AUTOMATIC DETECTION AND ESTIMATION OF INCIDENT PROBABILITIES FOR INCIDENT MANAGEMENT PURPOSES. A CASE STUDY IN BARCELONA.

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SUMMARY

Real-time models for automatic Incident Detection and Estimation of Incident Probabilities contribute to the improvement of the effectiveness of incident management policies devoted to increase road safety. New, advanced-technology hardware and software, and new models make possible the improved monitoring, surveillance and management of high-risk road locations in urban and rural areas of the European Union (10). Fast and reliable detection and prediction models for incidents, imbedded in traffic management environments, is instrumental in the development of control strategies to reduce traffic delay and the likelihood of new incidents before they occur.

INTRODUCTION

The authors are responsible of the design and implementation of some of the detection and prediction algorithms in the PRIME Project (Prediction of Congestion and Incidents in Real Time for Intelligent Incident Management and Emergency Traffic Management) in the "*Information Societies Technology Programme*" of the EEC. The selected algorithms for detection purposes rely on different proposals: Delos (5,4) and Persaud (2, 3) algorithms. The calibration of both algorithms on Barcelona test-site will allow the possibility of comparison of the performance of the algorithms on different traffic conditions, according a fixed-set of indicators. For the estimation of incident probabilities, a statistical oriented approach based on Generalized Linear Models (7) with politomous responses in a hierarchical scheme is being selected for calibration and implementation purposes (6): geometry, traffic and weather conditions are taken as explicative variables at a section level and a binary variable related to incident occurrence or not for the prevailing conditions as a response variable in the first level of decision.

Calibration and comparisons of algorithms will be done off-line by simulation, once the algorithms were incorporated in the microscopic simulation environment AIMSUN/2 (developed by TSS[1]) . AIMSUN/2 (11, 12) is going to emulate a traffic management environment, since it simulates traffic evolution and incorporates different modules of incident detection, prediction and traffic management in such a way that the impact of sets of traffic management strategies are able to be evaluated via the simulation tool.

A test site in Barcelona, located in a 10 km portion of the *Ronda de Dalt* Ring Road, is providing data for calibration and testing purposes. The selected site is equipped with 12

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CCTV cameras used for traffic monitoring purposes, 18 local controllers, 12 detection stations, 10 variables message panels and 13 variable speed signals. Detection stations provide measures of different traffic parameters at lane detail every minute.

AUTOMATIC INCIDENT DETECTION

Incident Detection subsystem in Prime project seeks to interpret collected data from the road network, the movement of vehicles, and the environment to decide on the occurrence of incidents. The objective of the subsystem is to accomplish this task at the highest possible detection rate, and the lowest possible false alarm rate. Incident detection uses different types of hardware and software to accomplish this task. Within this project, we focus on

(a) algorithms that can be implemented with any hardware; such are the algorithms that are based on neural networks, U06, and the Persaud *et al*. algorithm; and

(b) algorithms that function with machine vision hardware.

The above algorithms operate on static specifications (all except neural networks) or on specifications that allow them to learn from the ground truth during incident occurrences and incident-free periods (neural networks). Persaud *et al* (2) and DELOS (4), employ statistical indicators or time series models to describe normal traffic conditions and detect incidents when measurements deviate significantly from model outputs.

Incident Detection with Persaud Algorithm (IDPE)

The Persaud algorithm incorporates a mechanism for distinguishing between recurrent and incident-related congestion based on a model elaborated on the catastrophe theory to describe the relationships between flow occupancy and speed (1).

The Persaud_Congestion_Incident_Detection (PCID) subsystem uses the data from detectors (loop, machine vision, etc.) to provide estimates on incident/recurrent congestion occurrence. These data are analysed by the subsystem and compared with the values of operator defined thresholds and parameters calibrated using historical data to provide:

- Periodic incident reports at each detector on the site (30” would be recommendable, but some PRIME sites will only have available 1 minute data)
- Periodic recurrent congestion reports at each detector on the site (30” would be recommendable, but some PRIME sites will only have available 1 minute data)

<u>Description of the current implementation integrated in AIMSUN2 environment</u>: When the program starts its execution, and after internal start-up sequences and initialization, the Operator is presented with a screen that makes possible to:

- Enter manually a new model description.
- Enter local parameters
- Start up the incident detection

The model description, parameters and thresholds, for incident detection purposes should be defined and parameters estimated if the user does not supply an original set. According to user defined criteria, that will be defined in the testing phase, model parameters should be estimated again and/or model description might change.

The Operator is able, according to the functional requirements of the incident detection to enter manually an initial model description: set of parameter estimates. Under Operator request, parameter should be reestimated, unless it would be entered as input. During the process of the ID module, the operator always will be able to make an interruption, like change model description.

The PCID subsystem is able to show graphically, at a section level, the section on which the incident or the congestion has been detected, and display an operator's warning message. Inside the Persaud_Congestion_Incident_Detection subsystem we have the following modules:

- PCDI calibration module. Reads the Incident Data, and the traffic data stored in a historical database to calibrate the parameter values of the Persaud algorithm. The PCDI algorithm later uses these values.
- PCDI algorithm. Retrieves the current traffic data from a real-time source and uses the PCDI template to identify the conditions and produce the incident/congestion report.
- GUI module, the same proposed for the EIP module, providing either a report or an alarm and a warning for the Road Link which detector has identified an incident or congestion above a predefined threshold.

The principle of the basic version of the congestion detection logic is that a congestion flag can be given by operation in certain areas of the flow/occupancy diagram, or by a slow speed. If a flag is given for P consecutive periods, congestion is present and hence a potential incident is indicated : *the logic is designed for a system that provides speed and flow-occupancy data. The efficiency increases if data is for single lane.*

The algorithm's global idea can be expressed in the form of a template drawn on a flow-occupancy diagram, defining four different states of traffic. The template is composed of 4 areas, which are divided by the lower bound of uncongested data (LUD), the critical occupancy (Ocrit), and the critical volume (Vcrit). Area 1, above the LUD, is uncongested data. The area below LUD and Vcrit and to the left of Ocrit is Area 2, one type of congested traffic operation. The area to the right of Ocrit and below Vcrit is Area 3, more heavily-congested traffic operation compared with data in Area 4, which is below LUD but above Vcrit. The division between Areas 3 and 4 is used for detecting incidents within congestion. The look for the template for stations not affected by recurrent congestion is displayed in the following figure:

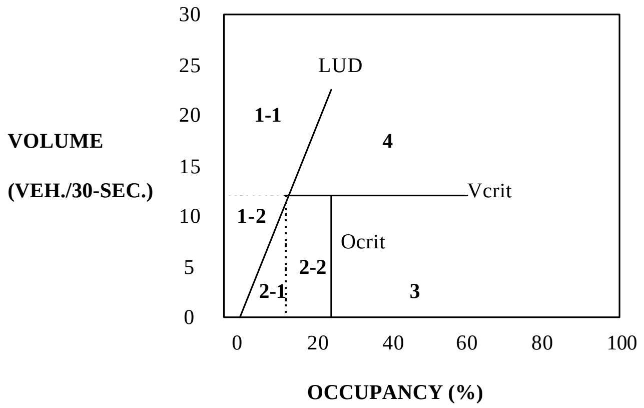


Illustration 1. Persaud template for stations not affected by recurrent congestion

Input Data Requirements: Description of the Road network and Traffic Data.

Name	Description
Equipment Location	Ideally this information will be provided as distance in kms from designated marker posts.
Carriageway	It must be possible to derive the Carriageway, where the incident occurred either directly from the Equipment Location.
Detection Code	This code will identify the source or method of the incident detection which for road-side equipment will be the equipment identifier and type of equipment which detected the incident.
Date&Time of Detection	The date and time of the incident detection to an accuracy of within 2 minutes.
Traffic Flow	% Occupancy every 30-60 secs in each lane and on each entry/exit ramp
	Volume every 30-60 secs in each lane and on each entry/exit ramp
	Speed (km/hr) every 30-60 secs in each lane and on each entry/exit ramp

Illustration 2. Input Data for Incident Detection with IDPE algorithm (Persaud et al.)

Output: Incidents detected (Recurrent congestion detected) by file and graphic display (as shown in the following Illustration 3).

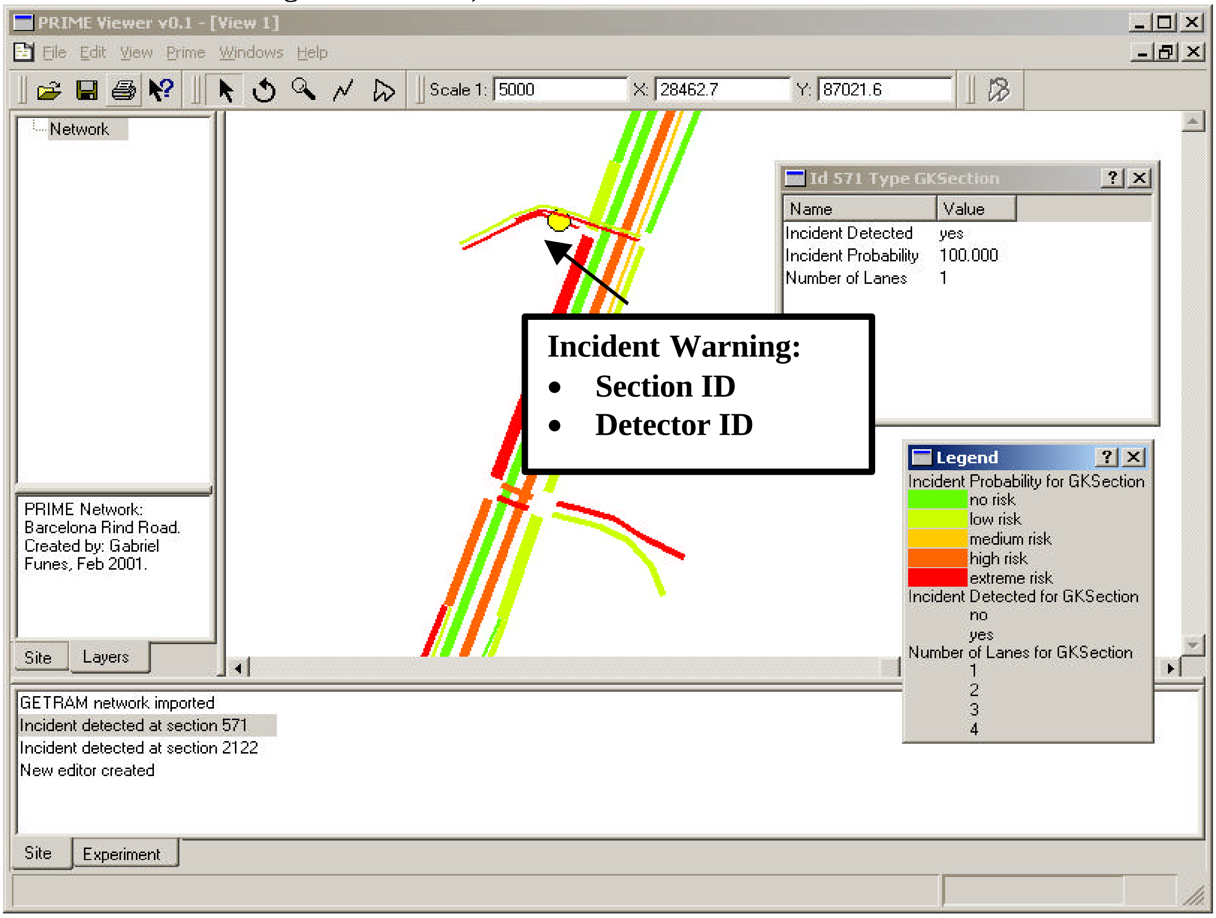


Illustration 3. AIMSUN2: GETRAM graphic display of incident detected (warning)

Incident Detection with DELOS

Incident detection with DELOS algorithm is used as a reference so that the results from this work can be connected with evaluation results of this algorithm (4). This reference is helpful for two reasons: the algorithm has been tested during earlier EU work (9), and it has been tested against the major of the previously existing algorithms in the literature.

DELOS (DEtection LOgic with Smoothing) algorithms involve smoothing occupancy measurements to distinguish short-duration traffic inhomogeneities from incidents. When an inhomogeneity is present, smoothing eliminates or diminishes its impact; on the other hand, smoothing does not substantially modify the incident pattern if its duration is greater than the number of terms in the smoother. Although smoothing may conceal the patterns of some non-severe incidents, the large reduction in false alarms compensates for a few possibly missed incidents. To be sure, this tradeoff can best be assessed by the user based on user priorities. Extensive test results indicate significant false alarm reduction compared to similar algorithms, e.g., Standard Deviation, Double Exponential, and California, that attempt raw data manipulations.

Performance indicators of selected ID algorithms

Detection Rate (DR) : Performance can be seen in terms of detection rate for each type of incident. Accidents, for instance, are more important to detect than stalls as they typically have a strong congestion effect and require prompt emergency assistance.
False Alarm Rate (FAR): A FAR=0.1-0.15 % is expected for DELOS.
Mean Time-To-Detect (MTD): DELOS detection times are slightly longer than those of algorithms employing raw data since it exhibits response up to 2 min.

Calibration of ID algorithms for Barcelona test-site is currently undertaken, from an off-line database containing traffic data of 6 months (2 Gb). Once an initial set of parameter estimates will be available for each integrated ID algorithm (IDPE and DELOS), simulation experiments with AIMSUN2 to compare both algorithms under different traffic conditions will be executed.

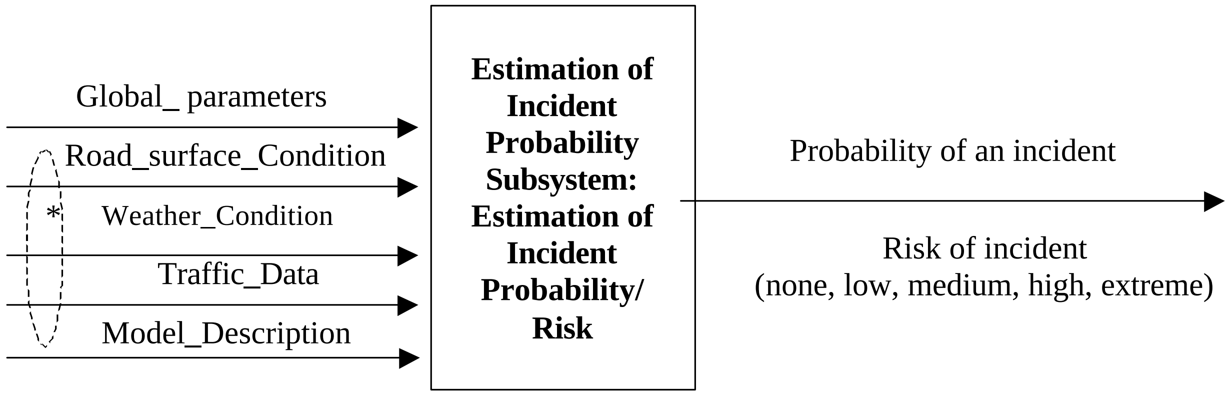
ESTIMATION OF INCIDENT PROBABILITIES

The aim of the Incident Probability Estimation subsystem in Prime project is to establish the association between traffic conditions, weather conditions and road geometry and incident occurrence. The association is established according to statistical models, taken traffic and weather conditions and road geometry as explicative variables and the presence of incidents, as a response variable, given as a result the probability of incident occurrence for each segment that constitutes the road network (8,6). The authors have implemented and integrated a statistical model approach in the AIMSUN2 environment.

The EIP module developed provides the Operator with the following possibilities:

- Parameter estimation of models from historical data relating the response and the explicative variables for the statistical approach based on a Hierarchical Logit Model (HLOGIT in the following references).
- Selection of model variables by means of a user-interface for the statistical algorithm and calibration of model parameters.
- Selection of model variables and parameters (externally calibrated) by means of a user-interface for the statistical algorithm.
- Recalibration of the current statistical model under user-requirement.

- Estimation of real time probability of incidents given current weather and traffic conditions, road geometry and the statistical model of association.
- Estimation of real time risk of incidents given current weather and traffic conditions, road geometry and the statistical model of association. Graphical output showing network geometry and related incident risk for each link of the network, provided that real time traffic data is available for the road section. The same interface showed for ID module is used.



* for each section

Ilustración 4. EIP-HLOGIT: Incident probability/risk prediction functionality

Real-time (AIMSUN2 simulated) traffic, weather and geometric data are necessary for the estimation of incident probabilities. Input data requeriments:

- Traffic Data (speed, flow, occupancy, etc.).
- Weather_Data (rain, wind, fog and snow...).
- Geometric_Data (lanes, ramps, capacity, road/surface conditions, etc.)

Calibration of EIP- HLOGIT algorithm for Barcelona test-site is currently undertaken, from an off-line database containing traffic data of 6 months (2 Gb), the same one being used for the calibration of ID algorithms. Once an initial set of parameter estimates will be available, simulation experiments with AIMSUN2 for generation of simulated real-time data will executed in order to evaluate EIP-HLOGIT performance.

EIP-HLOGIT: parameter estimation functionality

This functionality of the EIP module estimates model parameters for explicative variables included in the statistical model_description from historical data related to traffic, weather, geometry and registered incidents. Historical traffic conditions and incidents for model parameter estimation purposes are stored in a Historical Database for a given time interval before and after incident occurrence. The Historical Database contains:

- Traffic Data. For non-incident periods, a proportion of the total time.
- Incident_Data
- Weather_Data (rain, wind, fog and snow...).
- Geometric_Data

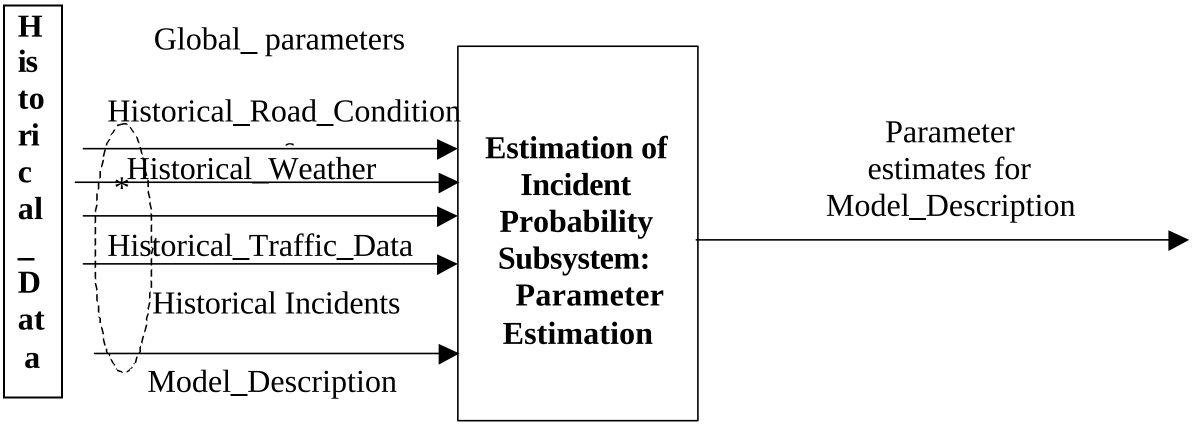


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Ilustración 5. EIP-HLOGIT: Parameter estimation functionality

The authors have developed a C++ procedure for estimating the parameters in the involved ***Hierarchical Logit Model (Multinomial Models):*** a particular case of the Method of Scoring for the estimation of Generalized Linear Models in Statistics**.**

Generalized Linear Models in Statistics are an extension of ordinary linear models (with normal responses) (8). A brief description is included in the following paragraphs:

Let $\mathbf{y}^T = (y_1, \ldots, y_n)$ be a set of n observations, from a random vector $\mathbf{Y}^T = (Y_1, \ldots, Y_n)$, whose components are statistically independent and distributed with mean values $\boldsymbol{m}^T = (m_1, \ldots, m_n)$:

- **The random component** requires $\mathbf{Y}^T = (Y_1, \ldots, Y_n)$ to be independent components belonging to the exponential family of distributions with $\mathrm{E}[\mathbf{Y}] = \boldsymbol{m}$.
- **The systematic component of the model consists on** the specification of a vector $\boldsymbol{h}$, the linear predictor, from the explicative variables in such a way that $\boldsymbol{h} = \mathbf{X}\boldsymbol{b}$ where the parameters are $\boldsymbol{b}^T = (b_1, \ldots, b_p)$ and regressors $\mathbf{X}^T = (X_1, \ldots, X_p)$. $\boldsymbol{h}$ *nx1*, $\mathbf{X}$ *nxp* and $\boldsymbol{b}$ *px1*.
- Vector $\boldsymbol{m}$ is related with the linear predictor $\boldsymbol{h}$, through the link function $\boldsymbol{h} = \mathbf{g}(\boldsymbol{m})$, $\boldsymbol{m}$ is *nx1*.

The method of scoring iterates a process (on m) for the computation of the singular point of the log-likelihood function involved. The algorithmic scheme for estimating each logit-model equations in the hierarchical scheme by the scoring method requires numerical solution since matrix and vectors defining the normal equations are non linear functions of the parameters $\boldsymbol{b}$:

1. Start with estimates $\mathbf{b}^{(0)}$. One particular choice of initial estimates is $\mathbf{b}^{(0)} = 0$. There are other possibilities.
2. At iteration *m+1*, compute the new estimates by solving:

$$\mathbf{b}^{(m+1)} = \mathbf{b}^{(m)} + \left(\mathbf{X}^T \mathbf{W}^{(m)} \mathbf{X}\right)^{-1} \mathbf{X}^T \left(\mathbf{y} - \mathbf{p}^{(m)}\right)$$

$$\text{where } \hat{y}_i = p_i^{(m)} = 1 \Big/ \left(1 + e^{-\mathbf{X}_i^T \mathbf{b}^{(m)}}\right)$$

$$\text{and } \mathbf{W}^{(m)} = \text{diag}\left\{ p_i^{(m)} \Big/ \left(1 - p_i^{(m)}\right) \right\}$$

3. Iterations continue until $\mathbf{b}^{(m+1)} \approx \mathbf{b}^{(m)}$, according to a prefixed tolerance. When convergence takes place $\left(\mathbf{X}^T \mathbf{W}^{(m)} \mathbf{X}\right)^{-1} \mathbf{X}^T \left(\mathbf{y} - \mathbf{p}^{(m)}\right) \approx \mathbf{0}$ and thus the estimating equations are approximately satisfied $\mathbf{X}^T \mathbf{y} = \mathbf{X}^T \mathbf{p}^{(m)} = \mathbf{X}^T \hat{\mathbf{y}}$.

Independent variables considered in the model are either covariates or factors. In the case of covariates, they are directly represented in the design matrix $\mathbf{X}$. In the case of factors, each *factor value* should be splitted into a dummy variable to be included in the design matrix, but finally, it has to be reduced (by transformation) to avoid singularities.

OFF-LINE TESTING IN BARCELONA

The IMSS module consists on a decision support process based on the pre-assessment by simulation of pre-defined strategies on a set of scenarios defined after the reconstruction of well identified incident situations. The conceptual approach to the off-line testing workplan at Barcelona site is depicted in the following illustration and will work as follows:

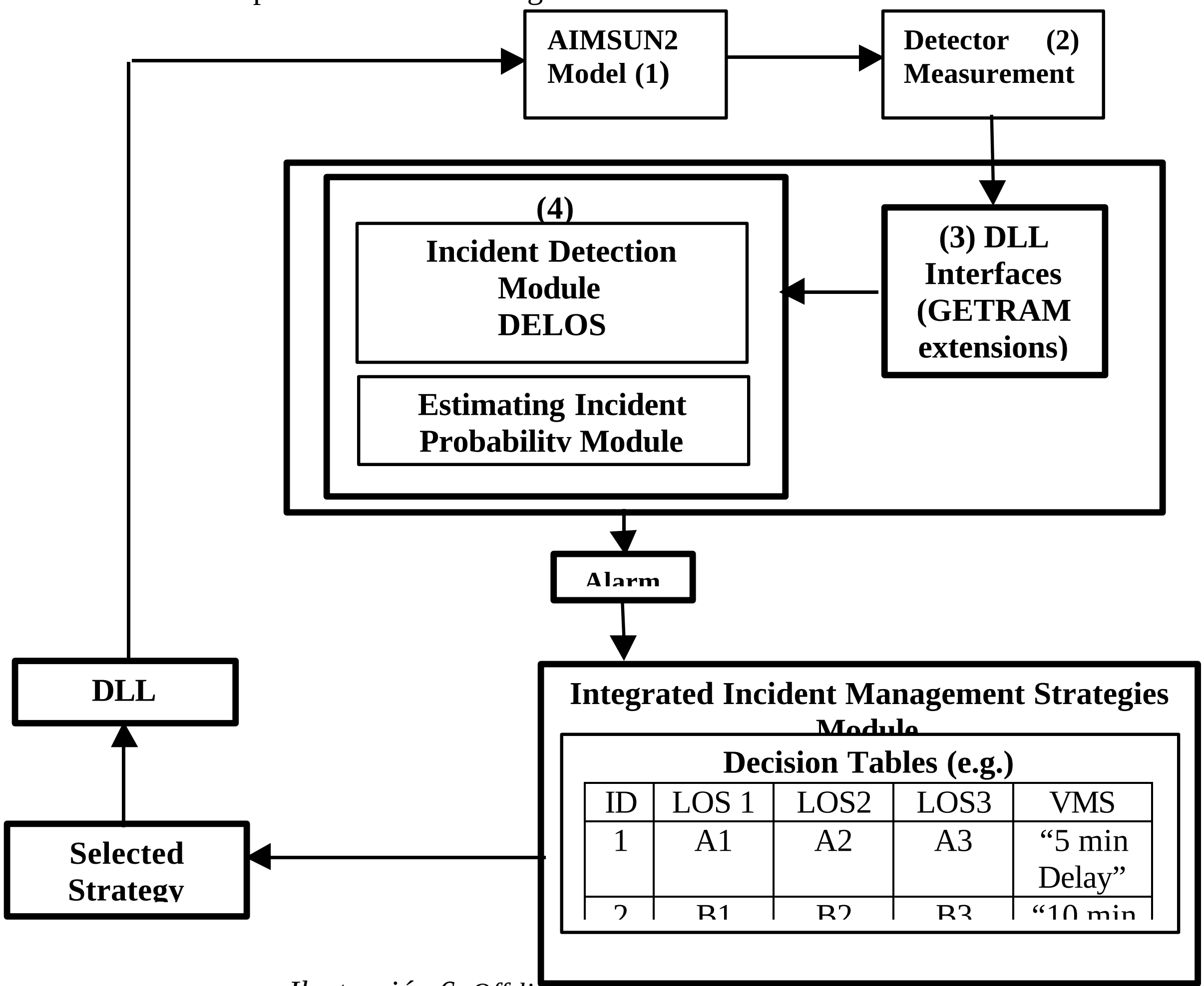

Ilustración 6. Off-line testing scheme: Barcelona site

- An AIMSUN2 model (Box 1) of the whole test site has been built (Model completed in January 2001). The model has been calibrated in February 2001 using the traffic data collected from September 2000 until January 2001 according to the data collection plan in Barcelona.
- On January 19, 2001, an additional data collection process was agreed with the municipality for collecting traffic data at entry and exit ramps during a week, with the purpose of estimating a local time dependent origin destination matrix using the procedures developed in the DACCORD project of the 4th Framework Program. The additional data collection survey has been done in February-March 2001.
- Once calibrated, the model emulates the traffic measurements (flow, occupancy, speed and traffic composition, Box 2) that would be provided by the available on-street detection systems. These data produced by the model for various simulated detectors will be stored.
- A site-specific DLL GETRAM interface to feed the simulated traffic data into their incident detection/probability estimation models has been completed in February 2001, along with the calibration process (Box 3). Once integrated by March 2001, the various incident detection and prediction algorithms can operate using the simulated data provided by the model.
- The algorithms, which make up the incident detection and estimating incident probability modules, will use the simulated traffic data generated by AIMSUN2 to predict and identify incidents on the simulated network via the GETRAM extensions (Box 4). The simulation experiments will start at the beginning of April after completing the calibration process.
- When incidents are predicted/detected, the Integrated Incident Management Strategies Module is alerted choosing traffic control plans and/or information dissemination plans according to the severity of the conditions encountered (Box 5).
- The selected strategy can then be fed back into the simulator in terms of VMS messages which are designed to divert certain proportions of drivers or control plans which will alter priority at traffic signals. A site specific DLL GETRAM-AIMSUN2 interface is required to feed the parameters of the strategy back into AIMSUN2, this component has been implemented by March 2001, but it is not fully tested yet. The effects of these strategies will be monitored.

The decision tables which make up the Integrated Incident Management system (IIMS module) are being developed off-line. These will form a dictionary of traffic control plans and information dissemination plans for each link in the simulated network. These site specific plans are derived by running various incident scenarios (duration and severity) on specific key links in the network. Where possible, data collected from real incidents should be used to determine the ideal proportions of drivers to try and divert using VMS and the most optimal signal control plans.

The most optimum management strategies could be picked manually, once the system has predicted/detected an incident. The characteristics of this strategy (VMS diversion proportions/traffic control plans) can be manually entered into the simulation model before discovering the effects of the proposed management scenario.

CONCLUSIONS

The calibrated simulation model of Barcelona-site is the engine that can be used to design potential scenarios for testing and evaluating by simulation the performance of the Incident

Detection and Prediction subsystems and the management strategies. In this work, two sets of scenarios has been designed:

- Scenarios for testing the incident detection / estimation of incident probability performance.
- Scenarios for testing and evaluating the Integrated Incident Management Strategies.

The Integrated Incident Management System in Barcelona will be evaluated in terms of the percentage of improvement on the selected LOS (Level Of Service) between the do nothing scenario (current situation without specific management strategies) and the scenario with the application of the selected management strategy. The results of the simulation analysis and assessment of scenarios are the basis for a decision making process which could lead to a real-life implementation of the defined management strategies.

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