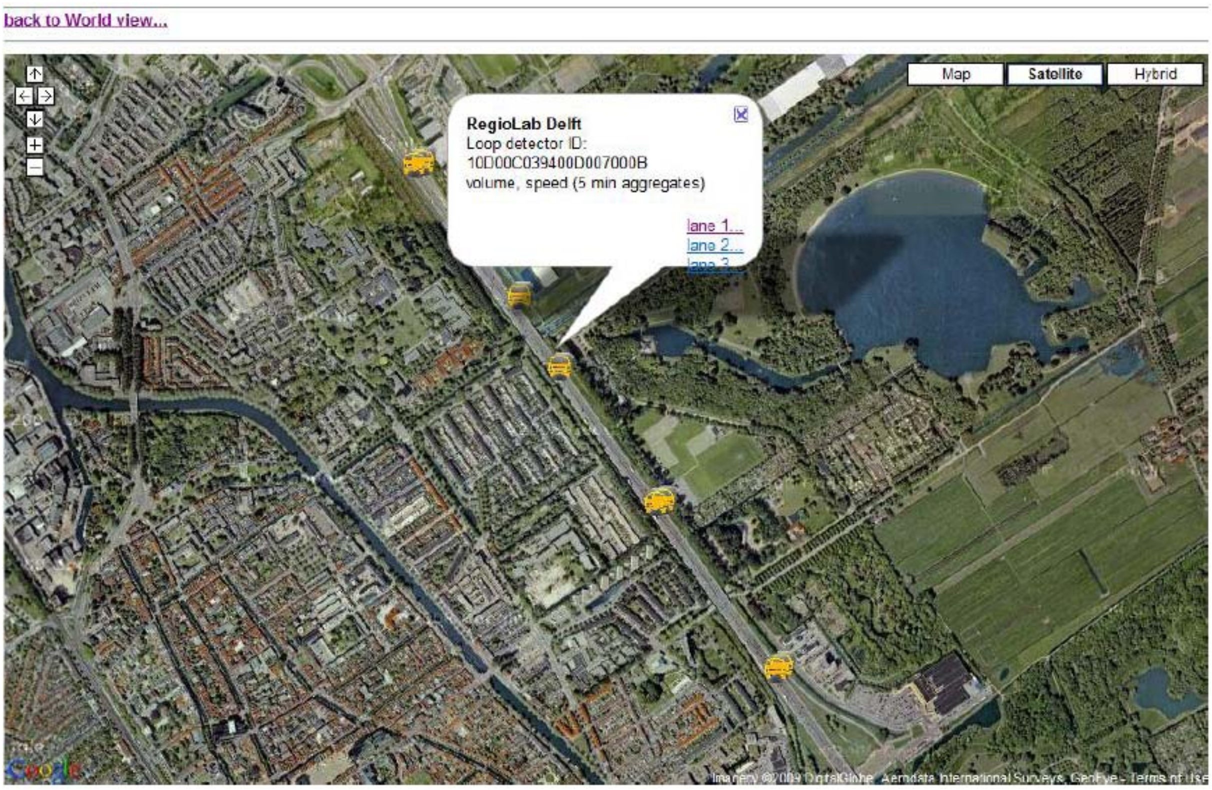

Figure 11. Area of the case study (International Traffic Database)

Figure 12 shows the schematic structure of the area. The stretch is 1800 metres long has one on and off ramp and has a dense network of sensors.

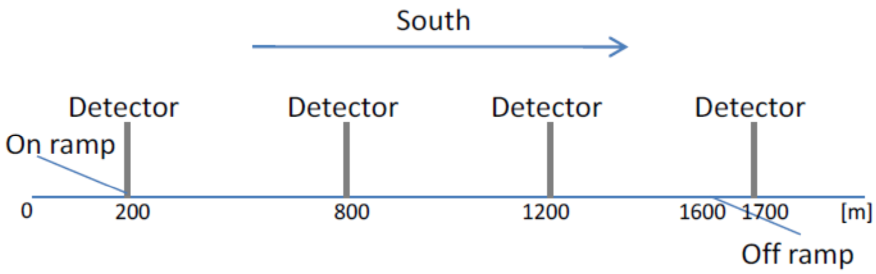

Figure 12. Abstract system of the real world road stretch

The close placement of sensors on a first look seemed very close and we were expecting a high rate of over detection. However, as Figure 13 shows the data demand from the network analysis, it reveals that the sensor spacing might be accurate. The grid in Figure 13 is longer than the road stretch we have chosen, so we are just interested in the area that carries demand, indicated by the coloured blocks.

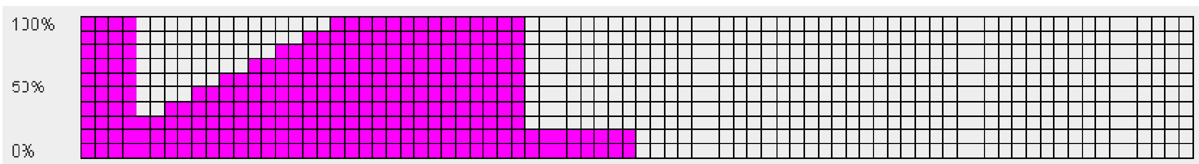

Figure 13. Data demand for the section as found by the network analysis

The first step is to determine the level of detection based on the actual placement of the detectors in the network. The position of those is indicated in Figure 14.

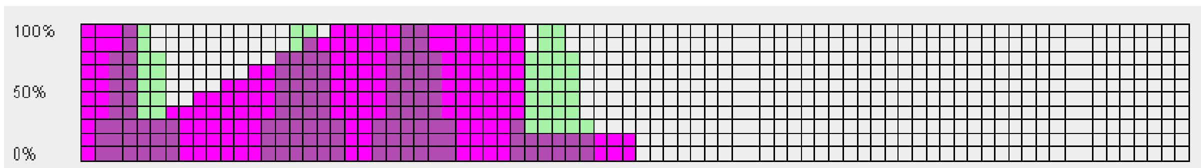

Figure 14. Actual detector location

Figure 14 shows that the detectors seem to follow the generated demand. The most right sensor seems a bit out of place, but that is partially due to the fact that our demand on the boundaries does not take into account the downstream situation. The system calculates a level of service of 44.3% and for the already mentioned reasons a high over detection value of Δ = 36.7%, which leaves room for improvement for the optimisation.

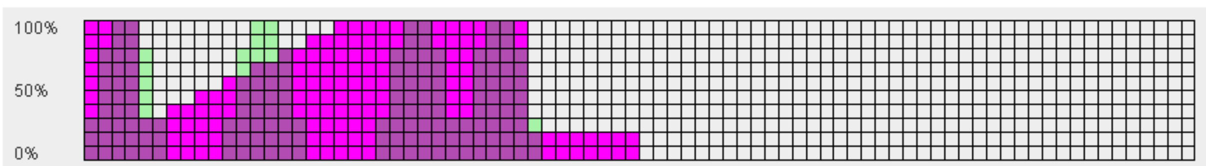

Figure 15. Detector placement according to the proposed framework

When using the optimisation tool for the original sensor pool of four loop detectors, the placement looks similar, but with the difference that the most right sensor moves in towards the high demand area. Figure 15 visualises the results of the optimisation, which results in a LOD of 55.0% and an over detection of Δ = 11.7%.

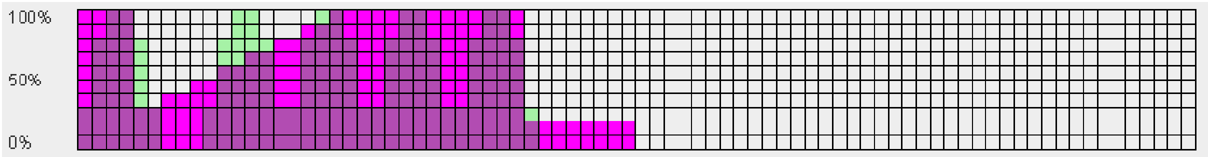

Figure 16. Optimal detector setting according to the proposed framework

An increase of the sensor pool to six sensors resulted in a placement as shown in Figure 16. The fact that the system just placed five sensors, instead of the allowed six detectors shows, that the system is sensitive to over detection and is not blindly placing unnecessary detection equipment. The calculated optimal placement achieves a level of detection of 69.3% with an over detection of Δ = 13.3%

Route 101, San Francisco, United States of America

For San Francisco we have chosen a four kilometre long stretch of the route 101 going North. This area has three on-ramps and three off-ramps and we have access to traffic data from four loop detectors for the duration of one month. Figure 17 shows the area in a screenshot.

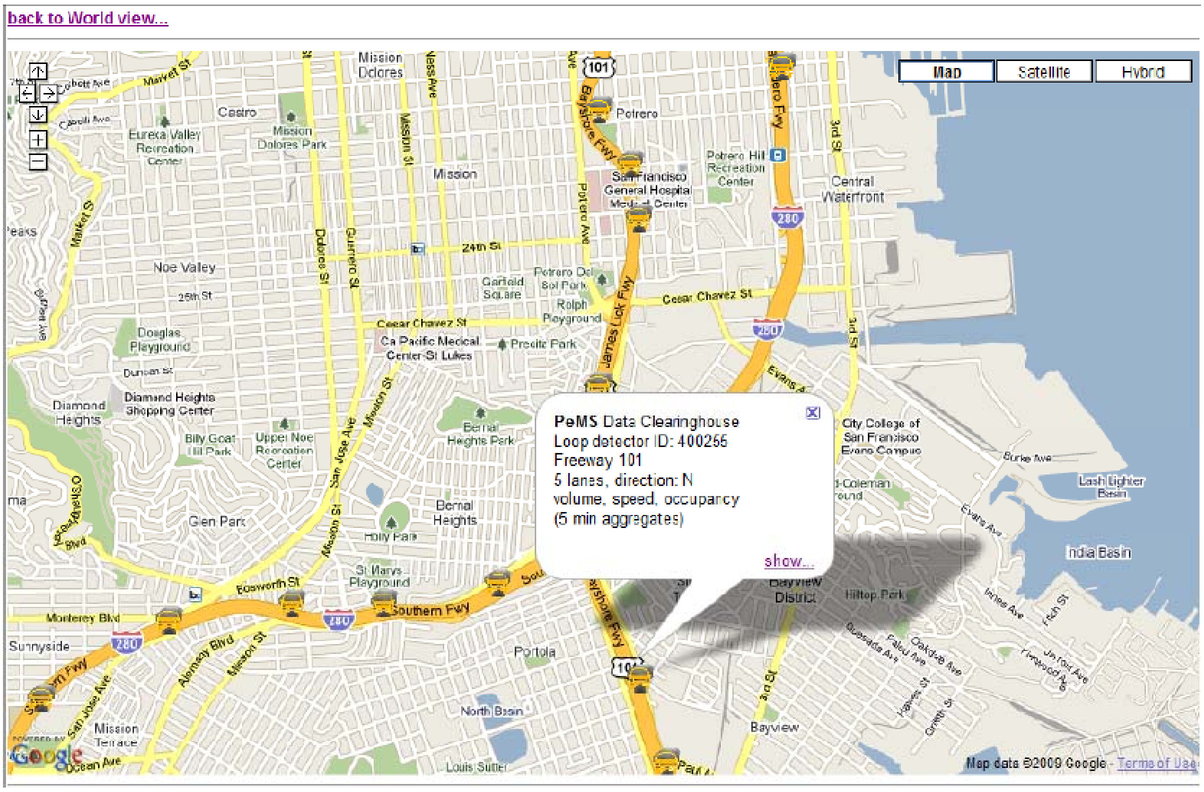

Figure 17. Area of the case study (International Traffic Database)

For the detection positioning optimisation the real world road stretch got transformed into an abstract system as shown in Figure 18.

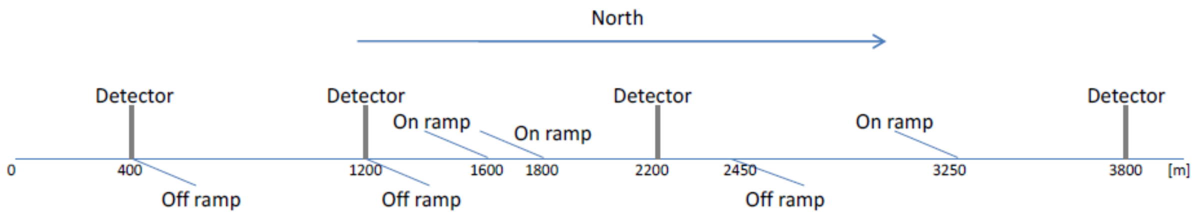

Figure 18. Abstract system of the real world road stretch

The network analysis marked the ramps as points of special interest and traffic data revealed that at the end of the road stretch the probability of queues, due to congestion is very high. Therefore the demand to monitor this area is spread wider (see Figure 19).

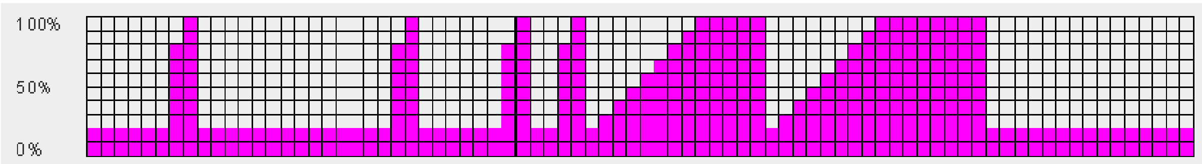

Figure 19. Data demand for the section as found by the network analysis

Again, the first step is to determine the level of detection based on the actual placement of the detectors in the network. The position of those is indicated in Figure 20.

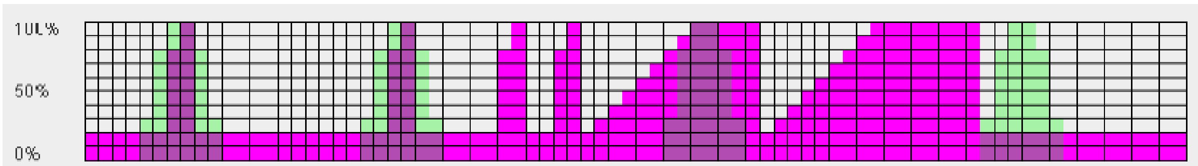

Figure 20. Actual detector location

Figure 20 reveals that the detectors are placed quite evenly distributed, but also close to the on and off-ramps. The level of detection calculated by our framework is 28.2%. The low number is easily explained with the last detector failing to cover the high demand area upstream of it. The over detection of the link Δ is 14.6%, which indicates that while a lot of demand remains unsatisfied, sensors are monitoring low demand area.

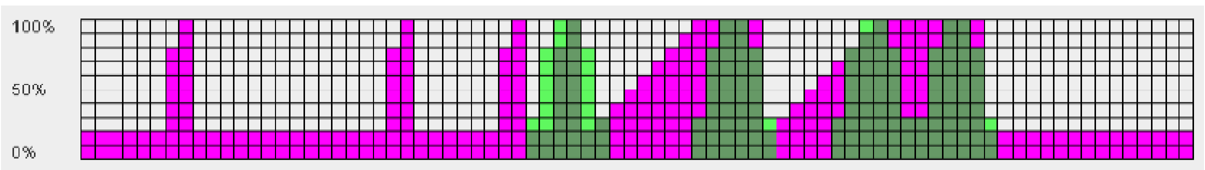

Figure 21. Detector placement according to the proposed framework

In the following we have used the detection optimisation tool with the actual sensor pool of four loop detectors and found a placement that results in a LOD of 39.9%. this indicates, that a different placement alone can change the level of detection by nearly 12%. This is possible, since the over detection ratio could be lowered to Δ=4.2%. Figure 21 shows the optimised locations of the sensors, leaving some ramps undetected, and strengthen the detection in the congested area to determine the queue lengths.

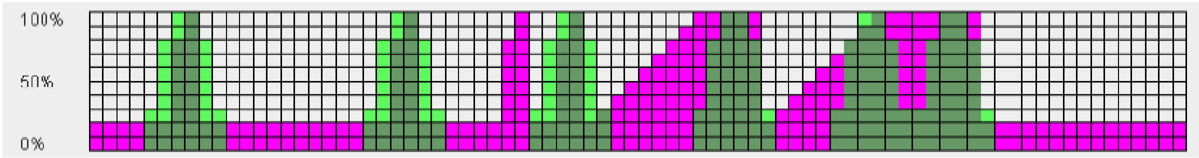

Figure 22. Optimal detector setting according to the proposed framework

In a final step we allowed the system to place two additional sensors in the link. Figure 22 shows the placement of the six loop detectors along the road. The LOD increases to 53.7% and the over detection ratio remains lower than in the original setting at Δ=11.8%. It can be seen that the optimisation does not keep adding sensors to the high demand area, but now places the additional detectors, as to be found in the real world.

Route 4, Tokyo Metropolitan Expressway, Japan

As a final example we have chosen a part of the Tokyo Metropolitan Expressway in Japan. We have chosen the area due to the fact that it includes an accident rich stretch including a tunnel. Figure 23 is showing the area.

Figure 23. Area of the case study (International Traffic Database)

The abstract scheme in Figure 24 shows the area described. The stretch is quite short, but the structure of the Metropolitan Expressway with sharp curves, many weaving sections and other special features, would render a larger area for our stage of implementation unfeasible.

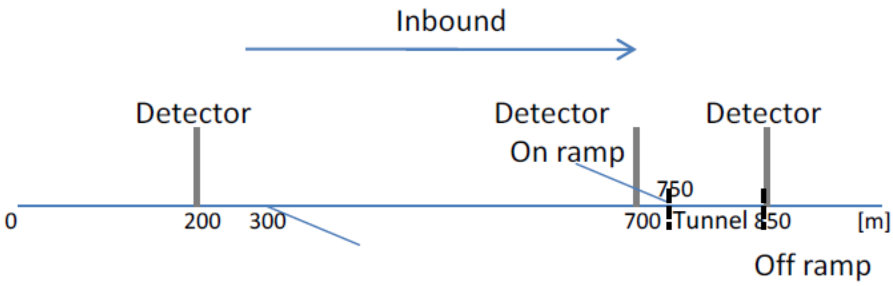

Figure 24. Abstract system of the real world road stretch

Figure 25, showing the demand after the network analysis shows a very high demand due to the tunnel and accident records. Tunnel entrances especially are valued as high risk areas in our framework.

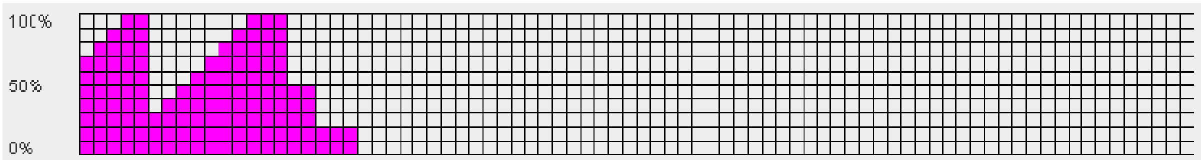

Figure 25. Data demand for the section as found by the network analysis

Probably for this reason, the authorities placed a dense detection at the tunnel, as visualised in Figure 26.

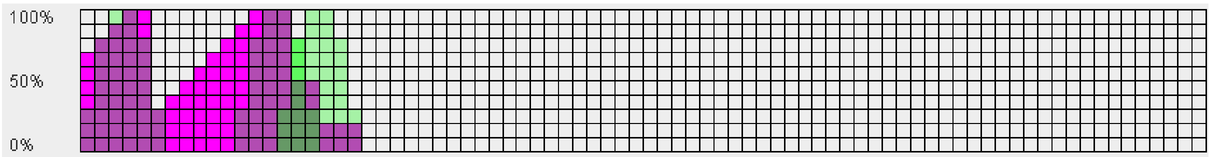

Figure 26. Actual detector location

The actual detection of the road stretch achieves a level of detection of LOD = 66.72% with an over detection value of Δ=35.3%. Again, the reader should be reminded that over detection, especially at boundaries can be due to missing information of the model.
Using the optimisation tool, the detectors move slightly decreasing the over detection value to Δ=26.5% and raising the LOD to 79.5%

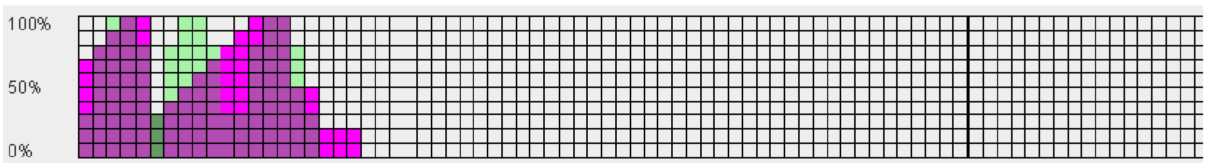

Figure 27. Detector placement according to the proposed framework

With the road stretch being so short, there is no sense in increasing the detector pool for the scenario in Japan. The over detection would render every additional placement unfeasible.

CONCLUSIONS

In this paper we have defined a framework for highway network detection system assessment. By analysing the network to find the challenging areas for traffic management we define a data demand per link and compare it to the data supply, based on sensor placements and sensor technology. This gives a good and objective indication of the detection system and its placement. While the functions for demand and supply still remain in a prototype state, we have shown in three case studies that the framework is feasible. The optimisation of the detection sensor placement has lead in all cases to the conclusion that an evenly distributed placement of detector is not useful, and that detection should be closely related to the network structure. Even though all networks showed the tendency to do so, an improvement was still possible. The strength of the formulated framework is that the utility function can easily be extended as demonstrated with the over detection ratio to avoid redundancy in the detection.

FUTURE WORK

Having shown that this framework is feasible, future work will consequently enhance the framework. Most effort has to be put into the definition of demand and supply functions. While supply function can take the physical capabilities of the sensors as basis, the demand function are less objective. However, basic shape and parameters would allow road authorities and traffic engineers to include their own expertise. As a third category we will include functions for not directly measurable values - at least not in one point - such as travel time. We will investigate algorithm with their data needs and accuracy to enrich the possibilities for optimisation.

Applying such a framework leads to efficient detection plans, however, one more and more important aspect should be taken into account as an additional limitation - environmental impact. The environmental impact should not be forgotten. With research projects going on to limit and reduce the carbon footprint of transportation with intelligent transportation systems (ITS) and efficient road management strategies, future work should ensure that the installation and usage of the necessary equipment for such efforts will not backfire in terms of the impact to our environment. This is why extending the proposed framework with a bi-level optimisation that can match the policy goals for both, traffic engineering and environmental goals.

ACKNOWLEDGEMENT

All observation data for this study was provided by the International Traffic Database (ITDb). The International Traffic Database is part of the Energy ITS project, funded by the Ministry of Economy, Trade and Industry of the Japanese Government. Data available to the public can be accessed through www.trafficdata.info.

REFERENCES

Klein, L. A., Data Requirements and Sensor Technologies for ITS, Norwood, MA, Artech House, 2001

U.S. Department of Transportation, Federal Highway Administration Report No: FHWA-HRT-06-139, Traffic Detector Handbook: Third Edition - Volume II, October 2006

Mimbela, L. & Klein, L.A., Summary of Vehicle Detection and Surveillance Technologies used in Intelligent Transportation Systems, 2007

Yang, H., and Zhou, J. Optimal Traffic Counting Locations for Origin-Destination Matrix Estimation. Transportation Research Part B, Vol. 32, 1998, pp. 109-126

Sisiopiku, V.P., Rouphail, N.M., and Santiago, A. Analysis of Correlation Between Arterial Travel Time and Detector Data from Simulation and Field Studies. Transportation Research Record, No. 1457, 1994, pp. 166-173

Thomas, G. The Relationship Between Detector Location and Travel Characteristics on Arterial Streets. Institute of Transportation Engineering Journal, Vol. 169, 1999, pp. 36-42

Oh, S., Ran, B., and Choi, K. Optimal Detector Location for Estimating Link Travel Speed in Urban Arterial Roads. In Proceedings of the 82nd Annual Meeting of the Transportation Research Board, Washington DC, 2003

Edara, P., Guo, J., Smith, B. L., McGhee, C., Optimal placement of point detectors on Virginia's freeways: Case studies of Northern Virginia and Richmond, Report No. VTRC 08-CR3, Virginia Transportation Research Council, Richmond, 2008

Cormen, Thomas H.; Leiserson, Charles E.; Rivest, Ronald L.; Stein, Clifford (2001). "Section 24.3: Dijkstra's algorithm". Introduction to Algorithms (Second ed.). MIT Press and McGraw-Hill. pp. 595–601

Chen, C., Skabardonis, A., Varaiya, P., Systematic Identification of Freeway Bottlenecks, Transportation Research Board 83rd Annual Meeting January 2004 Washington, DC

Miska, M., Real time Traffic Management by Microscopic Online Simulation, T2007/1, January 2007, TRAIL Thesis Series, The Netherlands TRAIL Research School

Miska, M, Torday, A., Warita, H., Kuwahara, M., International Traffic Database - Gathering traffic data fast and intuitive, Traffic Data Collection and its Standardization, Series: International Series in Operations Research & Management Science , Vol. 144, Barceló, Jaume; Kuwahara, Masao (Eds.), Springer, 2010 (in press)

Jiang, T., Miska, M., Kuwahara, M., Highway Network Analysis and Detection Assessment Framework, ITS World Congress, Busan, Korea, 2010 (in review)

Mitchell, M., An introduction to genetic algorithms, First MIT Press paperback edition, Massachusetts Institute of Technology, 1996

Alander, J.T., An Indexed Bibliography of Genetic Algorithms in Pattern Recognition. Report 94- 1-P A TTERN, University of Vaasa, 2002. ftp://ftp.uwasa.fi/cs/report94-1/.

Alander, J.T., An Indexed Bibliography of Genetic Algorithms with Fuzzy Systems. Report 94-1-FUZZY , University of Vaasa, 1995, ftp://ftp.uwasa.fi/cs/report94-1/

Tao, W-B., Tian, J-W., Liu, J., Image segmentation by three-level thresholding based on maximum fuzzy entropy and genetic algorithm. Pattern Recognition Letters, 24: 3069–3078, 2003.

Han, K-P., Song, K-W., Chung, E-Y., Cho, S-J., Ha, Y-H., Stereo matching using genetic algorithm with adaptive chromosomes. Pattern Recognition, 34: 1729–1740, 2001.

Yokoo, Y., Hagiwara, M., Human Faces Detection Method using Genetic Algorithm. In: Proceeding of IEEE Int. Conf. on Evolutionary Computation, 113–118, 1996.