Chapter 6
Dynamic Traffic Management: A Bird's Eye View

Jaume Barceló and Margarita Martínez-Díaz

Abstract Traffic systems evolved rapidly, becoming soon a specific case of a complex dynamic system, what raised the need for controlling them in order to achieve an efficient performance. One of the main factors of complexity of traffic systems is a consequence of the variable human traveling behavior in time and space. Therefore, traffic control, in the way it had been conceived and implemented, appeared as a restrictive approach just considering one of the control aspects: the time the vehicles are flowing through the network. This raised the need to move a step forward. Thus, traffic management could be seen as an extension of traffic control that simultaneously controls time and space, and is aimed at adjusting the demand and the capacity to avoid mismatching. This chapter summarily reviews the main concepts and approaches in the development of traffic management systems (TMSs) both in terms of managing the supply as well as managing (or influencing) the demand. In this context, travel times become one of the key factors to induce changes in drivers' behavior in terms of making decisions on departure times and route choices. To better achieve such objectives, it would be desirable that TMS have predictive capabilities. The main approaches addressed here support the predictive capabilities of dynamic traffic models, one of whose main components is an estimation of the dynamic mobility patterns in terms of origin to destination (OD) matrices. This chapter summarizes the architecture of such approaches.

J. Barceló (✉)
Department of Statistics and Operations Research, Polytechnic University of Catalonia, UPC-BarcelonaTech, Barcelona, Spain
e-mail: jaume.barcelo@upc.edu

M. Martínez-Díaz
Department of Civil and Environmental Engineering, Area of Transport and Territorial Infrastructures, Barcelona Innovative Transportation (BIT) Research Group, Polytechnic University of Catalonia, UPC-BarcelonaTech, Barcelona, Spain
e-mail: margarita.martinez.diaz@upc.edu

6.1 Introductory Remarks

The development and evolution of dynamic complex systems in engineering and other processes raised soon an increasing interest in controlling them, in order to ensure that they could behave in an efficient or optimum manner, while holding the stability necessary for such efficiency. In essence, from a conceptual perspective, a basic control system is supported by the idea of a feedback loop (Fig. 6.1), which assumes that the system S object of control is in state $E(t)$ at time t. This state is characterized by the values at that time of a set of variables $\{v_1(t), v_2(t) \ldots v_n(t)\}$, the state variables, which are the output of the system. The main hypothesis is that the state variables are observable, that is, measurable, and they provide the information required to act on the system to drive it into a desired state, more efficient or optimum than the current one.

A key assumption is that the system is equipped with a set of sensors from suitable technologies providing the measurement of the system output, that is, the values of the state variables defining the state of the system $E(t)$ at time t. The objectives of the control process are presumably defined in terms of control policies, formulated as control variables, which provide the references of the expected values of the state variables determining the desired optimal (and efficient) behavior of the system under control. Then, the measured values are compared with the desired ones and their differences, the error measurements, are the input to the controller. This is equipped with the means to implement the corrective control actions, defined in terms of the appropriate control variables, to achieve the expected objectives.

A fundamental underlying concept is that of the observability (Castillo et al. 2008, 2015). Formally, a system is observable if, for any sequence of state and control vectors defined by the values of the state and control variables, the current state of the system can be computed in a finite time using only as input the output of the system. In other words, assuming that the approach to the system representation is based on the *Space State* description, its behavior can be totally determined from the output measurements if these are appropriate, what depends of the sensors layout (Barceló et al. 2012). Castillo et al. (2008, 2015) and Barceló et al. (2012), as many other references, deal with the sensor layout problem from what nowadays could be considered a classical from the perspective of sensor technology, i.e., inductive
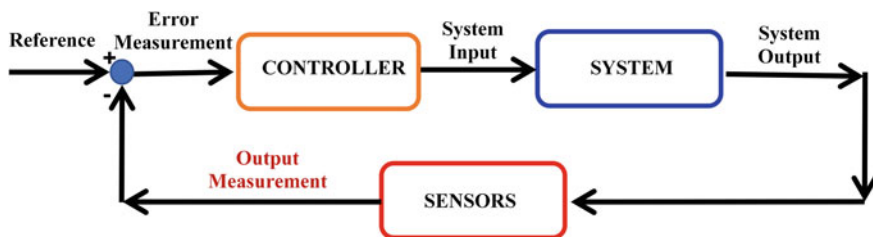

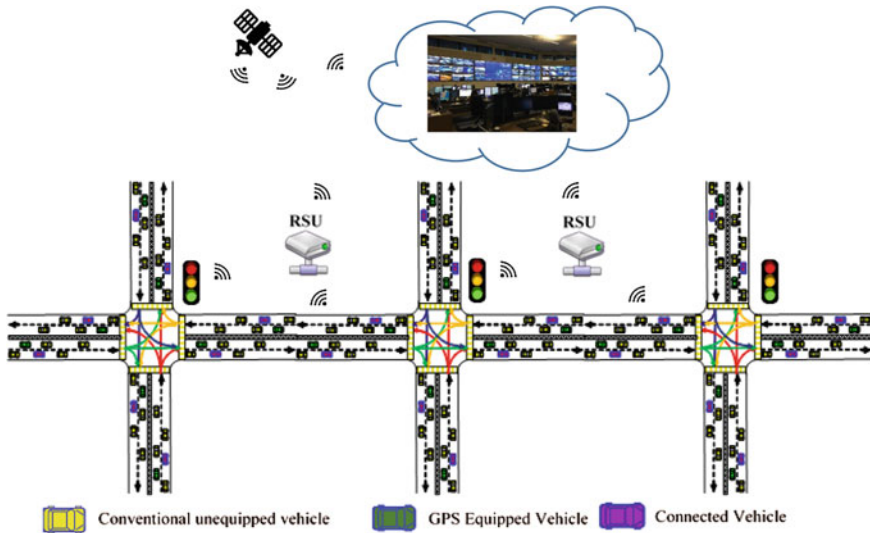**Fig. 6.1** Basic conceptual diagram of a feedback control loop of a system

Fig. 6.2 Conceptual example of an adaptive urban traffic control system

loop detectors, radar measurements, license plate recognition, or Bluetooth devices, among others. The irruption of new Information and Communications Technology (ICT) applications, i.e., smartphones or GPS, offers an amazing set of rich possibilities to enhance traffic data collection. Fang et al. (2016), Ibarra-Espinosa et al. (2019), or Antoniou et al. (2019) are good examples of these possibilities. More recently, the forecasted advent of Connected Automated Vehicles (CAVs) has prompted new possibilities (Montero et al. 2016; Xianfeng 2018; or Martínez-Díaz et al. 2019). These new technological scenarios are graphically depicted in Fig. 6.2.

Traffic systems were soon identified as a special case of a dynamic complex system, whose complexity is a consequence of the variable human traveling behavior in time and space. Therefore, the need for an effective control to optimize their performance was also soon detected (Papageorgiou 1983). The first versions of traffic control systems, namely in urban scenarios, were essentially static, based on the average observed traffic behavior, the physical attributes of the road object of control, and the type of available control actions, i.e., the traffic lights settings defined in terms of cycle lengths, splitting of light colors and offsets between successive intersections. These control systems have been continuously evolving toward real-time adaptive control systems aimed at making them as responsive as possible to better fit the time variability of the demand (Gartner 1985). This evolution has been determined by that of the technology, hardware, and software, and its ability to measure and processing in real time the values of the state variables.

Figure 6.2 schematically depicts an example of a hypothetical forthcoming adaptive urban traffic control system. In this system, in addition to the conventional traffic sensors (i.e., inductive loop detectors), GPS-equipped vehicles, and the envisioned CAVs capable of communicating with the traffic controllers become new information

sources, that could be potentially used either locally or in a centralized coordinated way through a "traffic control center" likely operating in the cloud.

For freeway/highway networks, with no signalized intersections, control is based on other approaches. For linear infrastructures, for instance, on freeways, where traffic flows are determined by input flows at on-ramps and exit flows at off-ramps (Martínez-Díaz 2018; Soriguera and Martínez-Díaz 2020), an example of control approaches are those based on ramp metering. This is precisely aimed at controlling these input flows to ensure the fluidity at the main stream.

The general increasing congestion trend, which is especially acute in large metropolitan areas, has prompted the interest in understanding its causes. Also, in looking for solutions, as congestion has clearly negative impacts on the quality of life due to its associated social costs (e.g., waste of time spent in congestion, adverse effects on sustainability in terms of energy consumption, contribution to greenhouse gases and obnoxious emissions endangering human health) (Barceló 2019). These solutions aim at remedying congestion in the long term, and at least alleviating its consequences in the short-medium term. Traffic management has emerged as the most appealing strategy to extend the concept of control in achieving these objectives of fighting congestion and its adverse consequences.

Traffic control, in the way it has been conceived and implemented, as summarily described above, could be considered as a restrictive approach to traffic management, as it only deals with one aspect: the time vehicles are flowing through the network. Traffic control tries to make traffic more fluid, that is, to minimize travel times and delays, while maximizing the use of the available local capacity. However, it does not consider how the space, that is, the total available capacity, is being used. The absence of this global view may lead, and in fact it leads, to unbalances in the use of this available capacity. The other way around, assuming that congestion is a consequence of the timely mismatching between traffic demand and supply (in terms of capacity), traffic management could be seen as an extension of traffic control that simultaneously controls time and space, and is aimed at adjusting the demand and the capacity to avoid this mismatching.

To achieve these objectives, primarily at freeway/highway networks, traffic management has usually combined two type of policies. First, those trying to influence the use of the road network increasing the throughput, regulating traffic inflows, and preventing spillbacks. These are management measures based on control policies that are aimed at preserving the fluidity in the main stream and at avoiding capacity drops, caused by fixed bottlenecks or generated by shock waves. Examples of these policies are the *speed control*, the *lane management,* and the *ramp metering*. Second, those trying to achieve a better distribution of traffic across de network. These policies, commonly referred as *Demand Management*, can be of different types:

- *Travel Time/Route Information Systems*

  They are aimed at influencing the way in which routes are selected and used from travelers' origins to destinations. In other words, they provide reliable information on the current and forecasted traffic conditions, so that drivers reach their

destinations at the desired or expected times. Another goal is to flatten the time distribution, lowering the pick periods of the demand by informing about departure times that minimize travel times while ensuring an acceptable degree of reliability. Thus, these systems shift drivers to off-peak periods.

- *Road pricing, Low Emissions Zones, Wide Area Access Control*, and similar measures

  These policies impose conditions to access a given area in order to reduce inflows to that area, or to ensure that only vehicles fitting certain technological (sustainability-related) conditions can access it.

- Policies that are the consequence of societal and technological changes

  For example those enabling teleworking or virtual access to the realization of any activity without physical displacement. Also, those shifting the current travel modes to other transportation modes (including the emerging micromobility modes), with the support of suitable and reliable information. Those policies that prompt modal chains using different modes for each trip leg (e.g., walking or cycling first, public transport like bus, metro, or commuting trains next, and finishing by using other alternative mode to reach the destination) must be highlighted, as they will become increasingly important.

Figure 6.3 translates these ideas into a conceptual scheme in which it is assumed that the traffic network is suitably equipped with all kind of sensors, both conventional and new technologies, and that an appropriate traffic surveillance system timely collects, stores, and processes the measured data. Traffic data are the main input to:

- A *Network Traffic State Estimation Module*, which determines the current state of the traffic network based on the available measurements and suitable models.
- A *Short-Term Traffic State Prediction Module*, which estimates the forecasted evolution of the traffic state according to the suitable traffic management policies determined by a *Traffic Management Decision Support System* (DSS). The latter is aimed at proposing the control actions to alleviate or prevent the deviations from the desired traffic state, usually defined in terms of a wide set of key performance indicators (KPIs) that translate traffic managers' objectives. These goals range from the conventional ones, i.e., maximizing the throughput, minimizing travel times, reducing congestion, avoiding bottlenecks, etc., to others addressing sustainability objectives like minimizing environmental impacts or energy consumption.
- The *DSS*, which recommends the traffic manager the alternative management actions to activate and indicates their respective potential impacts. Nevertheless, the traffic manager is the ultimate responsible for implementing the policies corresponding to such actions.

The TMS also includes a module to operate the appropriate actuators to impose the decided actions like ramp metering, speed control, lane management, in freeway networks, or gate-in/gate-out zone access policies in wide area control, for example.
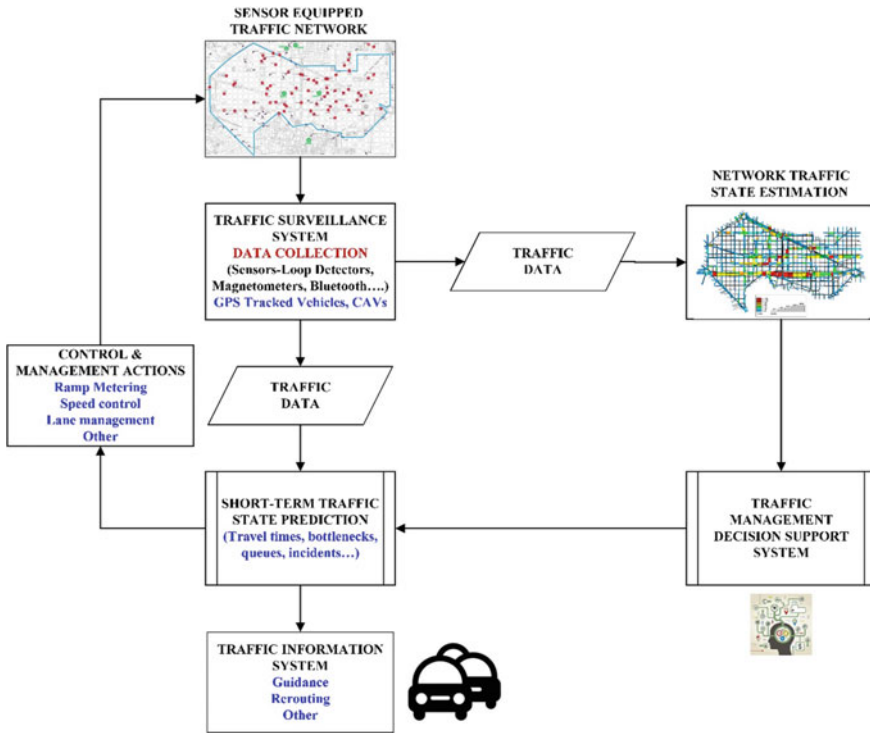
**SENSOR EQUIPPED
TRAFFIC NETWORK**

**NETWORK TRAFFIC
STATE ESTIMATION**

**TRAFFIC SURVEILLANCE
SYSTEM
DATA COLLECTION**
(Sensors-Loop Detectors,
Magnetometers, Bluetooth....)
GPS Tracked Vehicles, CAVs

**TRAFFIC
DATA**

**CONTROL &
MANAGEMENT ACTIONS
Ramp Metering
Speed control
Lane management
Other**

**TRAFFIC
DATA**

**SHORT-TERM TRAFFIC
STATE PREDICTION**
(Travel times, bottlenecks,
queues, incidents...)

**TRAFFIC
MANAGEMENT
DECISION SUPPORT
SYSTEM**

**TRAFFIC INFORMATION
SYSTEM
Guidance
Rerouting
Other**

Fig. 6.3 Conceptual scheme of a TMS

Demand management was soon also identified as a set of complementary manage-
ment actions that, if properly implemented, could contribute to reduce the pressure
on the traffic network by flattening the peaks of the time variability of the demand
and spreading it over time. Additionally, it can balance the available road capacity
with suitable re-routing for a more efficient use of the space. This kind of poli-
cies were usually implemented conveying the information to users by displaying the
corresponding messages in a set of variable message panels suitably located at key
locations in the traffic networks. This dissemination can currently be more pervasive
and efficient using the big variety of available mobile devices. That is, conveying the
information to drivers in real time, either on-route, i.e., while traveling, dynamically
recommending re-routing, or before starting the trip, proposing the most appropriate
departure time, routes, or alternative transport modes to use.

6.2 ITS Approaches and Artificial Intelligence

As explained, traffic management was soon identified as a step ahead beyond conventional traffic control, required by the increasing congestion in freeway networks and metropolitan areas, which in turn was a consequence of the growing motorization. Moreover, in the late eighties of the past century, new ICT applications that could potentially enhance traditional management systems started to emerge. The many projects addressing the topic from the early stages of the European Programs are a clear demonstration of the interest that traffic management has aroused and continues to arouse.

Leaving aside the technological aspects, i.e., data collection and management actuators, *grosso modo*, it is possible to differentiate two approaches to traffic management, including the network traffic state estimation, the short-term traffic state prediction, and the core traffic management DDS determining the policies that the traffic manager should implement to avoid or alleviate the conflictive identified situation. The first ones are those approaches inspired in an extension of the control theory conceptually illustrated in Fig. 6.1, and the second ones are those approaches based on Artificial Intelligence (AI). Kirschfink et al. (2000) document this interest in applying the new, and presumably more powerful, techniques of AI to complex traffic problems, expecting that they will be able to overcome the limitations of the current systems when facing critical conditions and congestions. They argue that these traditional systems have been usually conceived in terms of local traffic behavior, while the addressed problems are more global and, therefore, need strategic, high-level approaches.

Two meetings, the *ERUDIT Tutorial on Intelligent Traffic Management Models*, held in Helsinki on 1999, and the *European Symposium on Intelligent Techniques* ESIT'2000, held in Aachen, in 2000, provide a nice panoramic of the state of the art of the developments during more than 10 years (since the beginning of the European Programs) on what at that time was called *Advanced Transport Telematics* (ATM). ATM addressed the applications of the new emergent technologies, Computer Sciences (Informatics) and Telecommunications, to transportation systems and later become ITS. However, from the very beginning, AI was considered one of the main technologies to account for. Rass and Kyamakya (2007) provide a more extended overview of this progress. For their part, Kirschfink et al. (2000) summarize the application of *Advanced Knowledge Modeling Techniques* to *Intelligent Traffic Management Systems* (ITMS), assuming that these systems are conceptually defined to implement two types of measures:

- Direct control measures, that is, measures aimed at managing the infrastructure. For example, control of traffic lights, ramp metering, speed control or variable message signs.
- Indirect control measures, aimed at managing the demand, consisting on recommendations for drivers by means of variable direction signs (VDS), text panels,

or Relational Database Management System-Traffic Message Channel (RDMS-TMC) messages (nowadays replaced by advanced journey planners and navigation systems).

They also explain that TMSs are supported by a global architecture with two main components:

- A *Traffic Surveillance System* that collects and stores traffic and environmental data.
- A *Traffic Control Centre* (TCC) that must be able to suitably process all the detected data by the appropriate algorithms for different purposes. The most important ones are the estimation of the traffic state and the monitoring of the current traffic situation, the estimation of short-term predictions of the potential evolutions of the traffic state, the proposal and coordination of control measures, and the transmission of appropriate recommendations to drivers.

To overcome the above-mentioned limitations of the conventional systems, various approaches based on AI techniques, namely *Knowledge-Based* and *Inference* systems, have been proposed. Examples of these are TRYS (Hernandez et al. 1999), FLUIDS (Hernández 1999) or KITS (Kirschfink et al. 2000). The common idea to all of them is the development of a system that embodies a knowledge model of traffic behavior at a strategic level and is assisted both by knowledge management techniques supporting rule chaining for pattern matching methods, constraint satisfaction, etc., and inference machines able to reason on the acquired knowledge. To achieve such system, they propose adding a functional level in current TCCs, on the top of the existing facilities. This level consists on a *Traffic Knowledge Processing Layer*, whose goal would be to improve the online traffic monitoring and management system. Therefore, this layer would enhance TCCs operations for:

- The estimation of traffic load levels in space and time all over the network.
- The analysis and understanding of traffic demand and routes in the area.
- The qualitative prediction of demand and routes.
- The detection (prediction) of critical traffic situations and bottlenecks.
- The selection and implementation of congestion avoidance/reduction strategies.
- The management of conflictive control objectives and priorities in the different controlled areas.

The experience gained after the first developments and pilots projects reported in KITS (Kirschfink et al. 2000), conceives the knowledge models as a hierarchically structured problem solving, in which a problem domain can be naturally decomposed into substructures. Each of these substructures is specialized in the solution of a class of problem, which in turn can be decomposed into simpler and specialized issues to be addressed. The substructures considered in KITS are:

- *Agents*, which represent a local reasoning process that identify problems, interpret available information, perform specific tasks (i.e., short-term traffic prediction), support local decision processes, and detect inconsistent combinations (i.e., control actions in overlapping areas).

- *Actors*, which are knowledge units specialized in traffic evaluation and management within a particular area. They include reasoning strategies that use agents to solve interpretation and decision problems in the area. They are in correspondence with the topological decomposition of the traffic network.
- *Supervisors*, which are combinations of actors and can be of different types. For example, *Masters* act in a prescriptive way, *Mediators* negotiate conflicts and *Facilitators* act as managers and recognize which Actor has the external knowledge eventually required by each other Actor to perform local tasks.

KITS and TRYS are examples of such architectures whose knowledge modeling approach, quoting from Kirschfink et al. (2000), is supported by two structuring principles:

- A *functional organization*, which functionally decomposes the domain knowledge in specialized units targeting specific types of problems in this domain.
- A *topological organization* that spatially breaks down the traffic network into a set of so-called *Problem Areas*.

Functional and topological organizations should match to ensure that the knowledge and reasoning levels correspond. The envisaged knowledge-based traffic management system would then consist of a "*structured collection of knowledge units, providing specialized knowledge and reasoning mechanisms to deal with the different types of traffic management activities and reflecting the functional and topological knowledge.*" The main agents considered in KITS (Boero 1999; Kirschfink et al. 2000), whose architecture is illustrated in Fig. 6.4, were:
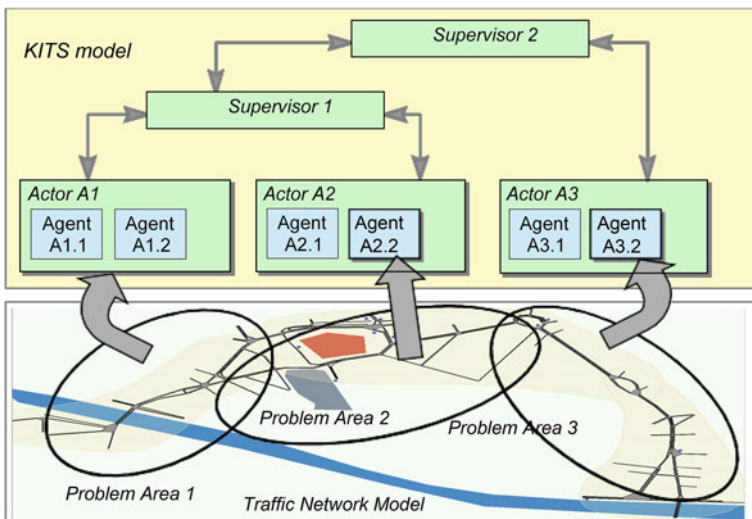

Fig. 6.4 KITS model of AI-based traffic management Boero (1999)

- The *Problem Identification Agent* and the *Traffic Flow Behavior Modeling and Causal Agent*. The first one identifies the problems using heuristic classification criteria based on the historical knowledge of problems in the area and evaluates the information provided by the data collection system. The second one performs the analysis and short-term evolution of traffic flows and looks for causal explanations of the detected problems. The type of agents based on traffic flow models has represented one of the most successful evolutions of these systems, as will be discussed later on.
- *Local Decision Agents* that support the suitable control actions for specific problem areas as consequence of the previous processes, and agents to detect inconsistencies of multiple control actions or actions that could potentially interfere between overlapped areas.
- Finally, a *Strategy Completion Agent* based on a global overview of the controlled network, which synthesizes and harmonizes the local proposals.

For its part, the MOTIC concept (Boero et al. 1997; Kirschfink et al. 1997; Boero and Kirschfink 1999) depicted in Fig. 6.5 could be considered as a hybrid architecture. In this approach, the AI components are combined with traffic simulation models to assist both in the analysis of the situation and in the evaluation of the impacts of the planned control strategies prior to their implementation. Additionally, instead of predefined *Problem Areas* as in KITS, a more flexible concept is introduced. This is that of *Scenario Definition*, enabling a graphic interactive process to dynamically determine the area potentially affected by the identified problem. Thus, once the
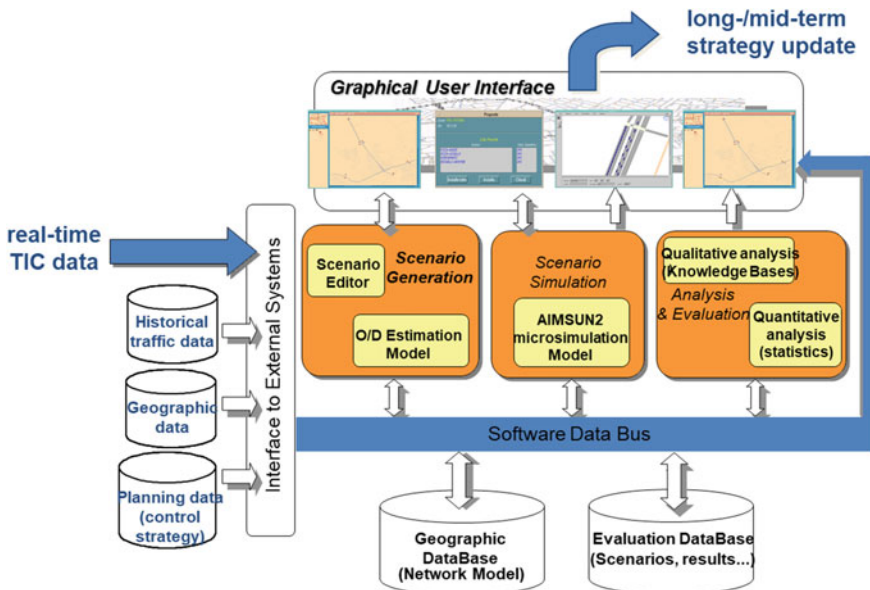

Fig. 6.5 The MOTIC approach to traffic management (Boero and Kirschfink 1999)

scenario is defined, it can be simulated. The simulation results in terms of KPIs can then be used to analyze the scenario before generating the information that will be used to apply the suitable policies and, thus, before disseminating the corresponding suggestions/orders. The use of microscopic simulation in the scenario analysis also enables a simulation-based learning process based on the collected data before and after the actuations. This allows defining and evaluating new management strategies, optimizing the existing ones, assessing the potential impacts of any variations of the strategies, determining the optimal timing to activate actuations, etc. MOTIC was developed and preliminary tested in a pilot test in the project ENTERPRICE, of the ATT European Program of DG XIII of the 4th Framework European Programme 1997–1999 (Boero and Kirschfink 1999).

A differential fact of MOTIC with respect to other approaches, which results evident when analyzing the architecture depicted in Fig. 6.5, is its hybrid structure, which includes AI and traffic models. AI is used to analyze and understand what is going on. In other words, to interpret the identified network state based on the current analysis and past experiences from similar situations. However, traffic models support this network estate estimation as, for example, microsimulation models. Aimsun2 (Boero et al. 1997), an earlier version of Aimsun, was particularly used in the above-mentioned applications. The interactively generated simulation model of the selected scenario, corresponding to a Problem Area, is used to evaluate the alternative strategies to solve the identified problem in terms of specific KPIs, to support the decision-making process.

Another differential aspect of this approach that deserves to be highlighted is that the support of an advanced microsimulation model (Barceló et al. 2004; Barceló 2010), requires an input that is not yet directly observable from traffic measurements: **the model of the mobility patterns in terms of an OD matrix** (see Chap. 7). The dynamic simulation model will describe how the trip makers use the paths connecting origins and destinations depending on traffic conditions. Therefore, it will be able to identify how congestions are generated as well as the spillback across the network and, consequently, to emulate how road users will likely react to the management actuations. A deeper insight into the role of microscopic simulation in ITS applications can be found in Barceló et al. (2004).

A system inspired in MOTIC was developed and applied in the Intermodal Strategy Manager ISM (Barceló et al. 2002; Kirschfink et al. 2003). This was a development within the framework of the Hessian WAYflow-project, with the goal of improving traffic management in the Rhine-Main area by supporting the planning of new strategies, starting with their impact assessment and coordination up to their implementation, as well as by optimizing the already existing strategies. The *Scenario Analysis Module* (Barceló et al. 2004), in Aimsun/ISM uses an Aimsun microscopic traffic simulation model of the traffic network under study to define, verify, and optimize traffic management strategies, evaluate their expected impacts, and determine the triggers for their activation, according to prevailing traffic conditions. A scenario is a microscopic simulation model of a traffic network (or a subnetwork of a large network) in which a traffic problem has been identified. This is consistent with the so-called *Problem Network*.

The model input reproduces the traffic demand in the problem network for the time period for which the traffic problem has been identified with a great degree of accuracy. Also, the current operational conditions in the road network, such as current traffic control at signalized intersections, reductions of capacity at specific parts of the network caused by road works, incidents, etc. The analysis of the scenario consists of a set of simulation experiments whose purpose is to help traffic managers to develop and evaluate the impacts of the single actions or combination of actions. These actions are situation-related measures (i.e., re-routings and/or speed control using variable message signs—VMS—changes in control, etc.), with the objective of alleviating or eliminating the traffic problem identified. This concept of action composed by the various situation-related measures is called a *Strategy*. The evaluation of alternative scenarios, i.e., models of the same problem network with alternative traffic management strategies, compares the values of performance indexes that express saturation levels, quality of service, total travel time, average delays, average queue lengths, or total vehicle-kilometers traveled, among others.

The main objective of Aimsun/ISM is to allow the fast and convenient manipulation of input data to create simulation scenarios and to present result data in a compressible way. It has two main components: the *Simulation Experiment Specification* and the *Result Analysis*. The *Simulation Experiment Specification* includes the setup of a Problem Network (either the network of the whole area or a sub-network), the creation, modification, and adjustment of OD matrices (again global for the whole area as well as local or traversal for the sub-networks), the addition of traffic management policies and their triggers and the simulator tuning. For its part, the *Result Analysis* includes the output data presentation and the comparative study of the performance of a solution, either with previous solutions or with real data. Since a problem can have different solutions and taking into account that these solutions may not be obvious, users can define several experiments combining different policies until the best option is found. During this experimentation, users can also reuse previous solutions and add new ones to, as said, comparing their performance among them and/or with real data. This process can be repeated iteratively until a satisfactory solution is found. The above-mentioned components provide the support for the generation, evaluation, and optimization of traffic management strategies.

The Aimsun/ISM operation is illustrated in Fig. 6.6, where the WAYFLOW Global Network and a potential Problem Network are shown. A Problem Network corresponds to a sub-network of the road network on which a specific traffic problem may arise or is identified by the user. This user can define the target Problem Network graphically by opening a window on the screen on which the WAYFLOW network is displayed (the rectangle in Fig. 6.6 corresponds to the selected Problem Network). Any Problem Network is characterized by the road network within the defined window and an OD database with their distinct demand patterns under various circumstances (season, day of the week, time of the day, special event, etc.). Also, by a strategy database containing the specifications of the potential traffic management strategies to operate on the Problem Network depending on the identified or expected traffic problem and on the demand pattern.
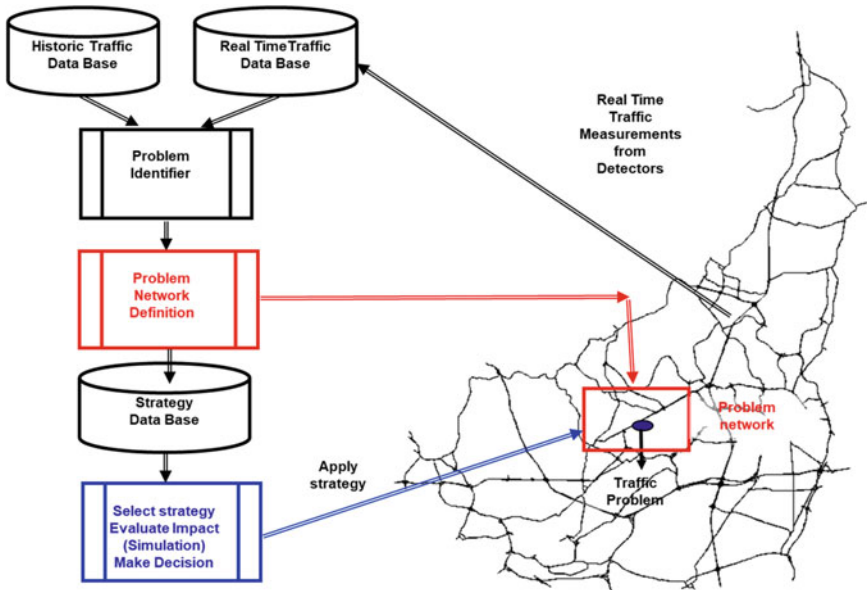
Fig. 6.6 ISM system in the WAYFLOW network in Hessen

Variants of the former approaches can be found in Barceló et al. (2007a, b, c) or Krishnan et al. (2010), among others. Figure 6.7 summarizes the main aspects of this evolution, which are:

- Traffic flow models to estimate the traffic state and its likely short-term evolution can be either basic as in KITS, TRYS, Krishnan et al. (2010) or Hegyi et al. (2009) or complex, usually based on dynamic simulation, as in Barceló et al. (2007a).
- There exists a *Basic Inference* (i.e., set of rules) *System* to infer the primary interventions/actions (i.e., policies) to apply based on the current state.
- These new approaches assume that, during its operational life, the TMS has generated two complementary databases that complement the real-time collected data. First, a historic database of recorded traffic data, identifying specific scenarios (i.e., recurrent congestions and their time evolution at specific locations). Second, a historic database of the control actuations applied to alleviate or solve specific conflicts and all data and related information associated to them.
- New approaches use more complex AI engines, based either a variety of knowledge-based or inference approaches, as explained for KITS, TRYS, or MOTIC, or on a pattern matching process. The latter find similarities between the identified situation and others previously recorded. This looking for similarities is usually a task for specialized clustering approaches, like in AURA (Krishnan et al. 2010).
- The applied advanced traffic models enable an estimate of the likely short-term evolution of traffic conditions in the network, and therefore an evaluation of the
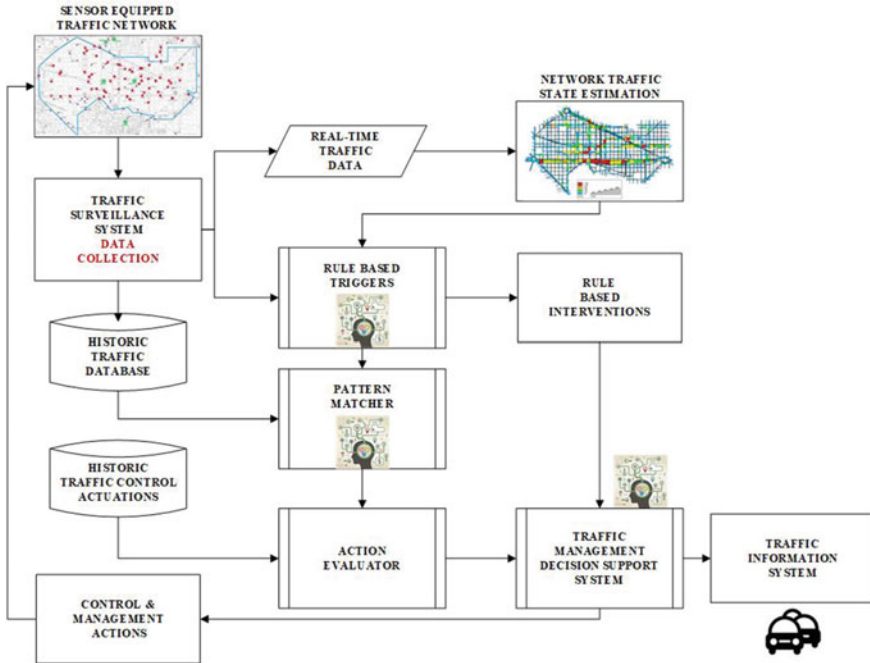
Fig. 6.7 Generic evolution of the AI traffic management-based architectures

potential impacts of the planned actions in terms of a selected set of KPI's, Barceló
et al. (2007a).

- These approaches include a *DDS*, i.e., a generalization of the previous inconsis-
tency detection and strategy completion actions, combining the primary rule-based
actions and the evaluated actions after the pattern matching. It is responsible for
making the final recommendation that the human operator will implement.

6.3   Current Hybrid Approaches

The pursuit of increasingly sophisticated traffic models continues beyond those intro-
duced in the previous sections. However, the goals of these models have not varied.
First, they aim at estimating the traffic state and at analyzing its similarity with other
already experienced situations. Second, they address the short-term forecasting of
its likely evolution under the planed management strategies as well as the evaluation
of the potential impacts of these strategies in terms of selected sets of KPIs. This
willingness for improvement has prompted the evolution of the generic architecture
described in Fig. 6.7 toward some of the commercial systems used in projects that
are more recent. Some of their key characteristics are:

- Their ability to dynamically identify the problem area within a la large managed area.
- Their capacity to estimate and adjust the OD matrix by identifying the current traffic patterns in the problem area from both historic records and current traffic measurements.
- Their pattern matching process to find similarities between the identified situation and the historically recorded ones (Mounce et al. 2012).
- They deliver a set of KPIs to evaluate the alternative scenarios according to the possible strategies to apply. Professional platforms usually offer the possibility of customizing the type of KPIs that will support the traffic management decision-making process. However, KPIs based on speeds, travel times (usually path travel times), expected delays, queue lengths, etc., are always present. Therefore, their forecasted values for complex traffic networks in these traffic management platforms are usually based on dynamic traffic models able to estimate path travel times, for example, the dynamic traffic assignment models.

Figure 6.8 adapted from Barceló et al. (2007a), depicts the adaptation of this architecture, to Madrid Calle-30, evolved as described from the ISM project. This became the basic version of Aimsun On-Line, (https://www.aimsun.com/aimsun-live-case-studies/madrid/). The conceptual diagram in Fig. 6.8, highlights this hybridization of AI and analytic components:
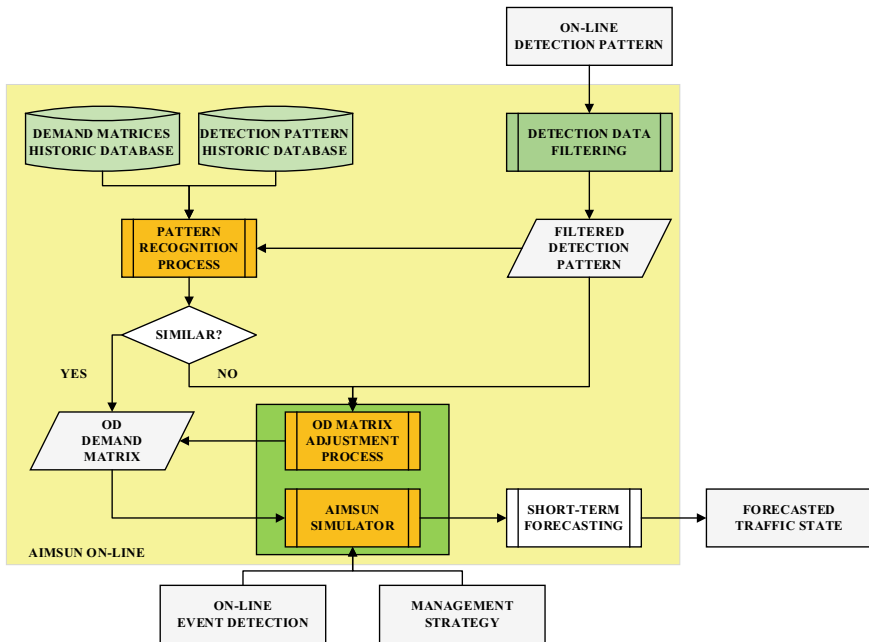

Fig. 6.8 Conceptual diagram of Aimsun on-line platform for real-time traffic management

- The pattern recognition process matches the traffic state identified after the measurement of traffic data with a likely OD pattern, in terms of the demand generating such situation, with some previously historically recorded similar situation.
- In case such similarity does not exit, a new OD is adjusted based on the historical and the current information.
- A traffic simulation model of the target network (Aimsun in this case) is fed with this information and the information from the event detection (incidents or scheduled special events) and the planned strategies, to estimate the forecasted traffic state that will be evaluated in terms of the selected KPIs.

These platforms have been continuously evolving since then. Figure 6.9 depicts the most recent version of Aimsum's platform, called Aimsun Live (Aimsun 2020).

The process has two operational modes: training and prediction. The training mode, as depicted in Fig. 6.10, is responsible for generating the set of mobility patterns. Input data is preprocessed (i.e., data filtering and missing value imputation) and standardized. Next, mobility patterns are extracted using a guided clustering algorithm with the aim of minimizing their number while maximizing their quality, i.e., minimizing cluster variability. The algorithm allows external (or previous) mobility patterns as optional input. This feature is of especial importance for an incremental (or iterative) pattern extraction methodology.

The prediction process is illustrated in Fig. 6.11 and it consists, again, of preprocessing and standardizing input data. Next, the pattern matcher uses traffic data and exogenous variables to estimate the likelihood of each pattern. Note that
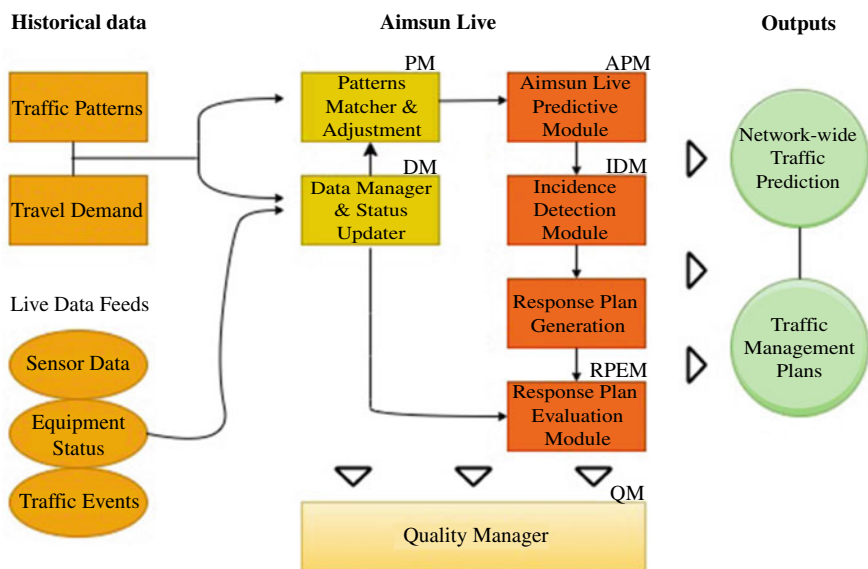

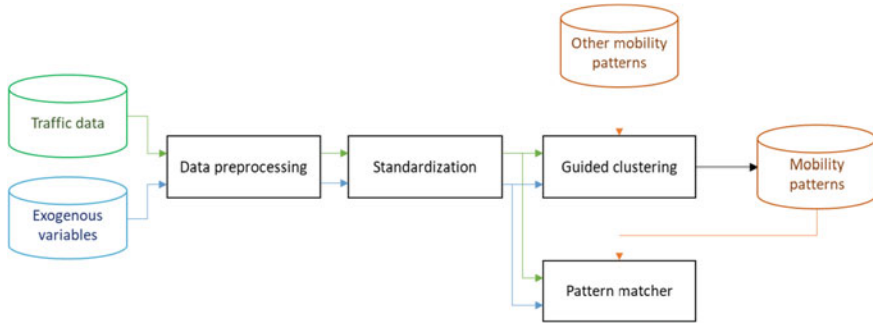**Fig. 6.9** Conceptual structure of Aimsun Live

Fig. 6.10 Training workflow of pattern generation and matching process. The colors of the arrows represent the type of data (green for traffic data, blue for exogenous variables, orange for mobility patterns). The solid arrows represent mandatory input/outputs and the dashed arrows represent the optional ones
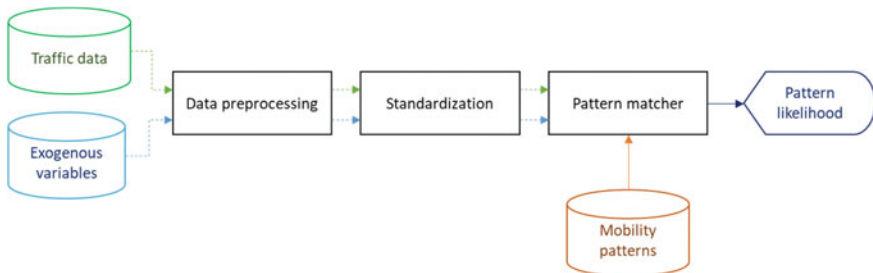

Fig. 6.11 Prediction workflow of the pattern matching process. The colors of the arrows represent the type of data (green for traffic data, blue for exogenous variables, orange for mobility patterns). The solid arrows represent mandatory input/outputs and the dashed arrows represent optional ones

this likelihood is estimated using input data that was either measured or predicted. It is also important to highlight that traffic data and exogenous variables are optional inputs of the pattern matcher. Therefore, depending on the type of input data used to feed the pattern matcher, it will estimate the likelihood of each pattern to occur in the present or in the future. For example, if we feed the pattern matcher with calendar features regarding today and the last N hours of traffic data, it will return the probability of each pattern of happening today. But if we input only calendar features of next Monday, it will return the probability of each pattern to occur next Monday. Therefore, the pattern matcher can be used to predict current and future patterns.

Additional references on traffic management systems based on the use of Aimsun Live can be found in the websites of San Diego Interstate 15 Integrated Corridor Management System, Sydney—M4 Smart Motorway, Wiesbaden DIGI-V, Florida DOT or Aimsun Live Technology Trial (Singapur), among others.

6.4 Other Approaches

At almost the same time, in parallel but independently, approaches different from those addressed in Sect. 6.3. were developed to tackle the problem of traffic management. A good example is that represented by RENAISSANCE (Wang et al. 2006). Conceptually, its architecture is a simplified version of the one depicted in Fig. 6.3, supported by METANET. This is a macroscopic freeway modeling method based on the fundamentals of traffic flow theory (Kotsialos et al. 2002; Papageorgiou et al. 2010), including enhancements from Wang and Papageorgiou (2005). Further extensions can be found in Wang et al. (2008), and Wang et al. (2009).

In this modeling approach, the freeway traffic state is estimated in terms of the traffic flow variables, i.e., flow, mean speed and density for each freeway stretch. All of them are defined with a suitable discretization in both time and space, exploiting the corresponding available real-time measurements. The proposed traffic state estimation combines traffic flow theory with Extended Kalman Filtering (EKF) in an efficient way that jointly estimates the model parameters online, including the fundamental traffic flow variables, the free-flow speeds, the critical densities and the capacities, adding significant adaptive capabilities.

However, the initial version of the RENAISSANCE approach does not consider, in either its modeling or its operation, the potential of control measures like ramp metering, route guidance, or variable speed limits. In case these control measures are applied, RENAISSANCE only allows the estimation of their impacts from the real-time traffic measurements. For example, the impacts of ramp metering can be estimated from the on-ramp inflows and densities at the downstream segments after the on-ramp, route guidance affects the estimates of the turning percentages in junctions, and speed control influences the estimates of the model parameter values. The potential consequences of these control measures in the prediction accuracy is limited by a continuous updating of the prediction horizons in terms of an efficient rolling horizon technique. In this sense, RENAISSANCE is designed to be used as an intermediate layer between the traffic data collection system of the freeway network, which provides the real-time traffic measurements, and the traffic managers, which will take management decisions on guidance and control supported by the provided information. Supported by the same freeway modeling approach in RENAISSANCE, Carlson et al. (2010) developed coordinated control strategies at the network level combining variable speed limits and ramp metering.

The DynaMIT (Dynamic Network Assignment for the Management of Information to Travelers) of Ben-Akiva et al. (2010) is also included in this category of approaches based on traffic flow theory. DynaMIT is "*a simulation-based dynamic traffic assignment (DTA) model system that estimates and predicts traffic conditions.*" However, it has also been designed as a real-time system for the generation of predictive traffic information to support traffic management decisions, in this case primarily intended for route guidance. An example would be the dissemination of travel times by means of any technologies supporting the ATIS, either those placed in-vehicle or that located on the road side (e.g., VMS). A relevant differential feature

of DynaMIT is its objective of avoiding the adverse impacts of improper traffic information. In fact, the proposal and application of management decisions without a previous insight of their potential consequences could be risky, and later corrections would be necessary to deal with unexpected reactions. To achieve such objective, the models in DynaMIT are aimed at providing predictive information consistent with the conditions that drivers will experience in the network, thus accounting for traffic evolution.

A conceptual view of DynaMIT (Ben-Akiva et al. 2010) adapted to the generic framework in Fig. 6.3 is depicted in Fig. 6.12. It integrates models and algorithms designed to fuse data from various sources with two main functions: the network state estimation and the prediction of its short-term evolution. This is achieved by taking advantage of two main modeling components, a demand simulator and a supply simulator, and their interactions. The travel patterns in the network are captured by the demand simulator, whose main input are the time-dependent origin–destination flows, expressed as time-dependent OD matrices. Individual trips are defined in terms of the origin and destination of the trip, the departure time, and the selected
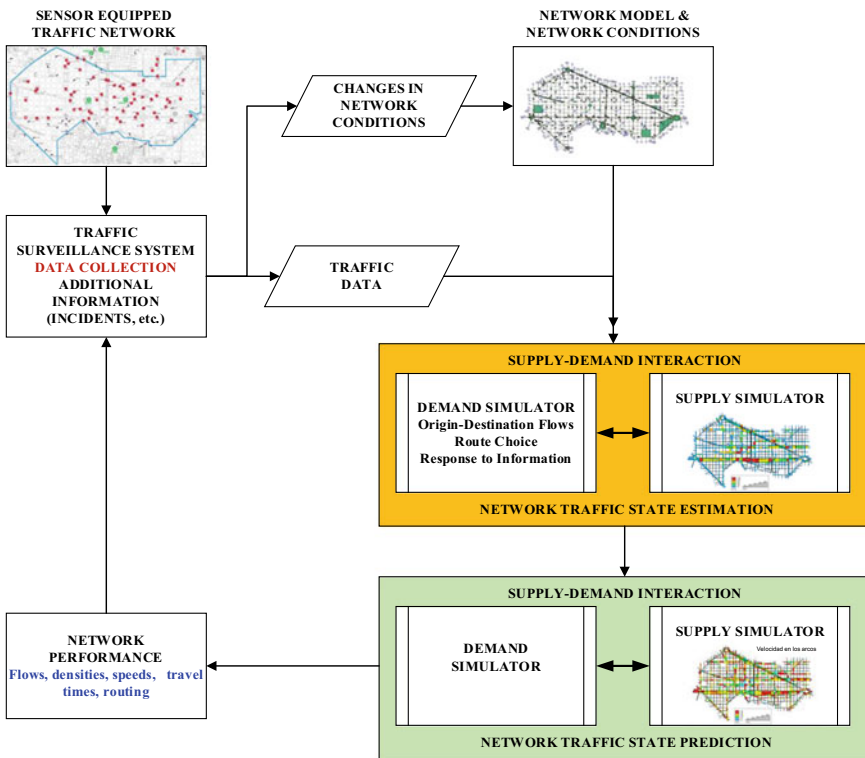

Fig. 6.12 The conceptual architecture of DynaMIT adapted to the general framework of Fig. 6.3

route, considering that these decisions are taken before the trip begins. The aggregated representation of the demand also accounts for individuals' socioeconomic characteristics. To anticipate the response of travelers to the information planned for dissemination (Ben-Akiva et al. 1997), DynaMIT also considers their potential access to such information. The supply simulator, which is mesoscopic, captures traffic dynamics, and evaluates the performance of the network, including the formation and dissipation of queues, spillback effects, or the impacts of incidents and bottlenecks. It represents traffic dynamics using speed–density relationships and queuing theory (Ben-Akiva et al. 2002). The algorithms (Ben-Akiva et al. 2010), used to estimate the current network state, to perform the short-term prediction of its evolution and to support the generation of the anticipatory route guidance and control strategies are suited to properly account for the complex demand–supply interactions. A critical aspect for the quality of the results is to ensure that the models are consistent with the prevailing conditions, which is achieved by means of the dynamic adjustment of the key model inputs and parameters.

Although with conceptual similarities with the framework approaches for traffic management discussed so far, Meschini (2017) proposes a different professional implementation in the platform developed by PTV SISTeMA. In this case, the TMS is the central component of the TCC. Functionalities are split in such way that the TMS is responsible for the collection of data regarding current traffic conditions, the physical implementation of the management decisions (whose final responsible is assumed the human operator) and the dissemination of the information and management decisions to other operators as well as to users. The TCC would be responsible for the continuous monitoring of traffic conditions based on the available measured data. However, the assessment of the current traffic state and its short-term evolution, accounting for the evaluation of alternative management strategies and for incident detection is implemented with the assistance of a DSS. This DDS, suited for real-time management, should support the ATIS and the Optimal Traffic Control (OTC). In agreement with the conceptual frameworks discussed in previous sections of this chapter, Meschini (2017) considers traffic management as a loop involving situation monitoring, identification of disruption, proposal of corresponding mitigation actions, and action implementation (Fig. 6.13). This loop should be fulfilled in time intervals short enough for real-time operations (i.e., within 1 and 10 min).

The real-time data collection envisaged in this approach goes beyond the conventional traffic data measurements provided by the usual technologies, i.e., traffic counts, flows, and occupancies on links, or instantaneous speeds. It accounts for floating car data (FCD), for instance, those provided by GPS devices placed in passenger vehicles, commercial vehicles, or public transport bus fleets, enabling the tracking of vehicle trajectories. It also considers travel time measurements, as those derived from automatic number plate recognition (ANPR) or systems of wireless network sensors. Such rich variety of traffic data coming from different sources is intrinsically heterogeneous. Therefore, there is a need for a data fusion process that merges all of them in homogeneous estimates of traffic variables, i.e., in flows, speeds, densities, and capacities of the links of the underlying transport model supporting the functionalities. This process requires a previous map matching procedure that
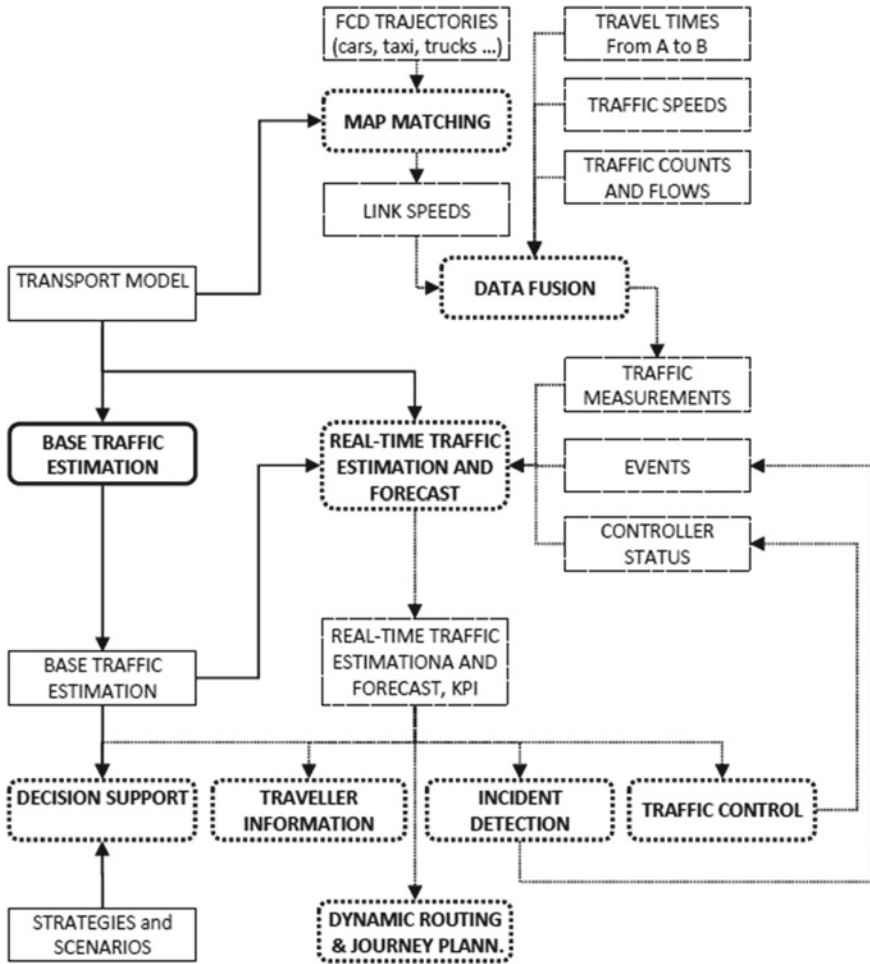
Fig. 6.13 Functional overview of the traffic management system proposed by Meschini (2017). Rounded boxes represent functions or elaboration activities and rectangle represent collected data and inputs produced or exchanged between functions

associates the measured data with the transport model. In the case of OPTIMA, the platform developed by PTV SISTeMA, this consists, first, of the topological representation of the network: links, nodes, turnings, connectors, zones, their attributes (e.g., link id, node id, link maximum speed, number of lanes, capacities, allowed transport modes, etc.). Second, of the functional representation of the road network, including all field related devices such as VMSs, traffic detector locations, traffic signals (and in this case the detailed information of timing and phasing), etc. The model-based traffic prediction also requires the definition of the transport demand defined by OD matrices, their temporal profiles and the modal segmentation.
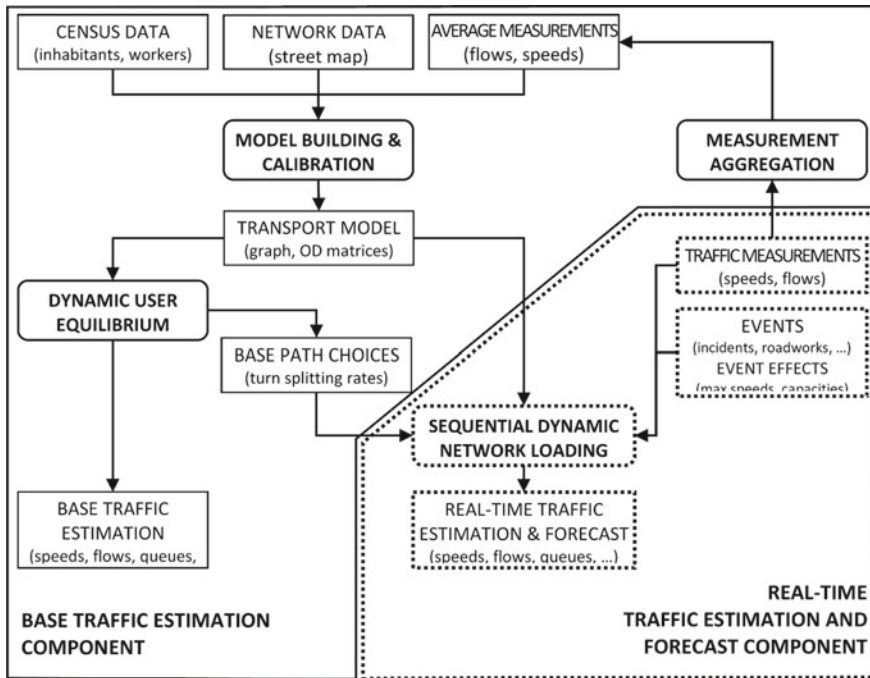
Fig. 6.14 Schematic description of OPTIMA model-based traffic estimation and prediction

In the case of OPTIMA, the proposed simulation and forecast approach is based on a methodology consisting of models and algorithms for dynamic traffic simulation. The logical architecture of the proposed system (Fig. 6.14) is composed of two parts: the offline and the online parts. The offline part is supported by a DTA model, which in turn is based on a dynamic user equilibrium (DUE) model (Bellei et al. 2005; Gentile 2010; Gentile et al. 2007, 2010; Meschini and Gentile 2010). Also, on the transport model that calculates the evolution of link flows, queues, travel times, and path choices over different time intervals within each typical day. The online part uses the model and the base traffic conditions provided by the offline part and combines them with the real-time measurements from the detection system. This is done by means of a traffic model that adjusts the estimations and forecasts to the measured conditions of that particular day. The online part runs automatically on a continuous basis providing a new traffic estimation and forecast in terms of travel times, traffic flows, and queues every few minutes.

OPTIMA was applied, for example, in the Regional Traffic Supervision Centre of the Piedmont region, in northwest Italy, in 2014. Its goal was to provide traffic information over the regional road network of Piedmont, thus enabling traffic management in the region. Another example of OPTIMA's applications is the customer-oriented traffic service www.AnachB.at, in Austria, which provides a comprehensive and effective traffic information system for travelers.

Other references to OPTIMA related traffic management projects are "2015–2020 PTV FR, Direction des routes Ile-de-France (DiRIF)—Supply of traffic data in real time and traffic supervision platform for Traffic operator of Ile-de-France motorways," or "Far EasTone Telecommunications (FET) for Taichung DOT, Taiwan-Development of a real time traffic management and control system for the City of Taichung." The latter provided proactive traffic management, short-term traffic prediction of up 1 h, incident management, alternative route guidance through VMS, and Active Warning using PTV Optima and PTV Balance.

In summary, all these approaches to traffic management are aimed at influencing simultaneously the supply, that is, the capacity of the network and the traffic demand so that they better match in time and space. The usual problems occurring in the road network primarily concern the generation of bottlenecks at specific points at given times, either at peak periods, when the demand exceeds the available capacity (i.e., in a recurrent way) or generated by incident or special events (i.e., in non-recurrent situations). The aim of traffic management is to prevent or alleviate these situations either spreading the traffic demand to different parts of the network or dynamically adapting the available capacity so that it serves the current demand. As explained in Sect. 6.1, ramp metering, dynamic speed limits, lane management, and similar policies are aimed at regulating the inflows, increasing the throughput or preventing spillbacks. They primarily act on the infrastructure maximizing the available capacity given the estimated traffic state and its likely evolution. Therefore, they are usually considered *Supply Management* policies. For their part, transportation *Demand Management* policies are aimed at spreading the demand over time, avoiding high concentrations at peak hours by (i) providing an alternative accessibility to the activities generating the trips (i.e., the case of teleworking), (ii) distributing the demand across the traffic network to use more efficiently the total capacity, or (iii) favoring modal split, particularly shifting the trips to transportation modes other than the private vehicle (i.e., public transport, cycling, walking, or, more recently, micromobility modes). Demand Management is usually implemented in terms of *Travel Time Information Systems* conveying the travelers, as in the case of DynaMIT, reliable information on travel times and their short-term forecasting. This information allows them to make better decisions in choosing the routes from their origins to their destinations. *Advanced Journey Planners* that enable trip makers to make better decisions when choosing the routes and transportation modes (or combinations of them) and, therefore, to achieve their goals more efficiently, also belong to Demand Management.

These approaches to traffic management, usually conceived for freeway networks, can be extended to urban areas adopting the concept of the *Network Fundamental Diagram* (NFD). This seminal concept, developed by Geroliminis and Daganzo (2007) in terms of what they called the *Macro Fundamental Diagram*, is a consequence of their willingness to figure out whether it a fundamental relationship between traffic variables, similar to the fundamental diagram of the basic traffic flow theory for freeways, exists at the network level. That is, if it exists a maximum capacity of a network that can be interpreted as a generalization of the concept of capacity in traffic theory. If it would exist, it would be suitable to define ad hoc management actions by generalizing those strategies extensively used for traffic management on

freeways. Indeed, this relationship was demonstrated (Daganzo 2007; Geroliminis and Daganzo 2007, 2008; Daganzo et al. 2012; Mahmassani et al. 2013) and it can be explained intuitively as follows. The approach assumes that an urban traffic network behaves similarly to a reservoir, with an input flow q_{in} that can be considered a function of time $q(t)$, and an output flow $e(t)$ depending on some system function of the state of the system $n(t)$ at time t, $G[n(t)]$ (Eq. 6.1). The time variation of the accumulation (state) in the system $n(t)$ could then be modeled as in Eq. 6.2:

$$e(t) = G[n(t)] \tag{6.1}$$

$$\frac{dn(t)}{dt} = q(t) - G[n(t)] \tag{6.2}$$

Based on this approach, Geroliminis and Daganzo (2008) show that such NFD exists and can be estimated in terms of the total number of vehicles in the links of the network, measured by traffic detectors, and the total production. The latter should be estimated as the total distance traveled by all vehicles in a link in a given time interval Δt. The resulting diagram is as the one depicted in Fig. 6.15, which was built by simulating microscopically the traffic in a network. This allows estimating the network capacity, that is, the maximum number of vehicles that can be allocated to the network. The possibility of having such measure of maximum capacity of a network and the availability of such an NFD allows exploiting real-time measurements to identify at which point of the diagram (i.e., in which traffic state: free flows, transitions, congested flows, etc.) the network is performing. Moreover, this opens the door to *Active Wide Area Traffic Management Strategies*, as illustrated graphically in Fig. 6.13.

Let us consider a large area to manage and a selected critical subnetwork in this area. For example, the Central Business District (CBD) of Barcelóna depicted in Fig. 6.16. The real-time measurements from sensors allow identifying whether the network is performing at point A, B or C. Point A corresponds to free flow, i.e., the managed subarea has still remaining capacity to allocate more vehicles. At
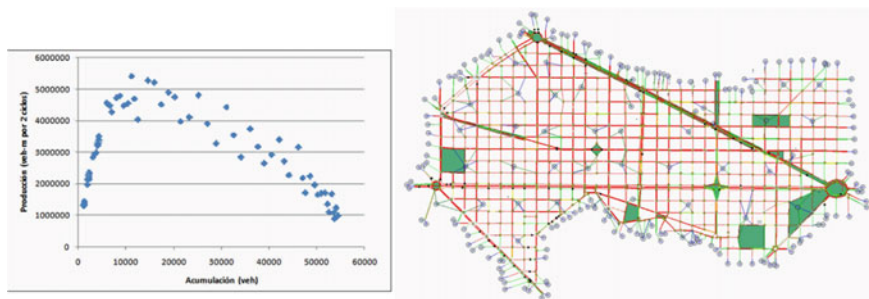

Fig. 6.15 The macro fundamental diagram of Barcelona's central business district built by simulation
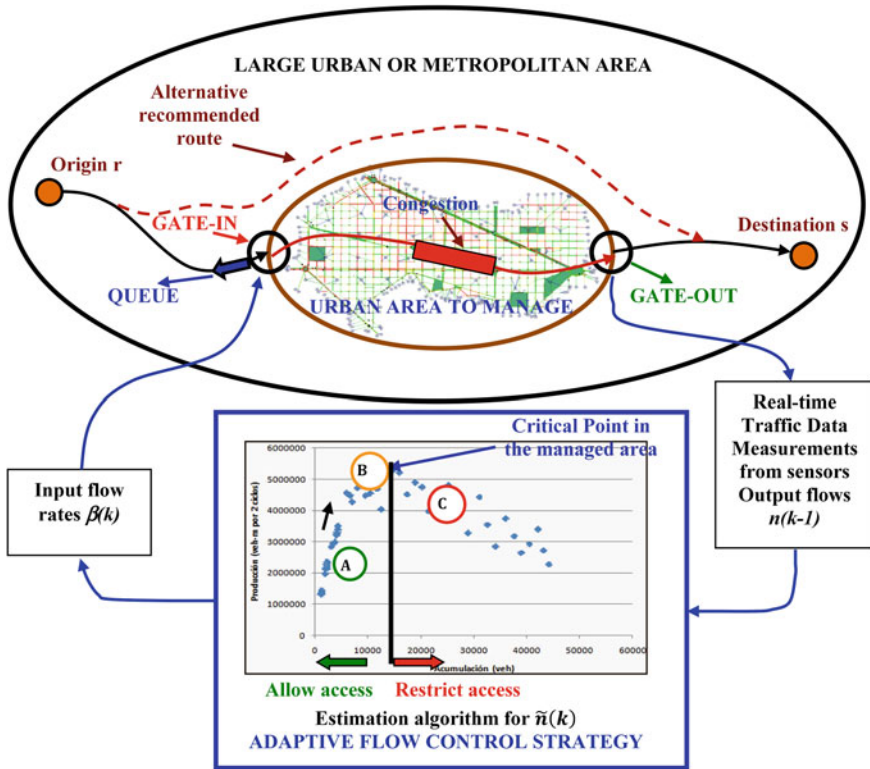
Fig. 6.16 Potential use of the network fundamental diagram to support active traffic management strategies

point B, the subnetwork is reaching the capacity and actions limiting the access to the subnetwork would be desirable to avoid the growing of congestion. Finally, at point C, the network is congested (beyond capacity) and no more vehicles can be allowed to enter the area. Gate-in and gate-out control policies at the boundaries of the area, which are an extension at the network level of the widely used ramp metering policies to manage freeways, can be implemented to, respectively, restrict the access and facilitate the evacuation of the congested area. However, such policies must be applied carefully, as they can generate problems at other parts of the large network due to the queue spillback at entry gates. These gate-in and gate-out policies must be combined with a queue management system and re-routing policies, which in turn require the appropriate dynamic traffic model to account for dynamic traffic patterns between origins and destinations, to balance the situation, (Allström et al. 2017).

The existence of the NFD (or Macro Fundamental Diagram) has been its initial proposal extensively investigated, as well as the procedures to build it from available traffic measurements (Leclercq et al. 2014). At the same time, research has shown

that a proper Macro Fundamental Diagram requires some homogeneity conditions on the network (Geroliminis and Sun 2011), which, in the case of large networks, implies the need for dividing it into homogenous regions (Ji and Geroliminis 2011, 2012). This allows the analysis of the particular phenomenon that takes place in each part and the proposal of an efficient methodology to solve it.

As explained, the existence of a network capacity as a generalization of the key concept of capacity and the availability of practical procedures to estimate it, led very soon to the idea of using it for traffic management in a network, also generalizing the well-known ramp metering strategies. If ramp metering on freeways has the main objective of rating the input flows to the main stream in order to avoid reaching capacity and subsequent consequences as capacity drops, a gate-in–gate-out process could achieve similar objectives at the network level (Aboudolas and Geroliminis 2013). Figure 6.16 illustrates this idea conceptually. Let us assume that output flows $n(k-1)$ are measured in real time by sensors placed at the output gates of a selected subnetwork at time interval $k-1$. Also, that measurements from other sensors placed along the network allow the estimation of the current operational conditions in the network (e.g., A, B or C in Fig. 6.13). Then, an adaptive flow control strategy will determine the input flow rate $\beta(k)$ at time interval k through the input gates (the "gated flows") that keeps the operational condition in the network close to an optimal estimated number of vehicles $\tilde{n}(k)$. This management problem and its variants has generated a rich literature, as Geroliminis et al. (2013), Ampountolas and Kouvelas (2015), Keyvan-Ekbatani et al. (2015, 2016, 2017).

6.5 AMS Approach and ATDM

The cases summarily described so far mostly correspond to a view of traffic management focused on freeways, namely freeway networks, and, in the case of the Wide Area Management discussed in Sect. 6.4, on urban networks. However, there have been also attempts to expand the managed networks, widening the scope to account for mixed networks where freeways and urban roads coexist. An example can be found in Papageorgiou (1995), which considers the concept of corridor as "*a general highway network including both freeways and urban roads.*" That was a first step ahead toward a wider and deeper conception of traffic management, as the traditional one, oriented to single-modal corridor control, was insufficient. Indeed, all traffic management approaches described previously implicitly consider only a transportation mode, i.e., vehicular traffic, ignoring other modes like public transport in all its modal variants, (bus, metro, railways, etc.). This limitation was the natural consequence of freeway networks being the only targets of previous approaches. However, when urban networks or mixed transportation networks spanning large metropolitan areas were considered, it became evident that the other available transportation modes could no longer be disregarded. Responding to this need, Reiss et al. (2006) provided a refined definition of transportation corridor in their Integrated Corridor Management (ICM) initiative report:

A corridor is a largely linear geographic band defined by existing and forecasted travel patterns involving both people and goods. The corridor serves a particular travel market or markets that are affected by similar transportation needs and mobility issues. The corridor includes various networks (e.g., limited access facility, surface arterial(s), transit, bicycle, pedestrian pathway, waterway) that provide similar or complementary transportation functions. Additionally, the corridor includes cross-network connections that permit the individual networks to be readily accessible from each other.

Shortly before this definition emerged, the US government had envisaged the potential benefits of ICM and started to document the research on this topic. In 2005, the U.S. Department of Transportation's (USDOT) Intelligent Transportation Systems (ITS) Program launched the *ICM Systems Initiative* (FHWA 2005), whose ultimate goal was "*to provide the institutional guidance, operational capabilities, and ITS technology and technical methods needed for effective ICM Systems.*" The initiative further propelled the research on ICM in a regulated way, including the refined definitions for transportation corridor and ICM. Quoting from the TRS 1210 (2012) report:

In the ICM Program Plan, ICM is defined as the coordination of individual network operations between adjacent facilities that creates an interconnected system capable of cross-network travel management.

To differentiate the ICM from other advanced traffic management systems, Reiss et al. (2006) provided a more detailed definition of ICM:

ICM consists of the operational coordination of multiple transportation networks and cross-network connections comprising a corridor and the coordination of institutions responsible for corridor mobility. The goal of ICM is to improve mobility, safety, and other transportation objectives for travelers and goods.

Figure 6.17, from Alexiadis (2008a), visualizes this concept of corridor considered as a complex dynamic system composed by a variety of interactive subsystems that need to be considered and managed in an integrated way to achieve the ICM goals. Examples of the subsystems considered in ICM are:

- Different infrastructures, e.g., freeways with on- and off-ramps, arterial streets and local streets.
- Different transportation modes, e.g., passenger car and public transport (bus, metro, light rail).
- Different control systems, e.g., traffic lights at signalized intersections, ramp meters at on-ramps, variable message signs, etc.

Each subsystem may have its own control strategy, such as ramp metering, signal coordination, public transport preemption, or information provision for guidance to foster modal splitting. In the conventional approaches, these strategies would had been developed and integrated independently. The main novelty in ICM is that they must be integrated and coordinated looking at the system as a whole and not only at the individual parts. This is consistently with the view of the transportation corridor in the *ICM Program Plan* (FHWA 2005) as "*a combination of discrete parallel surface transportation networks (e.g., freeway, arterial, transit networks) that link the same*
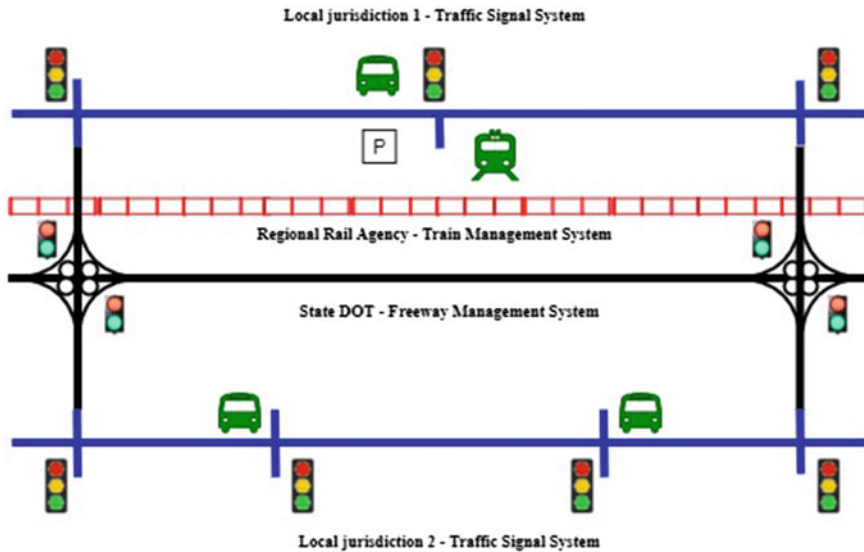
Fig. 6.17 Conceptual scheme of corridor as envisaged by ICM (inspired in Alexiadis 2008a)

major origins and destinations. It is defined operationally rather than geographically or organizationally," which emphases the operational aspects.

ICM is therefore considered in the sphere of the ATMS because of the broad complex operational concepts, the versatility of the integrating subsystems and the variety of management strategies that must be supported, integrated and synchronized by ITS technologies. That is, it must ensure the coordination of the multiple transportation networks that constitute the corridor as well as that of the institutions responsible for each of them. Miller et al. (2008) describe the ICMS in the report on the San Diego ICM project, as a "*system of systems, i.e., a TMS that connects the individual network-based TMS, provides decision support and enables joint operations according to a set of operational procedures agreed to by the network owners.*" They continue explaining that ICMS accounts for the following operations:

- Information share/Distribution: manual information sharing, information clearinghouse (information exchange) between corridor networks and agencies, 511 (pre-trip traveler information), on-route traveler information (smart signage and smart parking), access to corridor information by Internet Service Providers and other value-added entities; automated information sharing (real-time data), common incident reporting system, and asset management system.
- Junctions/Interfaces improvement: signal pre-emption (identifying "best route" for emergency vehicles), multi-modal electronic payment, signal priority for transit, bus priority on arterials, transit hub connection protection, multi-agency/multi-network incident response teams/service patrols, and training exercise.

- Accommodation/Promotion of Network Shifts: modification of ramp metering rates to accommodate traffic (including buses) shifting from arterials; promotion of route shifts between roadway and transit via on-route traveler information devices, promotion of shifts between transit facilities via on-route traveler information devices, congestion pricing for managed lanes, and modification of arterial signal timing to accommodate traffic diverted from the freeway.
- Capacity/Demand Management (short-term): land use control, modification of HOV restrictions, increase of roadway capacity by opening HOV or toll (HOT) lanes/shoulders, scheduled closures for construction, coordination of schedule maintenance and construction activities among corridor networks, planning of temporary addition of transit capacity, and modification of parking fees (smart parking).
- Capacity/Demand Management (long-term): peak spreading, ridesharing programs, expansion of transit capacity, and land use around Bus Rapid Transit (BRT) stations.

Alexiadis (2008a, b) formalizes the Analysis, Modeling and Simulation (AMS), as a methodological proposal for ICM. The proposed AMS methodology combines a variety of traffic models as required. It starts with a trip table manipulation that has its origin in a *Regional Travel Demand Model*, and whose goal is the determination of overall trip patterns, which can be refined and time-sliced as long as the necessary feedback is available. "*In this AMS framework, macroscopic, mesoscopic, and microscopic traffic analysis tools can interface with each other, passing trip tables and travel times back and forth looking for natural stability within the system.*" The elements of this methodological framework were explicitly considered later on by Cronin et al. (2010), who stated that "*conducting analysis, modeling, and simulation tests enables corridor partners to identify the most promising strategies and informs decisions for design of ICM systems.*" They concluded that managers should integrate this methodology with ICM DSS to facilitate the predictive, real-time, scenario-based operational decision-making. The proposed concept of a DSS is in this case "*the interactive, computer-based system that uses historical data and models to identify and solve problems as defined by* Sprague and Watson (1986)." All of them agree that the practice of real-time traffic management must be supported by DSS that assist traffic managers in making sound decisions to avoid, or at least alleviate, conflictive situations in traffic networks occasioned by congestions (recurrent or not), incidents, or any other potential causes. An efficient DSS must help and guide the manager decisions based on a quantitative assessment of the traffic conditions in the network and, if possible, of a short-term prediction of their likely evolution. However, it must be noted that the estimation of the current network state quantified in terms of values of associated indicators (e.g., level of service, queues, delays, travel times, etc.) as well as their short-term forecasting requires the use of suitable dynamic traffic models.

The idea of assisting managers in making decisions with the help of this type of DSS was also explored by Barceló et al. (2005). A first practical implementation was described in Barceló et al. (2007a). Key components in the architecture of these

systems are respectively the traffic models and the trip tables, and the OD matrices and the critical problem of the time updating of these OD matrices. Zhou et al. (2008) provide a seminal exploration on the use of models for the analysis of multimodal urban corridors. The draft report on an AMS Framework (2013) describes the predictive tools as a key component and raises concerns about the current approaches based on travel demand simulators to feed such tools, underlining the limitations of the usual practice of performing a time decomposition of the 24-h trip OD tables. The application of this methodology for the design and development of ICM models has some major challenges:

- The availability of reliable data sources and related data collection and management processes. This an aspect becoming increasingly relevant, considering the availability of new data sources from the pervasive penetration of mobile devices.
- The estimation of the origin–destination time dependent patterns. A key input for most of the existing dynamic models to generate specific control and management decisions, i.e., predictive dynamic re-routing, as discussed for DynaMIT. This input is, however, extremely difficult to estimate, especially under congested scenarios.
- The accuracy and reliability of the information supporting decisions (e.g., travel times, travel time reliability).
- The driver's compliance rate estimation in response to the given control strategies.

Examples of ICM projects implementing this approach using the professional platforms described in Sect. 6.3 are, for instance, the San Diego Interstate 15 Integrated Corridor Management System (SANDAG 2009), led by the San Diego Association of Governments (USA), active since 2013. Also, the Regional ICM System in Florida (USA) for the Florida Department of Transportation (FDOT 2020). Both were powered by Aimsun Live.

Mahmassani et al. (2017) extend the application of the AMS methodology to two programs of the USDOT that represent a step beyond the ICM: The *Active Transportation and Demand Management* (ATDM) and the *Dynamic Mobility Applications* (DMA). A set of effective and reliable tests beds were selected to define a rigorous DMA bundle and to perform a comprehensive ATDM strategy evaluation. These were the San Mateo (US 101), Pasadena, ICM Dallas, Phoenix, and Chicago Testbeds. All tests had the objective of providing valuable mechanisms to refine and integrate research concepts in virtual computer-based simulation environments prior to field deployments. The goals were to (i) "capture a wider range of geographic, environmental and operational conditions under which to examine most appropriate ATDM and DMA strategy bundles, (ii) add robustness to the analysis results and (iii) mitigate the risks posed by a single testbed approach." Mahamassani et al. (2017) particularly report the findings for the Chicago Testbed, in which the strategies tested, all them part of the ATDM strategy bundles applied, were:

- The ATM strategies analyzed were Dynamic Shoulder Lanes, Dynamic Lane Use Control, Dynamic Speed Limits, and Adaptive Traffic Signal Control.

- The ADM Strategies consist of Predictive Traveler Information and Dynamic Routing.
- Weather-related Strategies, including Snow Emergency Parking Management, Traffic Signal Priority for Winter Maintenance Vehicles, Snowplow Routing, and Anti-Icing and Deicing Operations.

These applications were tested considering a proactive network management approach that adopts simulation-based prediction capabilities. The research questions addressed were the impact on any application performance of different facility types under varied operational conditions, the synergies and conflicts among applications, the impact of prediction accuracy and communication latency, and the impact of connected vehicle data versus legacy systems data. The Chicago Testbed was developed using the enhanced, weather-sensitive DYNASMART (Mahmassani et al. 2005) platform in conjunction with a microsimulation tool developed specifically for connected vehicle applications (Talebpour 2016) belonging to the DMA bundle. The authors summarize that the following six algorithmic modules trigger a comprehensive DYNASMART-X simulation:

- A Network State Estimation (RT-DYNA) module, which provides up-to-date estimates of the current state of the network. It has the full simulation functionality as DYNASMART-P, and its execution is synchronized to the real-world clock.
- A Network State Prediction (P-DYNA) module, which provides future network traffic states for a pre-defined horizon, as an extension from the current network state estimated by RT-DYNA.
- An OD Estimation (ODE) module, which uses a Kalman Filtering approach to estimate the coefficients of a time-varying polynomial function that is used to describe the structural deviation of OD demand in addition to a historical regular pattern.
- A OD Prediction (ODP) module, which uses the predicted OD coefficients provided by ODE to calculate the demand that is generated from each origin to each destination at each departure time interval. The predicted time dependent OD matrices are used for both current (RT-DYNA) and future (P-DYNA) stages.
- A Short-Term Consistency Checking (STCC) module, which uses the link densities and speeds of the simulator to evaluate the consistency of the flow propagation with the real-world observations and correct the simulated speeds.
- A Long-Term Consistency Checking (LTCC) module, which compares the simulated and observed link counts to calculate scaling factors that are used to adjust the demand level in both RT-DYNA and P-DYNA.

6.6 Concluding Remarks

From the various approaches and conceptual architectures of traffic management systems discussed in this chapter, a common critical component is the one that provides the system with capabilities for the prediction of the short-term evolution

of the traffic state as a consequence of the envisaged management strategies. This component is usually a dynamic traffic model that, along with the forecasting, evaluates the performance of the system in terms of a selected set of KPIs. One of the key inputs to the KPIs, or a KPI in itself, are the forecasted travel times (sometimes also their reliability) and the subsequent likely route choices.

The dynamic traffic models to be used could be based on various approaches: from pure microscopic, as in certain applications of Aimsun Live depending on the size of the managed scenario, to mesoscopic approaches, based on the concept of Dynamic User Equilibrium (DUE), as in OPTIMA and ATDM, for medium to large scenarios. In any case, all of them share as common input a dynamic OD matrix and its temporal profiles to properly mimic the time dependency of the demand. Nevertheless, dynamic OD matrices are not directly observable yet. Even when direct observations are available, for example, when onboard GPS devices allow vehicle tracking, they only correspond to a sample. The expansion of this sample to the whole population, as required by DUE models, is not always a straightforward exercise. This raises the question of how to accurately estimate such matrices, a question that will be addressed in Chap. 7.

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