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PRESENT AND FUTURE METHODOLOGY FOR THE IMPLEMENTATION OF DECISION SUPPORT SYSTEMS FOR TRAFFIC MANAGEMENT

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Abstract

Real-time predictions are an indispensable requirement for traffic management in order to be able to evaluate the effects of different available strategies or policies. The combination of predicting the state of the network and the evaluation of different traffic management strategies in the short term future allows system managers to anticipate the effects of traffic control strategies ahead of time in order to mitigate the effect of congestion.

This paper presents the current framework of decision support systems for traffic management based on short and medium-term predictions and includes some reflections on their likely evolution, based on current scientific research and the evolution of the availability of new types of data and their associated methodologies.

1. Introduction

Traffic is a social issue of enormous economic and environmental importance. Due to the high cost of infrastructure and present financial constraints, a series of traffic control and management techniques have been developed to achieve a set of objectives: increase infrastructure capacity; increase efficiency; prevent congestion and reduce its extent and duration; increase road safety and reduce environmental impact.

Traffic management relies on a set of tools or strategies that allow the optimisation of the objectives mentioned above. These strategies can be characterised as user information systems (such as transmitting information via variable message signs or broadcasts) or traffic control systems (such as control of access ramps, reversible lanes, variable tolling and adaptive signal control).

The optimisation of available traffic management strategies requires monitoring of the current and (short-term and medium-term) future of the system, permitting the evaluation of prospective control policies and ideally anticipating the impact of recurring or sporadic congestion.

Section 2 of this paper presents the current framework of decision support systems for real-time traffic management based on short and medium term forecasts of the state of the road network. Section 3 presents a collection of thoughts on the limitations of the current framework and its likely evolution, following the current state of scientific research in this area that depends on new types of data and their associated methodologies.

2. Decision Support Systems for Traffic Management: Current Framework

The generic architecture of decision support systems (DSS) for traffic management contains the following elements:

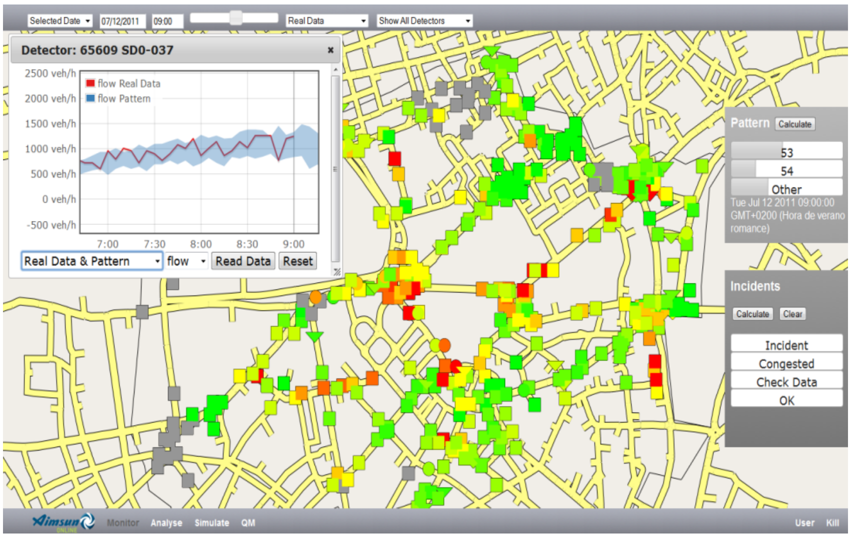
a) Real-time data: System input consists of real-time data from different types of detectors located in the network (detecting density, capacity, speed), as well as information relative to the day of the week, meteorological conditions, incidents, special events, road works and refurbishment on the road network.

b) Historical data: System input consisting of previous real-time data stored for later use in determining situations or recurring traffic patterns.

c) Monitoring: The system has a module for monitoring the state of the road network in real time. This information can be:

- Complete or partial on a spatial level: complete monitoring at all levels of the road network (lanes, sections, turns, crossroads, intersections, axes, etc) or a subgroup of network elements (this subgroup is normally limited to network elements located in the same areas as the detectors, see Figure 1 for an example).
- Complete or partial on the level of traffic variables: the simultaneous monitoring of different traffic variables in the network elements (densities, capacities, speeds, queues, journey times, levels of service, emissions, consumption etc) or limited to a subgroup of variables (this subgroup is normally limited to variables provided by detectors located in the network, typically capacities and speeds).
- With different levels of physical aggregation (lane, turn, section, intersection, system etc) and temporal aggregation (5, 10, 15, 60 minutes)

Figure 1: Example of partial monitoring

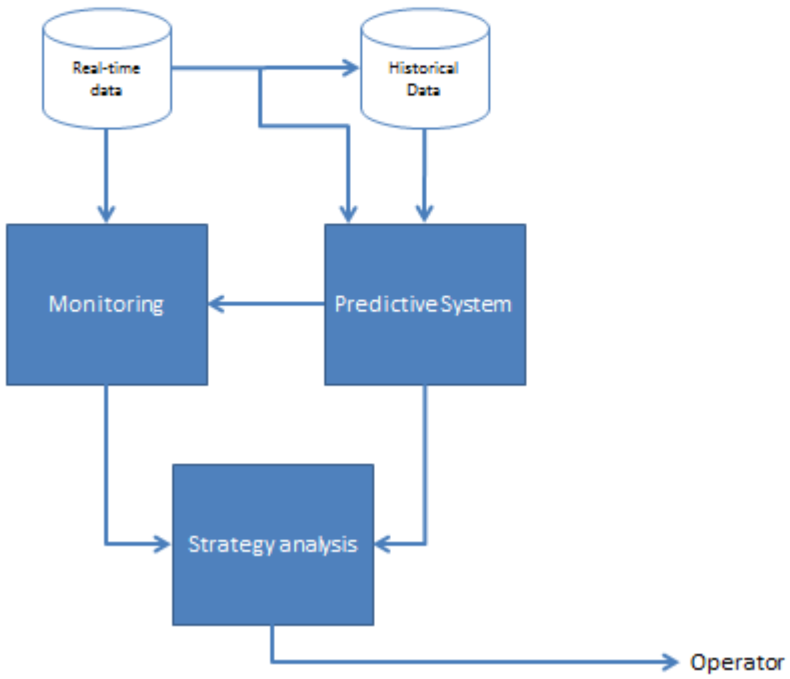


d) Predictive System: The system has a module for predicting the state of the road network based on historical data and real-time data. Predicting the state of the network provides, depending on the methodology used, complete or partial future data in terms of space as well as the number of traffic variables.

e) Strategy analysis: The system has a module that can determine the set of strategies to evaluate for the mitigation and anticipation of congestion(s) using network monitoring of the current state as well as the future state. As a result, this module a set of indicators for each strategy so that the operator can determine which strategy is best to implement on the streets.

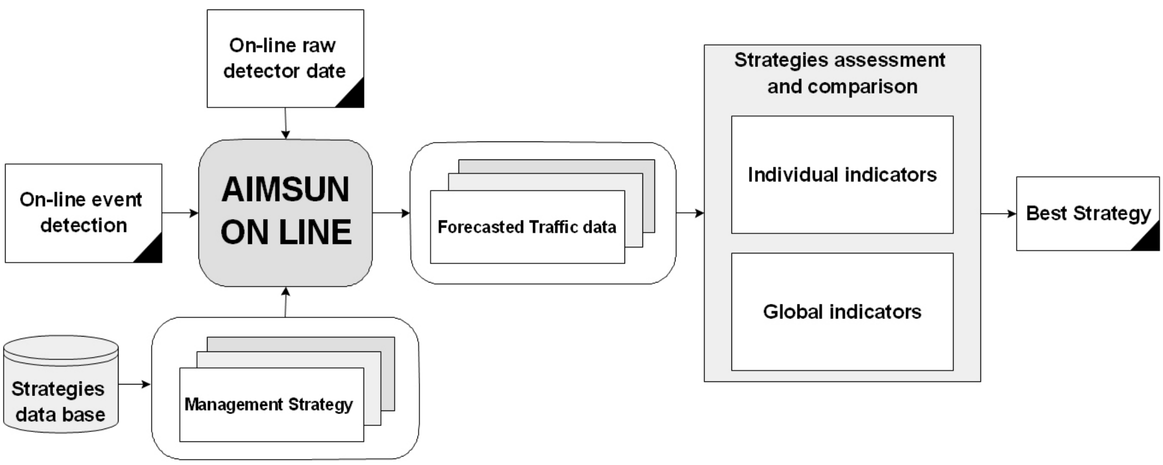
Figure 2 shows the generic outline of a DSS.

Figure 2: Elements of a DDS



An example of a DSS (Figure 3), is the architecture of Aimsun Online (Torday and Aymamí, 2012).

Figure 3: Architecture of Aimsun Online

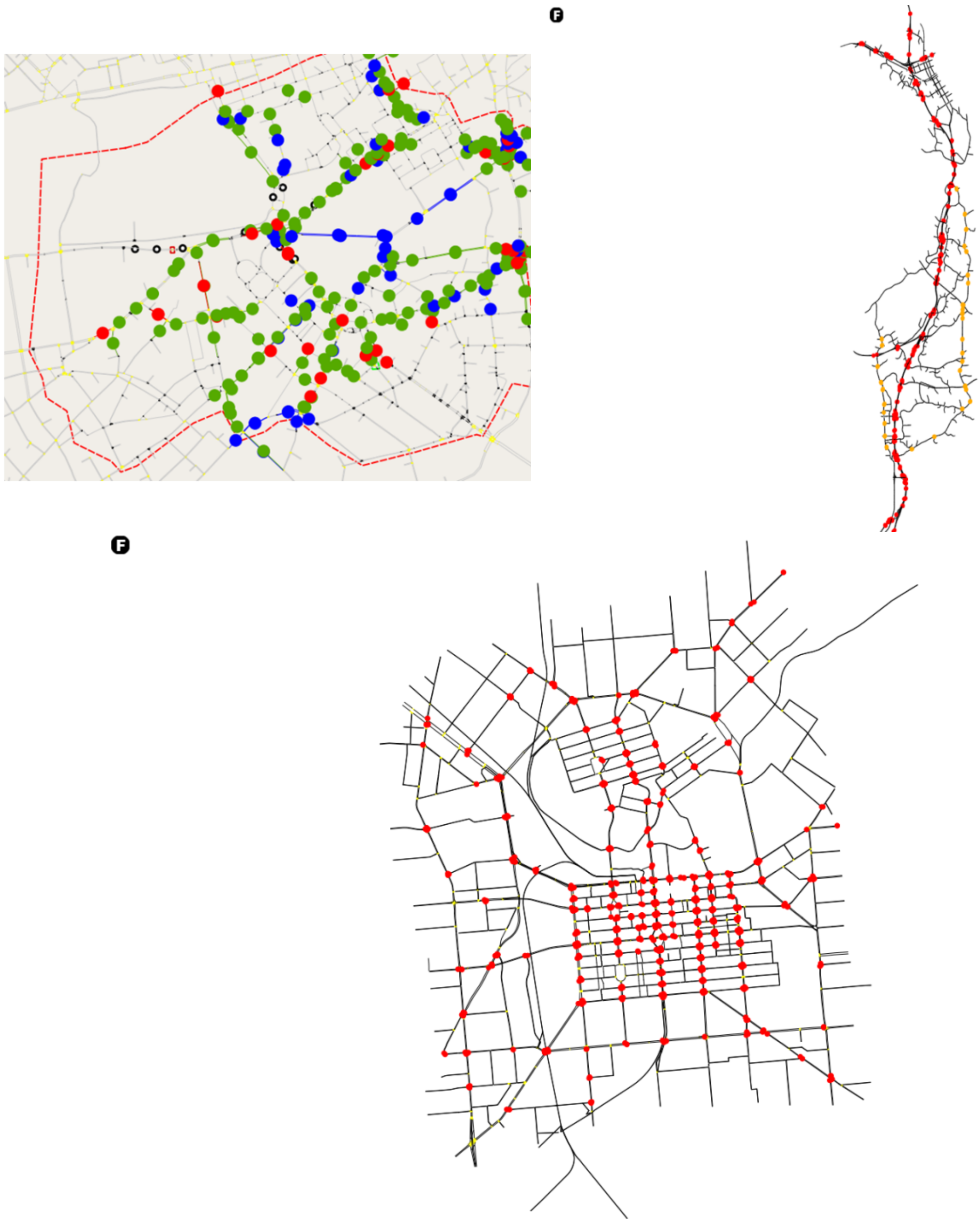


2.1 Real-time data /historical data

Currently, real-time data in most cities is limited to what is available from detectors, which basically provide capacities and occupancy. The problem with the location of sensors is that this is determined by the specific objective of their original implementation, which is in general limited to traffic signal control. This initial objective does not always meet the requirements of spatial coverage necessary for good traffic monitoring.

Figure 4 shows different networks with the location of all the available detectors in real time and the partial coverage they provide.

Figure 4: Detector location in London, San Diego and Adelaide

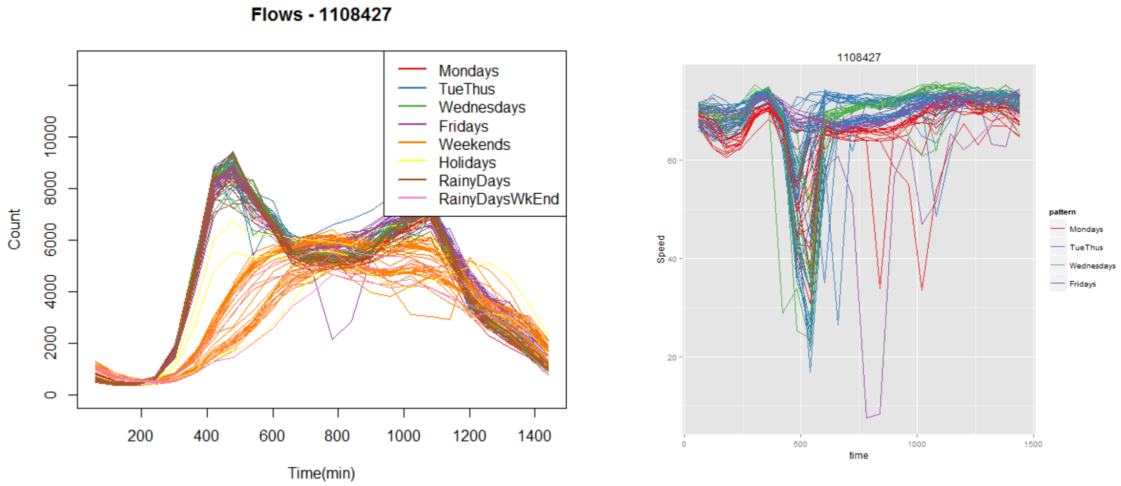


2.2 Identifying patterns and outliers

The predictive system should analyse real data to determine the future state of the network in the short term. To carry out the prediction requires the classification of the real data into ‘similar’ days, determining these days by classifying detection data into patterns. (Kantz and Schreiber 1997) and (Casas et al, 2012) show different methodologies for classifying patterns in the real data and the determining anomalous situations (outliers).

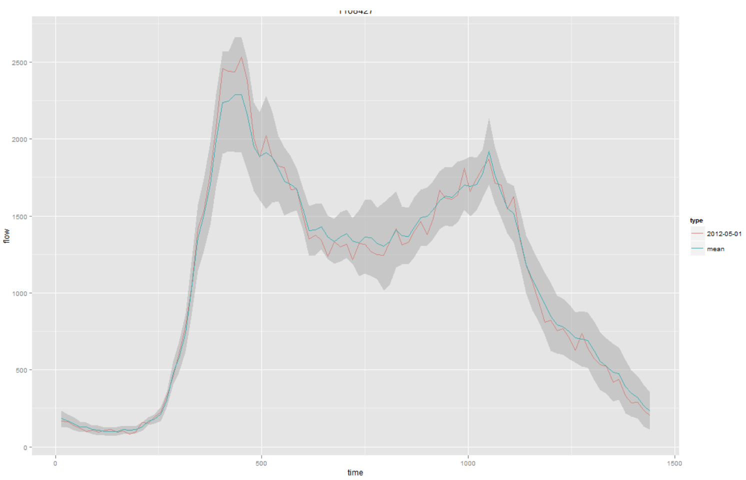
Figure 5 shows a graph of the historical capacities (left) and speeds (right) of a detector in an interurban network, classifying different typical days by colour.

Figure 5: Historical data from a detector



Using historical data, patterns are extracted for different typical days (depending on the qualitative variables: day of the week, meteorological conditions, season etc) as shown in Figure 6.

Figure 1: Pattern on a week day from a detector



2.3 Predictive System

Various techniques have been developed for real-time prediction. Among the different techniques, two groups of methodologies stand out: one based on analytical methods and another group based on the use of simulation. The analytical models are based on models that use historical data. This means that they are limited when the prediction is carried out in non-recurring situations, which are usually the cause of cases of severe congestion. On the other hand, the models based on simulation, despite being capable of reproducing non-recurring situations, are limited by the time available for computation. However, faster hardware and using multithreaded architecture to run parallel simulations means that this limitation is gradually receding.

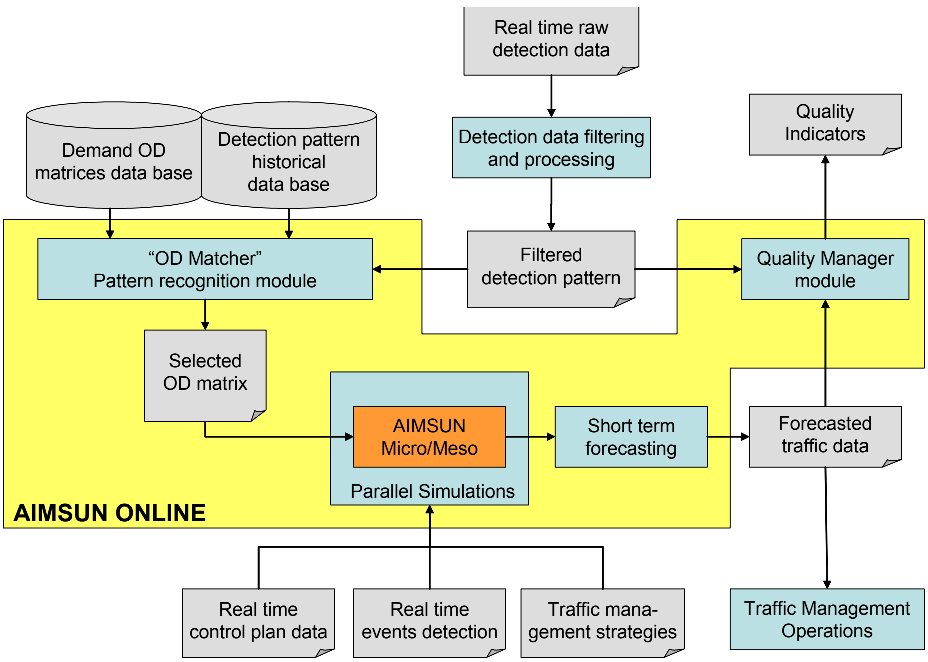
2.3.1 Analytical models

There are many analytical techniques for traffic prediction using real data and/or historical data. Some use statistical methods others use neural networks, fuzzy logic, support vector machines (SVMs). (Vlahogianni et al, 2004) gathered different methodologies, with some examples being: (Smith and Demetsky, 1996) describe a non-parametric regression method; (Williams et al. 1998) introduce seasonal autoregressive and exponential smoothing methods, time series analysis using the ARIMA family of models (Davis et al. 1991; Hamed et al. 1995; Williams 2001, Stathopoulos and Karlaftis, 2003), neural networks (Smith and Demetsky 1994; Dia, 2001; Ishak and Alescandru 2003). Other methodologies have also been analysed: support vector machines (Chen and Grant-Muller, 2001; Zhang and Xie, 2007; Castro-Neto et al, 2009; Zhang et al, 2011) and fuzzy logic (Stathopoulos et al, 2010).

2.3.2 Simulation-based models

Another focus for the predictive system is the use of dynamic simulation models built with real data. Examples of simulation used for predictive systems are (Ruiz et al, 2007) and (Torday et al, 2010) with a microscopic or mesoscopic traffic model as the engine of the predictive system. Figure 7 shows the integration of the dynamic simulation model in the DSS.

Figure 7: Diagram of Aimsun Online



2.4 Strategy Analysis

Strategy analysis involves three types of decision: the first, generally made during the system implementation phase, is to determine the set of strategies to analyse according to the traffic management tools available; the second is to choose which indicators (MOEs) to use to select the 'best' strategy; the third decision, taken when the system is up and running, is to choose the subset of strategies to analyse depending on the current and future state of the network.

2.4.1 Selecting a set of strategies

Selecting a set of strategies for analysis should be a process that is carried out during the implementation period of the system, which usually makes use of the operators' 'know-how' and depends on the traffic management tools available.

As an example, in 2011, Transport for London required a decision Support system for traffic management where the strategies would be limited to different configurations of SCOOT-UTC adaptive control (Torday and Aymamí, 2012).

2.4.2 Indicators for strategy evaluation

The indicators used to provide a classification of all the analysed strategies, bearing in mind the optimisation objectives. These indicators depend on the current or future state of the network and are evaluated using the following variables:

- Flows
- Travel times
- Delay times
- Speeds
- Number of stops
- Fuel consumption
- Emissions
- etc.

And also for different levels of aggregations: sections, roads, or systems.

The following is an example of an indicator:

$$IG = \frac{\alpha \cdot \sum_{i=1}^{P} \sum_{j=1}^{N_i} (Delay_{ji} + 17 \cdot Stop_{ji}) + \sum_{k=1}^{S} \sum_{l=1}^{M_k} (Delay_{lk} + 17 \cdot Stop_{kl})}{\sum_{i=1}^{P} N_i + \sum_{k=1}^{S} M_k}$$

2.4.3 Strategy subsets

Selecting a subset of strategies to evaluate for congestion mitigation is a process that can combine the experience of the operators, forming analogies with similar situations in the past, with 'automatic' systems that make the selection using artificial intelligence techniques. Examples of these implemented methodologies are: Fuzzy logic (Hegyi et al, 2000), Multi-agents (Cuena et al. 1995) and (Hernández et al. 2002), genetic algorithms (Abu-lebdeha and Benekohalb 2003).

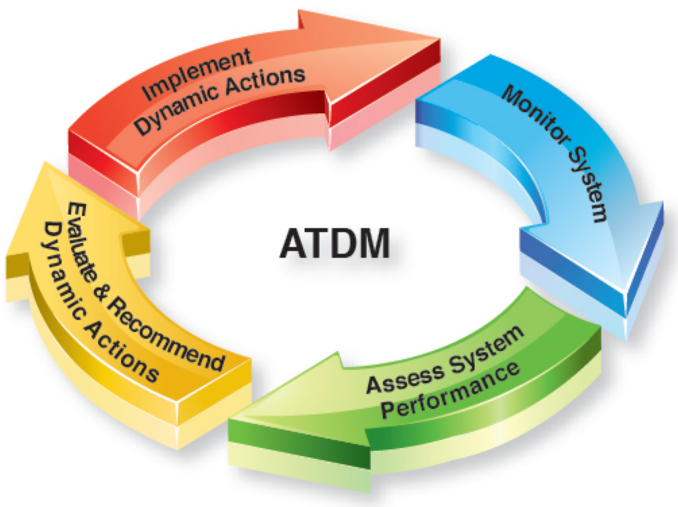
3. Decision support system for traffic management: new challenges

The new challenges for decision support systems for traffic management lie in the inclusion of data provided by the use of new technologies in the monitorisation of network traffic and predictive systems.

Another issue up for consideration, and thereby generating debate and research in the scientific community, is the creation of support systems for mobility management, that is, systems that improve global mobility in multi-modal networks. This concept represents a transversal vision of mobility management between the different administrations or agencies responsible for each mode of transport. An example of this new focus is the FHWA's "Active Transportation and Demand Management (ATDM) Program" in 2013. The ATDM program focuses on dynamic real-time transport management including demand management to maximise system efficiency (see Figure 8). The set of strategies included in the program are the following:

- Active management of demand: dynamic ridesharing, public transport, travel time prediction.
- Active traffic management: dynamic reversible lanes, dynamic variable speed limits, congestion information, access ramp control.
- Active parking management: dynamic pricing, dynamic reservation management, dynamic route suggestion management, dynamic carpark capacity management.

Figure 8: Active Transportation and Demand Management (ATDM)



3.1 Using new technologies: new data and shared information

The increase in availability of data means rethinking data usage in 'traditional' methodologies, where the origin of data used to be limited to data provided by detectors physically implemented in the road infrastructure. The new technologies and their increasing market penetration provide a set of 'new' data:

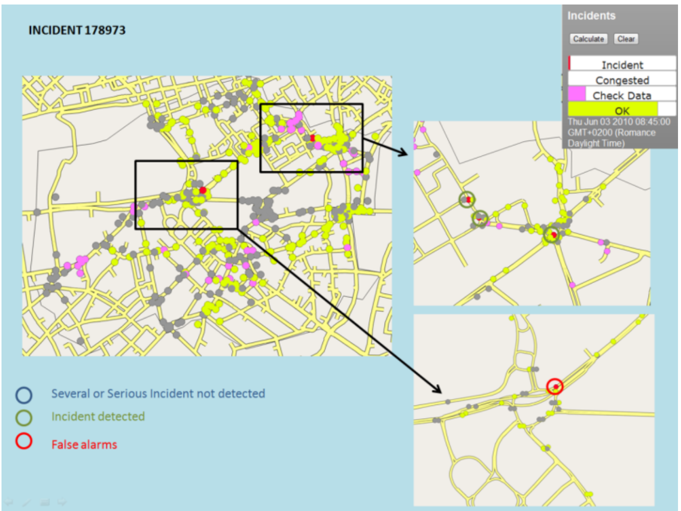
- Individual vehicle tracking: smart phone or satellite navigation geo-localization can provide not just aggregate information (origin, destination, mode, route followed) but also the chain of each trip of each user in the transport system. An example of using geo-localisation data is (Cici et al, 2013).
- Non-intrusive detection systems: current technology permits the installation of new types of detectors (such as Bluetooth detectors) that provide the point-to-point travel times of each user.

The availability of these new types of data will act as a complement to traditionally obtained data from detectors that provides capacities and occupancies. This completion of data will permit other methodological focuses o improvements in implementation of current predictive systems.

3.2 Monitorization

Partial or complete monitorization (in space or type of variables) needs to be complemented with automatic incident detection systems and thereby be able to achieve a better application of congestion mitigation strategies and the ability to anticipate the evaluation of strategies up for analysis. This anticipation requires incident detection algorithms, where an important parameter is the time that passes between appearance of the real incident and its detection. (Parkany 2005) analyses different methods applied to urban and interurban networks where, in this context, the current methods are lacking in certain areas.

Figure 9: Incident detection in the London network



3.3 Predictive System

The evolution of predictive systems seems to be heading towards hybrids of analytical models and models based on simulation. In addition, the ever-increasing complexity of the transport systems needing evaluation requires hybridization of simulation models owing to the broad spectrum of strategies for evaluation (from macroscopic to microscopic strategies). If we consider the requirement of analyzing strategies at the microscopic level, if this is focused on parts of the network, it is possible to carry out hybrid simulations – microscopic where it is necessary at the level of individual vehicles and mesoscopic for the rest - allowing the coverage of strategy evaluation and also with no penalizing the need to carry out faster simulations than in real time.

An example, already mentioned, is the ATDM program, with analysis from macroscopic strategies on the level of demand (e.g., active parking management) to microscopic strategies applied at the user or driver level (e.g., dynamic pricing, eco driving, ADAS systems).

Another component to note in future evolution of predictive systems, specifically those focused on methods that use dynamic simulation, is the estimation of traffic demand using real-time data. There are different initiatives that are developing new methods (or methodological improvements) for its implementation and use in large-scale networks. An example of this initiative is the European MULTITUDE Project (http://www.multitude-project.eu/).

And a final focus that is a future possibility is the disaggregated treatment of demand for simulation, that is, defining the demand as chains of trips at the level of each individual user, including transport mode, instead of defining the demand in an aggregated way as number of trips between zones. This treatment of the disaggregated demand is taking form in different research projects integrating activity-based models (ABM) and dynamic traffic assignment models (DTA).

3.4 Real-time strategy analysis

Key to a decision support system is the capacity to identify in real-time the strategies for analysis and that these are limited to a pre-determined set. The scientific community is developing methods that combine the use of dynamic simulation with different levels of aggregation (macroscopic, mesoscopic or microscopic), and the use of meta-models to cover the computation requirements in real time. A recent example of this line of investigation is (Osorio and Bidkhori, 2012), that gives an evaluation of traffic control strategies in the context of solving an optimization problem combining simulation and meta-models.

4. The San Diego example

4.1 Introduction

In 2010, San Diego was chosen as one of the US pilot sites for developing, implementing and operating an Integrated Corridor Management System (ICMS). This project, known as the Interstate 15 ICMS, aims to operate and manage individual transport systems as a unified corridor including the highway network, toll lanes, the surrounding arterials and the public transport network in the area. The I-15 ICMS is designed to optimise capacity and efficiency without having to invest in additional infrastructure (basically, more lanes for private traffic) in an area where investment is extremely costly, in both technical and economic terms.

The general vision of I-15 ICMS is the use of real-time tools to obtain predictions for the whole project network in order to obtain recommendations to manage congestion pre-emptively. For example, combining the controls of ramp access to the highway with changes in the control plans in the arterial network to manage recurring rush hour congestion, together with route diversions, properly monitored to avoid greater disturbance in non-recurring incident situations.

The aims are to reduce delays and obtain more reliable journey times.

The San Diego Association of Governments (SANDAG) is leading the project and works alongside the Department of Transportation (US DOT), Caltrans, the Metropolitan Transit System, the North County Transit District and the Cities of Escondido, Poway and San Diego. The project integrator is Delcan Corporation. The ICMS has been up and running since March 2013.

TSS-Transport Simulation Systems manages aspects related to prediction, mainly two modules: the Network Predictive Subsystem (NPS) and the Real-Time Simulation Subsystem (RTSS).

4.2 Description

The project covers a region of 3.1 million inhabitants bordering Mexico in the south and with Los Angeles County to the north, which makes the I-15 one of the main thoroughfares for long-distance traffic traveling between these areas. The project area is also a main mobility focus for northern metropolitan San Diego (daily commutes from home to work and vice versa). The project covers about 20 miles of this corridor, which already has in place express lane systems from a previous 1,300 million-dollar project, four reversible lanes in the central section that include exclusive access from outside the highway, plus multiple entrances and exits to the main lanes.

The project area, in addition to the highway, also covers:

• 260 intersections in the network

• 18 links to the motorway

• Bus Rapid Transit

• 5 “Park & Ride” areas with dedicated access

• A “511” information system via telephone and Internet

Figure 10 shows the area of the project, together with the simulation model developed that covers the area.

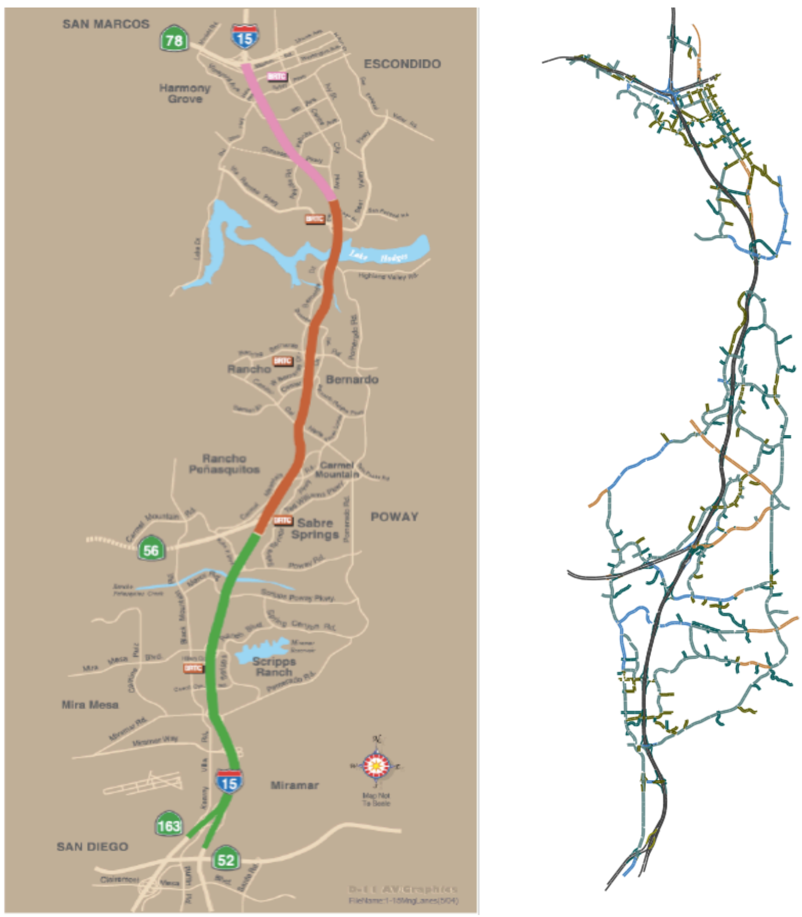


Figure 10: ICMS project area

4.3 Prediction in the ICMS

4.3.1 Prediction

Inside the ICMS, Aimsun Online has two main functions: the Network Prediction Subsystem (NPS) and the Real-Time Simulation Subsystem (RTSS).

4.3.2. NPS

The NPS covers two tasks: the first is to produce predictions for the upcoming hour in 15-minute periods that can be used by the Business Rule and Process Management Subsystem (BRPMS) to identify potential congestions and give sufficient input to allow the evaluated plans (a selected subgroup of possible options) to be compatible with the forecast traffic situation e.g., avoiding suggesting rerouting traffic to points that are predicted to be already overloaded; the second task is to generate optimized and up-to-the-minute OD matrices to be used in predictions based on the microsimulation.

The NPS gathers the operational and detection information in real time from the Data Hub, producing an analytically-based prediction for the detection stations in the project area. These predictions are used for quality evaluation and feed the process of matrix adjustment. This demand is then input for the microsimulation model, where a complete prediction of the network (at the level of sections, intersections, routes, ramp meters, express lanes etc) is generated and sent to the Data Hub to be used by the BRPMS and by external users, such as the public transport operator or the service provider of the I-15 express lanes. The NPS runs continuously, producing predictions every 5 minutes.

4.3.3 RTSS

When the BRPMS has identified, based on events or potential congestion, the need to apply traffic management strategies, a request to run simulations is sent to the RTSS. The RTSS imports the current traffic conditions from the services in the Data Hub (state adn configuration of regulators, ramp metering, price of toll lanes and the position of dynamic barriers, location of public transport vehicles, and weather conditions), as well as current and upcoming events and traffic management plans up for evaluation. One of the requests is always 'Do Nothing', to act as a comparison against the other plans of action. When the simulations are complete, an exhaustive set of results (MoEs) is sent to the Data Hub, and the BRMPS calculates the preferred plan of action using the aggregated indicators.

4.3.4 Strategies for evaluation

The evaluated strategies set out:

- Information to the user via variable message boards, informing of incidents and suggesting alternative arterial routes (evaluated as being compatible with the predicted traffic).
- Information about alternative route via 511
- Changes in dynamic entrance ratios applied to the control system for access to the interstate (the Ramp Meter Information System or RMIS) such as applying 'gating' strategies.
- Changes in express lane charges (in a 2+2 or 3+1 North-South configuration), including the possibility of opening them up free of charge to all drivers in accident or emergency situations or when there is particularly bad gridlock.
- Changes in the routes used by the bus network to avoid congested sections.
- Changes in control plans for the 260 intersections in the arterial network, particularly changes in the configuration of the TLSP system of adaptive corridor control (11 sections) applied to the routes running parallel to the interstate.

4.3.5 Simulation Model

The offline model is the foundation of the online system, so a validated model that responds faithfully to real traffic situations is absolutely essential. During implementation, extensive work was done on model calibration, importing the regional strategic model in TransCAD, allowing correct validation of a typical day.

Given the limited coverage of detection in the arterial network, which is now being expanded for the service phase of the project, the automated gathering was combined with manual data gathering at the intersection. These temporary detection points were obtained via an analysis of routes in the network that allowed the coverage of over 80% of the trips that did not use the interstate. Finally, the model was validated for a typical day using 500 detection points using criteria based on the percentage of detectors with differences under 15% and GEH (following FHWA recommendations), as well as overcoming an exhaustive visual validation by SANDAG and participating agencies, to determine that the model was a correct representation of a typical day in San Diego.

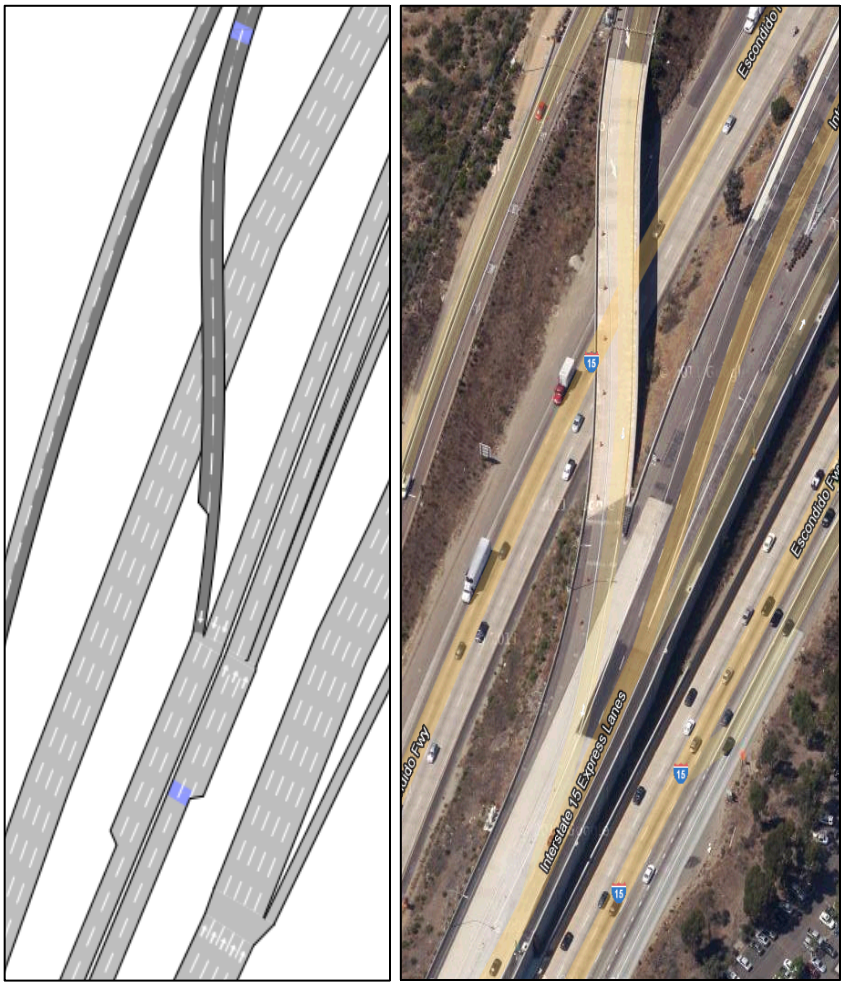


Figure 11: Comparative Model and aerial image of an access ramp to the Express Lanes

4.3.6 Simulation input

The simulation model is fed by demands originated from historic patterns that are dynamically adjusted according to the prediction generated in the previous period (both analytical and simulation). Besides, Initial Stages obtained from previous NPS simulations are used for the initial load of the simulation.

The simulation model requires and is updated with the following information in real time:

• System Demand (from previous NPS simulations)
• State of the controllers (both the plans and the corridor adaptive system)
• State of the ramp-metering
• State and fares of the toll for express lanes as well as the position of the mobile barrier that defines the number of lanes to the North and to the South
• Events (incidents, works and maintenance, etc.)
• Location of the public transport vehicles
• Weather forecast
• Traffic Management Plans

This information makes the simulations much more faithful to real conditions, which increases the reliability of the predictions obtained. This reliability is constantly monitored to guarantee the integrity of the system.

4.3.7 Prediction output

From the simulations, both constant monitoring and evaluating management strategies, a set of results is obtained which the UI of the system shows at the level of any indicator.

Table 1 shows all the results from online simulations (NPS and RTSS) sent to the Data Hub.

Intersections	***Sections***
V/C	*Speed*
Speed	*Volume*
LOS	*Occupation*
Delays	*V/C*
	LOS
Ramp Meter	*Journey times*
Speed on interstate	

Volume on interstate	***Public transport***
Queues at ramp	*Reliable journey times*
	Journey times
Express lanes	
Speed	***Routes***
Volume	*Journey times*
Journey time	*Total delay*
Tolls applied	*Available capacity*

Table1: MoEs – Indicators produced

4.3.8 Performance indicator

Besides the mentioned results, and in order to obtain a direct comparative among the strategies assessed, the RTSS produces information that is processed by the BRPMS to calculate a single performance indicator which allows you to compare the different strategies. This customizable indicator takes into account the different modes (it can penalize more or less the SOV, prioritize the strategies that minimize the delays on the public transport, etc.) and it is based on delays, occupation and proximity to an event (in concentric radius).

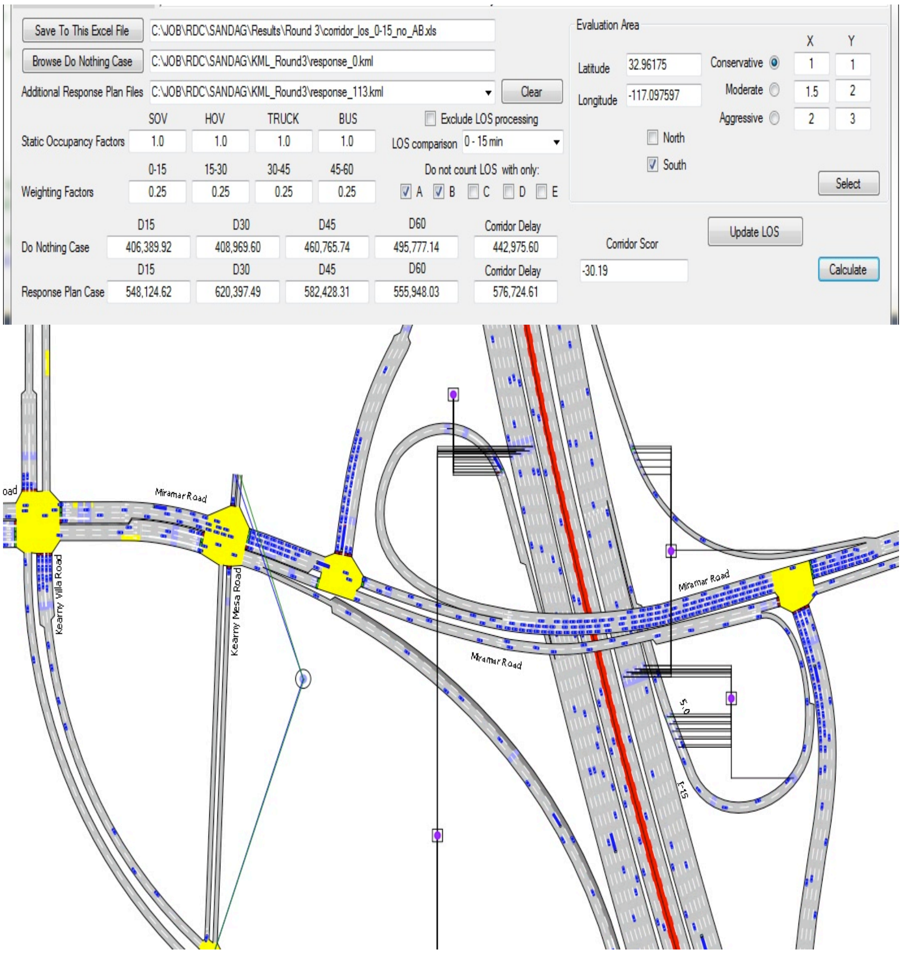


Figure12: Menu of indicator customization

4.3.9 Quality

In predictive systems it is essential to monitor the quality of the predictions. Aimsun Online, on which the NPS and the RTSS are based, includes a module of quality management that offers a quality indicator in this project based on the percentage of detectors with differences between reality and prediction below 15%, in this case within 15, 30, 45 and 60 minutes (the 4 prediction periods considered)

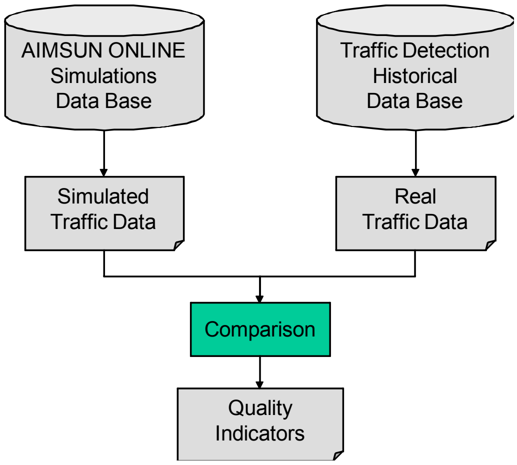
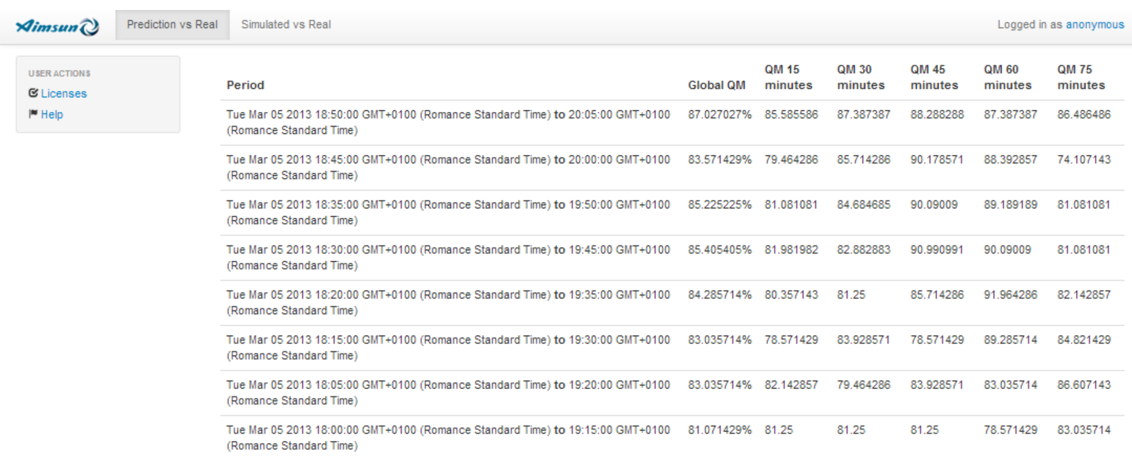


Figure 13: Quality Manager module

All the information about predictions is stored during a minimum of 90 days, which makes it possible to review, assess and analyze the prediction generation process. This prediction backup, transformed in a library of simulations and situations with events can also be used to train traffic operators. In case the quality of the predictions is detected to deteriorate, this information stored allows you to make a diagnosis and identify possible causes of this deterioration.

This information is displayed in a web interface which shows and compares the results using tables and specific view modes. Figure 10 shows the interface that monitors the quality of the predictions, global and within 15, 30, 45 and 60 minutes, assessing the differences between the real detection and the one predicted, using both an analytical prediction (NPS) and a simulated prediction (NPS and RTSS).



Period	Global QM	QM 15 minutes	QM 30 minutes	QM 45 minutes	QM 60 minutes	QM 75 minutes
Tue Mar 05 2013 18:50:00 GMT+0100 (Romance Standard Time) to 20:05:00 GMT+0100 (Romance Standard Time)	87.027027%	85.585586	87.387387	88.288288	87.387387	86.486486
Tue Mar 05 2013 18:45:00 GMT+0100 (Romance Standard Time) to 20:00:00 GMT+0100 (Romance Standard Time)	83.571429%	79.464286	85.714286	90.178571	88.392857	74.107143
Tue Mar 05 2013 18:35:00 GMT+0100 (Romance Standard Time) to 19:50:00 GMT+0100 (Romance Standard Time)	85.225225%	81.081081	84.684685	90.09009	89.189189	81.081081
Tue Mar 05 2013 18:30:00 GMT+0100 (Romance Standard Time) to 19:45:00 GMT+0100 (Romance Standard Time)	85.405405%	81.981982	82.882883	90.990991	90.09009	81.081081
Tue Mar 05 2013 18:20:00 GMT+0100 (Romance Standard Time) to 19:35:00 GMT+0100 (Romance Standard Time)	84.285714%	80.357143	81.25	85.714286	91.964286	82.142857
Tue Mar 05 2013 18:15:00 GMT+0100 (Romance Standard Time) to 19:30:00 GMT+0100 (Romance Standard Time)	83.035714%	78.571429	83.928571	78.571429	89.285714	84.821429
Tue Mar 05 2013 18:05:00 GMT+0100 (Romance Standard Time) to 19:20:00 GMT+0100 (Romance Standard Time)	83.035714%	82.142857	79.464286	83.928571	83.035714	86.607143
Tue Mar 05 2013 18:00:00 GMT+0100 (Romance Standard Time) to 19:15:00 GMT+0100 (Romance Standard Time)	81.071429%	81.25	81.25	81.25	78.571429	83.035714

5. Conclusions

This paper presents the current state of decision support systems for traffic management and their evolution into integrated mobility management systems (not just of traffic). It also presents the new challenges presented by some issues that are currently in the research and development phase.

6. References

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