

# Online Microscopic Traffic Simulation Supports Real-time Traffic-management Strategies

By J. Barceló, M. Delgado, G. Funes, D. García, J. Perarnau, and A. Torday

Quantitative decision-making relies on appropriate mathematical models of the systems about which decisions are to be made. Intelligent transport systems (ITS), which apply combined advanced detection, communication, and computer science technologies to traffic and transport systems, are important examples of such quantitative decision support systems. Figure 1, adapted from [10], depicts the logic diagram for an advanced traffic management system (ATMS), a paradigmatic case of ITS.

This generic ATMS assumes that the network is equipped with an appropriate layout of detectors that provide real-time measurements of traffic variables, flows, speeds, and occupancy levels; these measurements constitute the main input to traffic models that are solved to estimate the current state of the network and forecast its short-term evolution. System performance is estimated in terms of “measures of efficiency” (MOE): travel times, delays, mean queue lengths, and possibly others, depending on the manager’s objectives; the latter can include estimates of fuel consumption and emission levels when the sustainability of the transportation system is to be taken into account. The estimated system performance and its predicted short-term evolution are then compared with the management performance objectives (e.g., minimize congestion, travel time, or delays, or hold emissions under critical threshold values); in the case of significant deviations, appropriate management strategies are activated (linear speed control, ramp metering, rerouting policies, changes in signal timings, and so on) and put into operation by appropriate ITS devices (variable message signal (VMS) panels, adaptive controllers, in-car information systems, and so on). Of particular interest for real-life applications is the case in which the ATMS is called on to support real-time management in response to incidents or situations, recurrent or not. In such cases, the system needs additional functions, such as:

- a decision-making process that assists the traffic operator in selecting the most appropriate management strategy to solve the identified traffic problem;
- capability for testing the selected strategy before implementation; and
- capability for forecasting the short-term evolution of traffic conditions so as to prevent undesired impacts.

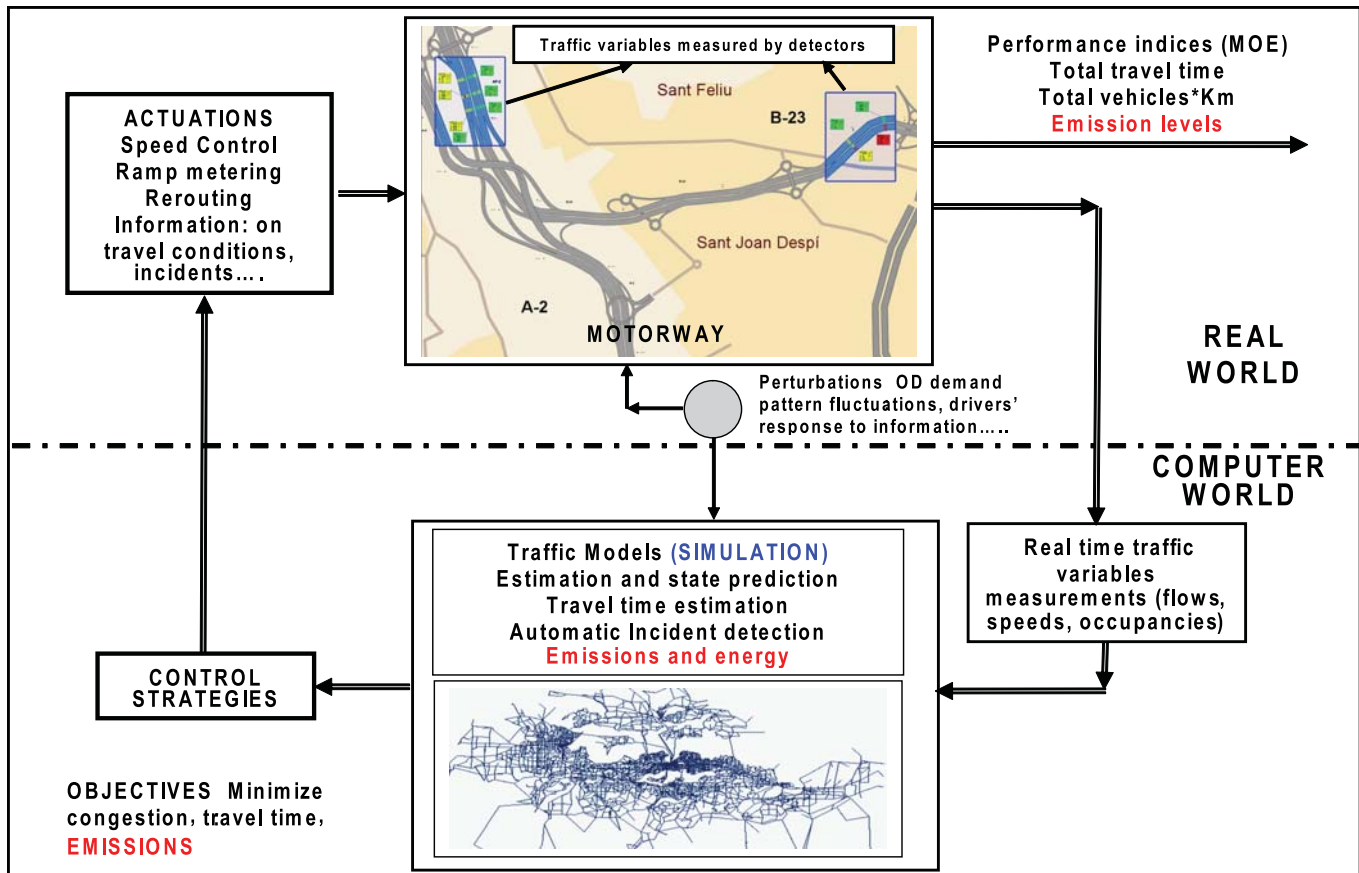


Figure 1. Conceptual scheme of an advanced traffic management system, or ATMS.

Figure 2 summarizes adaptation of the conceptual architecture from Figure 1 to management systems of this type. The real-time measured traffic data are stored in a database, which, along with data from a historical traffic database, constitutes the inputs to a process that identifies traffic patterns and determines by comparison whether the current data identify a problem at a given location.

In a large, complex network, it is unlikely that a local problem will affect the whole network. The traffic manager thus graphically defines a window spanning the area of the global network most likely to be affected by the problem (outlined in red in Figure 2). The process then selects the strategy that best matches the conditions of the problem area. For the example in Figure 2, once detectors along the normal route (highlighted in yellow) have identified a problem (incident, congestion, . . .) and the problem area has been defined, the traffic manager selects a strategy. Possibilities include informing drivers of the incident and, if possible, of estimated impacts (extent of congestion, estimated duration of delays) and recommending an alternative route, displaying the information and related messages on VMS panels at exchange nodes where drivers can still make use of alternatives.

An improved implementation would be supported by estimates of expected impacts of the selected strategy—in current traffic conditions, would it help solve the problem or make it worse? The estimates could be improved if, beyond current traffic conditions, they were used in a short-term forecast that accounted for the predicted evolution. For estimates of the impacts of the proposed strategy, an ad hoc traffic model is needed. The experiences described in this article are based on the use of two traffic models: the microscopic and mesoscopic traffic simulators embedded in the AIMSUN software platform [1,5].

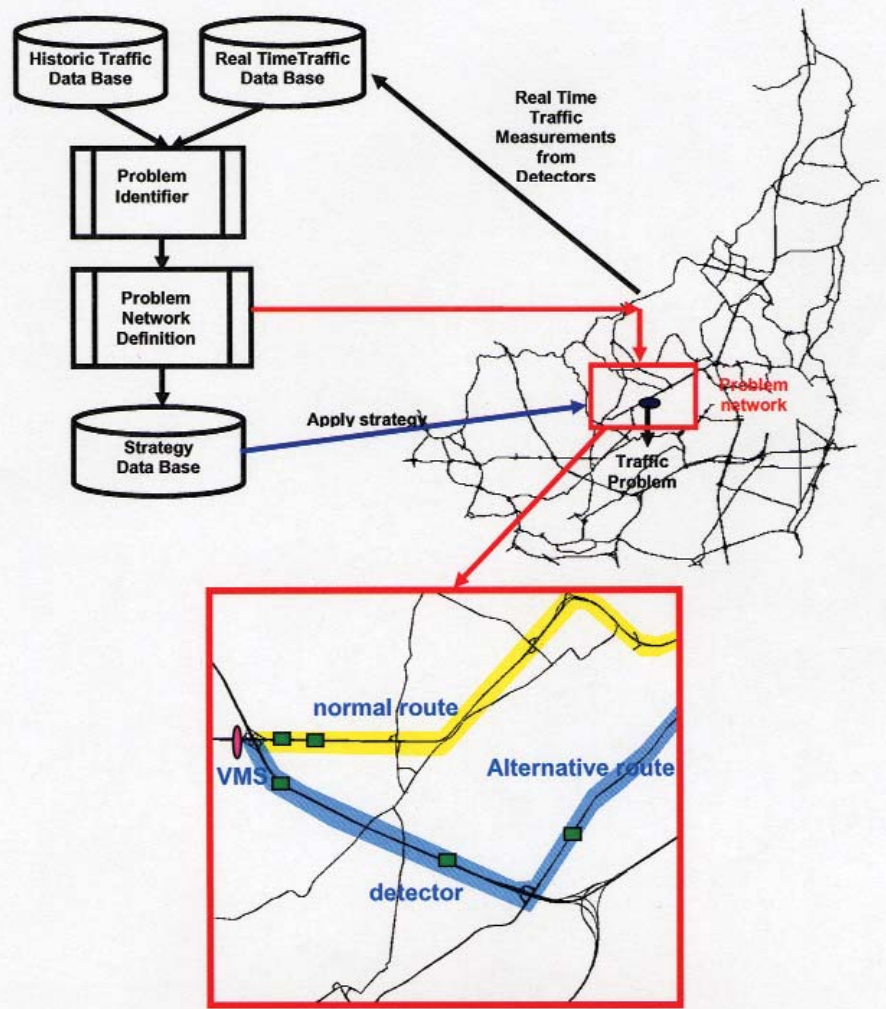


Figure 2. Sample implementation of an advanced traffic management system.

### Implementation of the Decision Support System in the AIMSUN Platform

Implementation of a decision support system for real-time traffic management with the functional capabilities described in the preceding section must be based on a software architecture that combines computer and transport modeling. The solution implemented with AIMSUN [6] fully exploits the architecture of the AIMSUN platform, which is based on an extensible object model that provides a unique representation of all system entities shared by all mathematical models in the system. Each entity is characterized by a unique set of attributes, and each traffic model accesses the attributes it needs. This information is stored in a unique database that is shared by all traffic models. This architecture makes possible the direct exchange of information among various transport models—that is, it provides the full model integration required by the decision support system. A user-friendly graphic user interface endowed with suitable editing and drawing tools gives the operator the following capabilities:

- interactive definition of the window spanning the problem network;
- automatic generation of the microscopic traffic simulation model for the problem network;
- initiation of the process for estimating the local (traversal) origin–destination matrix that best represents mobility in the problem network under current conditions based on the identified prevalent traffic pattern; and
- interactive simulation of different scenarios for the problem network, with explicit implementation of the selected strategies.

The main functions of the ATMS as conceptually depicted in Figures 1 and 2 are supported in AIMSUN by:

1. A raw data filtering and processing data management module. ALMO [2,4], a geo-referenced traffic-data analysis system, categorizes time series by type of demand (weekday, Sunday, holiday, . . .) and time of day (night, morning peak hour, mid-day, evening peak hour, . . .) to detect

patterns and provide data related to time, location, and traffic conditions; the analyst can select context-specific data relevant for analysis of the scenario corresponding to the selected strategy.

2. *Traversal origin–destination matrix estimation and adjustment.* Once the window for the problem network has been graphically defined, AIMSUN supports the mathematical models and algorithms that generate the corresponding local traversal OD matrix and adjust it, based on the currently detected traffic flow pattern, to represent traffic demand appropriately. The adjustment uses a bilevel optimization algorithm [7].

3. *Online simulation forecasting.* The online part of the system consists of a fully calibrated traffic simulator that estimates the expected evolution of the traffic network under current demand for a given time horizon. AIMSUN currently supports two simulation approaches:

- AIMSUN Micro** [3], a microscopic timestep-based approach,
- requires a detailed representation of the road network geometry;
  - emulates traffic flows by mimicking the movement of individual vehicles with varying characteristics and in multiple classes, updating their positions using car-following models and lane-changing rules, including stochastic components;
  - explicitly represents control strategies; and
  - has vehicles traveling from origins to destinations along time-dependent routes selected according to stochastic route-choice models.
- AIMSUN Micro has proved to be capable of realistically emulating the time evolution of vehicle flows on a road network.

- AIMSUN Meso** [5], a mesoscopic vehicle-based event-scheduling approach,
- uses a simplified node–link representation of the network;
  - provides an approximate description of vehicles’ trajectories in the links;
  - models link dynamics, splitting a link into two parts: the running part, in which the vehicles are not yet delayed by the queue spillback from the downstream node, and the queue part, in which nodes are modeled by a queue server approach that explicitly accounts for signal settings; and
  - has individual vehicles traveling along time-dependent routes from origins to destinations.

The microscopic simulation uses a “safe-following” approach, a variant of a Gipps model [8]. In Gipps models, a driver determines his speed based on the behavior of the vehicle immediately ahead. Using an estimate of the deceleration of the vehicle ahead one reaction time earlier, the following driver selects a speed such that one reaction time later he will be able to come safely to a stop. In the micro simulation, the deceleration estimate is multiplied by a sensitivity factor  $\alpha$  derived during model calibration, which allows for reaction times that are driver-dependent.

In the mesoscopic simulation, under the assumptions of steady-state conditions and similar deceleration for all vehicles, speeds in the safe-following model can be approximated by speed–density relationships. Vehicle speeds are simple functions of the current density on a link and the density on that link at which a jam occurs. The model includes speed–density functions of two types, one for free flow and the other for speed at link capacity.

Each approach is appropriate for specific objectives, but in the framework of the applications presented here, it is convenient to speed up the simulation by exploiting the best of each. Such a hybridized simulation is depicted in Figure 3. A vehicle traveling from origin  $i$  to destination  $j$  is continuously tracked by the simulation engine. The simulation mode switches from mesoscopic to microscopic as the vehicle enters the problem subarea, reverting to mesoscopic when the vehicle leaves the subarea. If congestion arises in the subarea, alternative paths circumventing it can become more attractive, as shown in Figure 3. An efficient implementation of this hybridization in AIMSUN exploits the integrated software architecture, in which network representations share the same object model and model database, and vehicles are unique and the same in meso and micro approaches; furthermore, path calculations can be carried out by a common “shortest-path server” and are the same with the two approaches.

4. *Pattern recognition.* The initial state of a simulation has to correspond to the real state of the traffic. To this end, real-time detection patterns are repeatedly compared with the stored categorized patterns. This pattern-recognition process determines the historical traffic situation to which the current situation is closest, and the corresponding demand (OD matrix) is loaded into AIMSUN. The pattern-recognition procedure provides the operator with a confidence score describing how similar the current detection pattern is to the closest one found in the database.

5. *Traffic management and scenario simulation.* Forecasting capabilities are used to compare the performances of various management strategies deployed in response to detection of a

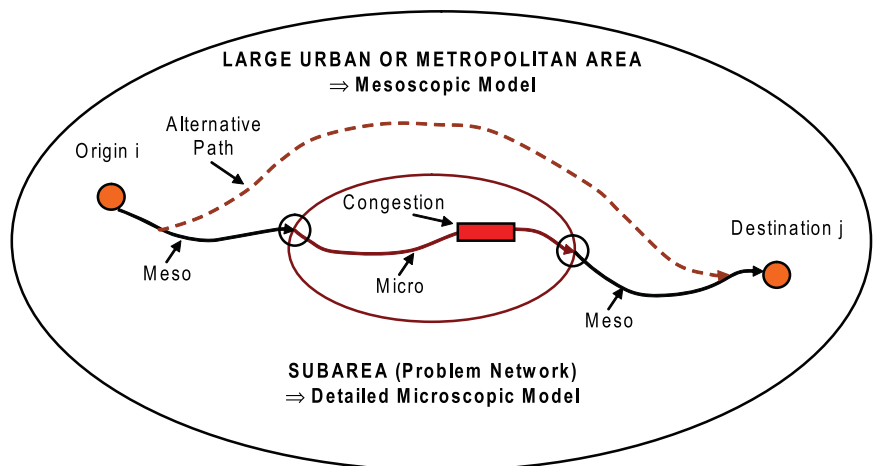


Figure 3. Hybrid meso–micro approach.

non-recurrent event. These scenarios are based on a set of actions—lane closure, rerouting, speed-limit variations, ramp metering—that can be activated manually or by detection triggers. Depending on the type of application, AIMSUN simulates one or more scenarios and predicts traffic outputs. In most cases, at least the “do nothing” scenario is simulated, with the detected event reproduced in the network model. For traffic management applications, this scenario is generally compared with scenarios reproducing other options. The results of the scenario comparison are displayed in various comprehensive forms to assist the traffic manager in the decision-making process. The traffic manager can select a set of MOE to determine the performance of the strategies in the corresponding scenarios and assign a weight to each MOE. Summary tables and graphical displays inform the traffic manager of the most effective strategy.

The microscopic simulation approach presented in this article was initially conceived and implemented as a prototype in the ISM project in the Rhein–Main region Hessen [9]. A project in Singapore consolidated the design that was implemented in an ad hoc version of AIMSUN, which has been used in a large project in Madrid [6]. The hybrid approach is currently in the testing phase.

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