Chapter 6
Models on the Road

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6.1 Traffic Simulation Modelling and Safety Aspects

Modelling has become a major part of all aspects in traffic engineering within the last decades. The models applied range from macroscopic models, treating network related facets of traffic, to microscopic models, which represent traffic flow by moving individual vehicles. The safety aspects can be integrated at several levels of modelling, targeting different parts of the driver behaviour.

The network effects of safety are typically handled by macroscopic models. They represent the supply, i.e. the road/street network, and the demand, i.e. the trips of people, and match both to create the traffic load on the network links. The basic idea of integrating safety in the microscopic models is to influence the routing behaviour of drivers in such a way, that either they observe the given safety levels on the links of the network, or to influence their route choice towards minimizing the (negative) safety effects of their trips. This has been a novelty introduced within IN-SAFETY project, which has gained significant momentum since.

The macroscopic approach adds safety as an additional parameter in the routing/ assignment. The information for the safety level comes either from actual traffic data for a specific network, or derives from known safety indicators for road/street

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types. The algorithmic extension consists mostly of integrating the supplementary data into the objective function. This approach is, of course, relevant only to the drivers, not to other road users.

The microscopic approach has a similar basis, but tends to optimize individual trips on a network, in such a way that the overall safety is maximized. In this nature, the safety of other road users, e.g. pedestrians in a traffic calming zone, is implicitly included. Of course, the safety optimal routes do not necessarily lead to an optimal travel time distribution and may, thus, be different from a system optimum in the traditional sense.

Microscopic models are applied for all aspects that directly influence the task of driving a vehicle. Generally speaking, driving a vehicle, in this context, means the driver's control task in lateral and longitudinal direction. This task can be assisted by new Advanced Driver Assistance Systems (ADAS) or In-Vehicle Information Systems (IVIS). They provide warning or even take over part of the driving task continuously, like Adaptive Cruise Control (ACC), or only temporarily, like Collision Avoidance, under specific conditions. Such systems lead to changes in the trajectory of the vehicle and, thus, they may also lead to changes in the overall traffic flow. The analysis of the trajectories in various ways reveals changes in traffic flow as a whole, e.g., changes in the speed-flow-relationship, and also on safety relevant parameters, like time-to-collision (TTC) and its derivatives. Other indicators, like the shape of the headway distribution, can also be used for the estimation of safety consequences.

In the following sections, first an overview over the models applied within the IN-SAFETY project is provided, followed by the description of sample applications, which show the potential of the models for safety analyses. Then, possible extensions of the models which would improve them for safety indications are shown and, finally, an outlook onto the future of model applications for safety analyses is given.

6.2 Microscopic Models

Microscopic Models create the traffic flow from the movements of individual vehicles. Their difference lies in the way these movements are generated. While there exist a wide variety of approaches, the focus here is on such models that apply a rather detailed model for the driver-vehicle-environment interaction. In the context of "safety" these interactions are of major interest. It must be noted, however, that other approaches exist, with much less detailed movement description (e.g. agent-based models). Such approaches save run-time for the sake of complexity; they can be seen as a bridge between microscopic and macroscopic models. While they are able to handle larger scenarios at reasonable resource consumption (concerning time and memory), their results cannot be used for detailed analyses, like for safety or emission calculation purposes. The models we describe here are not only widely used in the traffic engineering community; they constitute the current state-of-the-art in microscopic modelling and incorporate a development background of many years.

6.2.1 RutSim

The Rural Traffic Simulator, RuTSim, (Tapani 2005) is a traffic simulation model developed for rural road environments. The model handles all common types of rural roads, including two-lane roads and roads with separated oncoming lanes.

Rural roads place different requirements on the simulation model than urban or highway networks. This difference is due to the fundamental differences in the interactions between vehicles and the infrastructure. The travel time delay in an urban or freeway network is dominated by vehicle-to-vehicle interactions, whereas the travel time delay on a rural road is also significantly affected by interactions between vehicles and the infrastructure. For example, speed adaptation with respect to the road geometry has a more prominent role on rural roads than it has on urban streets. A model describing traffic flows on rural roads must, therefore, consider the interaction between vehicles and the infrastructure in greater detail than models describing traffic flows in urban areas or on highways. Interactions between vehicles are nevertheless important on rural roads, particularly in overtaking situations. For modelling of two-lane roads, it is for example necessary to consider interactions between the oncoming traffic streams.

A rural road traffic simulation model was developed at VTI during the 1970s. This model has been continuously improved during the following decade. These model improvements also included large calibration and validation efforts. However, the original model applied simple rules for updating vehicle positions and speeds and was limited to simulation of uninterrupted flow on two-lane roads. RuTSim was developed based on this original model, to allow modelling of interrupted flows and new types of rural roads.

RuTSim is a micro-simulation model that consists of sub-models that handle specific tasks. The use of sub-models simplifies the future modification of RuTSim and increases its flexibility. The model is designed to handle one road stretch in each simulation run; i.e. rural road networks are not considered. The main road may incorporate intersections and roundabouts, and the traffic on the main road may be interrupted by vehicles entering and leaving the road at intersections located along the simulated stretch. The traffic flows entering the road at various origins may be time dependent. Turn percentages at intersections for each traffic flow are used to determine vehicle destinations.

RuTSim uses a time-based scanning simulation approach. The simulation clock is advanced with a user-defined step size, e.g., 0.1 s. The time-based simulation approach is chosen for RuTSim, because it allows more detailed modelling of an individual vehicle's interactions with the surrounding traffic and the infrastructure. With a shorter time step, the movement of vehicles from one time step to the next becomes smoother and therefore more realistic. Hence, a shorter time step may, given an adequate modelling logic, result in the driving course of events for an individual vehicle to be closer to the driving course of events found in real traffic. The use of a shorter time step does, however, increase the model run time. The model time step should therefore be chosen in relation to the current application. Outputs, in the form of aggregated traffic measures, do not require a time step as short as the one required if a driving course of events for a representative vehicle is desired.

The following steps are performed in every time step during a model run:

1. Add vehicles that are to enter the road during the time step to virtual queues, with one queue for each origin.
2. Load vehicles from the virtual queues to the road, if possible, i.e. if acceptable space is available on the main road.
3. Update the speed and the position for every vehicle on the road.
4. Remove vehicles that have arrived at their destination.
5. Update the state, i.e. free or car following, overtaking or passed, and acceleration rate, for every vehicle on the road.
6. Save the data.
7. If animation is enabled, update the graphical user interface (GUI).
8. If the stop time has been reached, terminate the simulation or else increment the simulation clock and go back to Step 1.

Before the simulation, the speed profile of the road and the traffic that is to enter the road are generated from the input road and traffic data, respectively.

The current version of RuTSim applies a car-following based on the "Intelligent driver model" (Treiber et al. 2000, 2006). This model accounts for driver limitations and anticipation to allow more detailed studies of traffic impacts of driver assistance systems. Details of this current car-following methodology applied in RuTSim are out of the scope of this chapter. Overtaking decisions on two-lane roads are controlled by a stochastic model depending on the current road characteristics and the distance to the oncoming vehicle.

Previous applications of the RuTSim model include quality-of-service studies of alternative rural road designs (Carlsson and Tapani 2006). RuTSim has also been utilized in a study of possibilities to conduct safety evaluations of driver assistance systems using traffic simulation (Lundgren and Tapani 2006).

6.2.2 S-Paramics

The application of S-Paramics focussed on the safety effects of route choice in a road network. Therefore, this description refers to the route choice characteristics of S-Paramics.

In S-Paramics, each vehicle tries to find the shortest route from the road section on which it is located, to its destination zone. The shortest route is the one for which the general journey costs are lowest. Each time a vehicle enters a new road section, the route is evaluated again, on the basis of the general journey costs that are 'stored' in route tables.

The road hierarchy in a network can be used to change the journey costs on special road sections for familiar and unfamiliar vehicles. The road hierarchy in a network is made up of major and minor road sections.

Major road sections are equipped with signs; the journey costs of familiar and unfamiliar vehicles are the same.

There are no signs on minor road sections and the familiar vehicles view the journey costs on minor road sections as being the same as the actual costs. Unfamiliar vehicles have a lower consciousness of minor road sections; they view the journey costs on these road sections as being twice the actual costs. These 'penalty costs' make it less likely that these unfamiliar vehicles will choose routes along minor road sections and they will therefore tend to stay on the signed road sections (i.e. the major road sections).

Familiarity with the road network has a fundamental influence on route choice in a hierarchical road network. If this directly influences the quantity of routes passing along routes with and without signs, it is important to properly calibrate the level of familiarity.

The standard familiarity value for all vehicles is 85%. This means that 85% of the vehicles make no distinction between the costs of major and minor road sections. The other 15%, the unfamiliar vehicles, view the costs on minor road sections as higher and will be more inclined to travel along major road sections.

The level of familiarity can be set separately for each vehicle type. For example, if a model includes taxis, it would be quite possible to set the familiarity at 100%, because taxi drivers usually know the road network well.

The general journey costs and the road category can be set for each individual road section.

The journey costs of an individual road section can be calculated using the general cost comparison (referred to hereinafter by its Dutch abbreviation, GVK). This represents a combination of factors that drivers take into consideration when choosing between various routes. The most important factors are time and distance. If a toll is charged for using certain parts of a road, these costs will also be taken into account.

The general journey costs GK of a road section are measured in time, distance and (if imposed) toll charges and can be weighted by means of coefficients, depending on the road category and the familiarity of the road users with the road network.

The general journey costs GK of a road section can be set to the same (generic) value for all vehicles, or they can be set by vehicle type.

In addition to calculating the general journey costs of an individual road section as described above, it is also possible to calculate the general journey costs for a road category. This determines the general journey costs for all road sections that fall into a certain road category. This is done in precisely the same way as described above.

If an individual road section falls into a category for which the general journey costs are 2 and, furthermore, it is allocated a specific value of 3 that applies only to this road section, then the final general journey costs are 6 (GK of the category multiplied by GK of the individual road section).

The route tables are filled in using the general journey costs of the road sections. The route costs are equal to the sum of the general journey costs of the road sections that form part of the route. Route tables give vehicles the opportunity to calculate the costs of a route choice at each junction along the route. When a vehicle approaches a junction, it consults the relevant route table and, after deciding whether to apply perturbation and/or dynamic feedback, the vehicle selects the route that has the lowest journey costs to the destination.

As standard, there are two route tables in a model in S-Paramics: one table contains the costs for vehicles that are familiar with the road network (familiar vehicles) and the other table contains the costs for vehicles that are unfamiliar with the road network (unfamiliar vehicles). Familiar vehicles have a different perception to unfamiliar vehicles of a route through the network. This is achieved by making use of a road hierarchy in the network and by calibrating familiarity.

In addition, a separate route table can be created for each type of vehicle, thereby producing a set of route tables. Each route table is calculated each time that a simulation is started.

The following allocation methods are possible in S-Paramics:

- All-or-nothing allocation
- Stochastic allocation
- Dynamic allocation
- Stochastic Dynamic allocation

6.2.3 VISSIM

VISSIM is a commercial micro-simulator that has been developed over the last two decades. It is based on a very detailed driver-vehicle model developed in the mid-1970s. Basically designed to re-create traffic flows on carriageways, like on motorways or urban arterials, it has recently been enhanced to integrate non-lane-bound vehicles, like two-wheelers and even pedestrians. In the context of safety applications, we focus here on the safety applications of Intelligent Transport Systems, namely Advanced Driver Assistance Systems, which pertain to passenger cars and trucks. The following description of VISSIM therefore concentrates only on the issues that are important for such applications.

The quality of the traffic flow model properties constitutes a major concern of their users: The traffic flow model used by VISSIM is a discrete, stochastic, time step based (1 s) microscopic model, with driver-vehicle-units (DVU) as single entities. The model contains a psycho-physical car following model for longitudinal vehicle movement and a rule-based algorithm for lateral movements (lane changing). The model is based on the continuous work of Wiedemann (1974, 1991).

Vehicles follow each other in an oscillating process. As a faster vehicle approaches a slower vehicle on a single lane it has to decelerate. The action point of conscious reaction depends on the speed difference, distance and driver dependent behaviour. On multi-lane links moved up vehicles check whether their speed improves by changing lanes. If so, they check the possibility of finding acceptable gaps on neighbouring lanes. Car following and lane changing together form the traffic flow model, being the kernel of VISSIM.

Figure 6.1 indicates the oscillating process of this approach. The thresholds of Fig. 6.1 are explained in an abbreviated form. Driver specific perception abilities and individual risk behaviour are modelled by adding random values to each of the parameters as shown for AX. For a complete listing of the random values the reader is referred to Wiedemann and Reiter (1992).

AX: Desired distance between the fronts of two successive vehicles in a standing queue.
$AX = VehL + MinGap + RND1 \cdot AXMult$ with RND1 normally distributed N(0.5, 0.15).

ABX: Desired minimum following distance, which is a function of AX, a safety delta distance BX and the speed v.
$ABX = AX + BX \cdot \mathrm{v}v.$

SDV: Action point where a driver consciously observes that he/she approaches a slower car in front. SDV increases with increasing speed differences (vΔv). In the original work of Wiedemann an additional threshold cldv (closing delta velocity) is applied to model additional deceleration by usage of the brakes with a larger variation than SDV.

OPDV: Action point where the following driver notices that he/she is slower than the leading vehicle and starts to accelerate again. The variation of OPDV is large (Todosiev 1963).

SDX: Perception threshold to model the maximum following distance, which is about 1.5–2.5 times ABX.

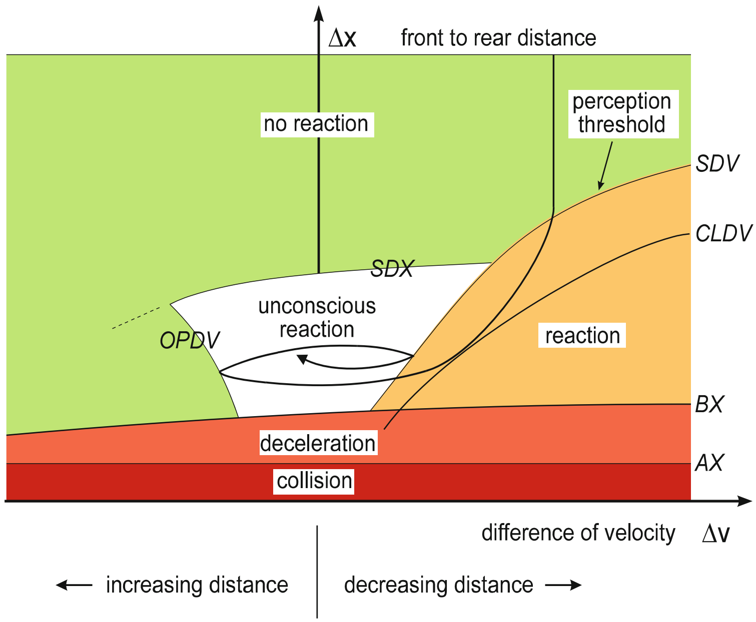

Fig. 6.1 Car-following model of Wiedemann – threshold and one vehicle trajectory

A following driver reacts to a leading vehicle up to a certain distance, which is about 150 m. The minimum acceleration and deceleration rate is set to be 0.2 m/s^2. Maximum rates of acceleration depend on technical features of vehicles, which are usually lower for trucks than the personal desire of its driver. The model includes a rule for exceeding the maximum deceleration rate in case of emergency. This happens if ABX is exceeded. The values of the thresholds depend on the present speed of the vehicle. Figure 6.2 denotes the values for two different speeds to display a current set of values.

In case of multi-lane roads, a hierarchical set of rules is used to model lane changes. First, a driver has a desire to change lane if he/she has to drive slower than his/her desired speed, due to a slow leading vehicle or in case of an upcoming junction with a special turning lane. Then, the driver checks whether he/she improves his/her present situation by changing lanes. Last, he/she checks whether he/she can change without generating a dangerous situation. In case of multi-lane approaches towards intersections, this method will lead to evenly used lanes, unless routing information forces vehicles to keep lanes.

The Network geometry is modelled using the graphical user interface of VISSIM. It is possible to load a scanned layout plan of the modelled network as a background for the network editor. Figure 6.3 show a layout plan and the resulting network model. VISSIM is using links and connectors between links. Each link has attributes, like number of lanes, gradient, free flow speed, etc. Nodes, like in transportation planning packages, are not required. Missing of nodes has the advantage that the full variety of lane allocations can be modelled. The network model of links and

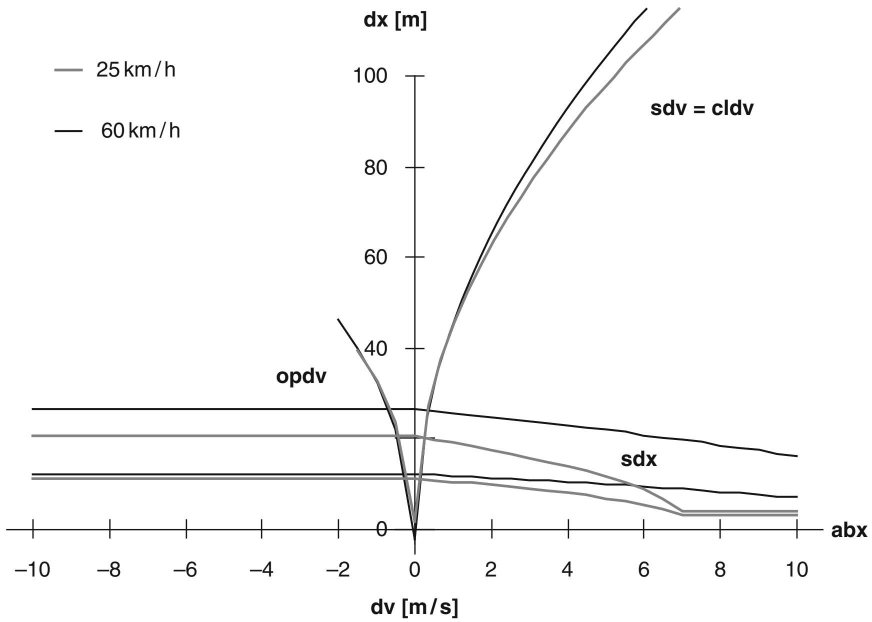

Fig. 6.2 Car-following threshold used in urban situations as a function of the speed

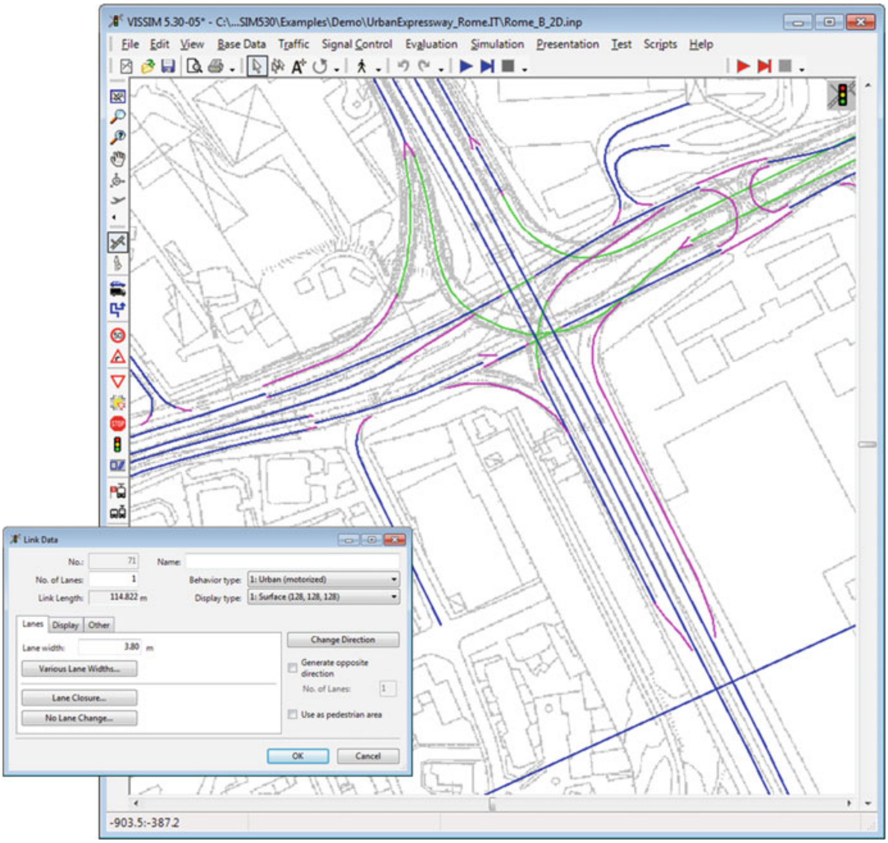

Fig. 6.3 Network model overlaid on junction layout plan in VISSIM model

connectors has been proven to be flexible enough to cover situations found in a variety of countries. Different driving habits between left-hand and right-hand driving are covered with the network model as well.

Additionally, traffic volumes and the vehicle fleet must be specified. It is possible to define different distributions of desired speeds, accelerations, vehicle lengths, and passenger boarding times. The road infrastructure, like signal heads, stop signs, yield signs, parking signs, speed signs, bus bays and tram stops are placed as particular objects allocated to links.

The following example shows how to model yield signs. Two tram tracks are displayed. The two trams are driving on sight instead of being signalized. One tram can only pass if the other has passed the conflicting area. Therefore, a time headway of 2.5 s plus a minimum spatial headway of 36 m (tram length plus reserve) has to be cleared (Fig. 6.4).

Since editing large networks may be time-consuming, VISSIM has now import filters from transport planning packages. The network model can be imported from the transportation planning model VISUM. VISUM is able to read

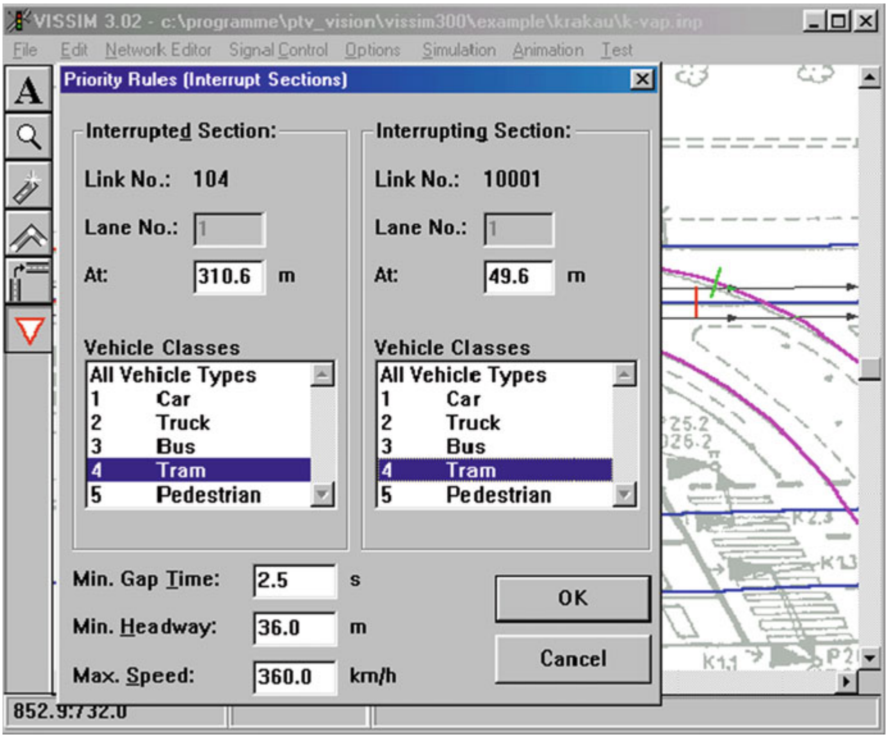

Fig. 6.4 Network model with yield signs for trams in VISSIM model

EMME/2-files. Therefore, VISSIM can read EMME/2 network and Origin-Destination data via the interface with VISUM. The largest networks currently modelled in VISSIM cover an area of about 400 km^2, including a little over 100 signalized intersections.

6.3 Macroscopic Models

Macroscopic models do not treat vehicles as individual entities but consider traffic as streams of vehicles. They apply macroscopic relationships between traffic volume, traffic density and average speed. Their original application is the assignment which matches the demand in terms of passenger (or goods) trips to the supply, i.e. the road or public transport network. This is indicated in Fig. 6.5. Their typical application lies in network-wide investigations that consider areas like cities or regions.

Over the years a number of such models have been developed – mostly for dedicated application; some, however, have become standard tools for transport planning, like SATURN or VISUM. In the following, we describe one of each category: SATURN as a standard tool and MT.MODEL as a dedicated tool.

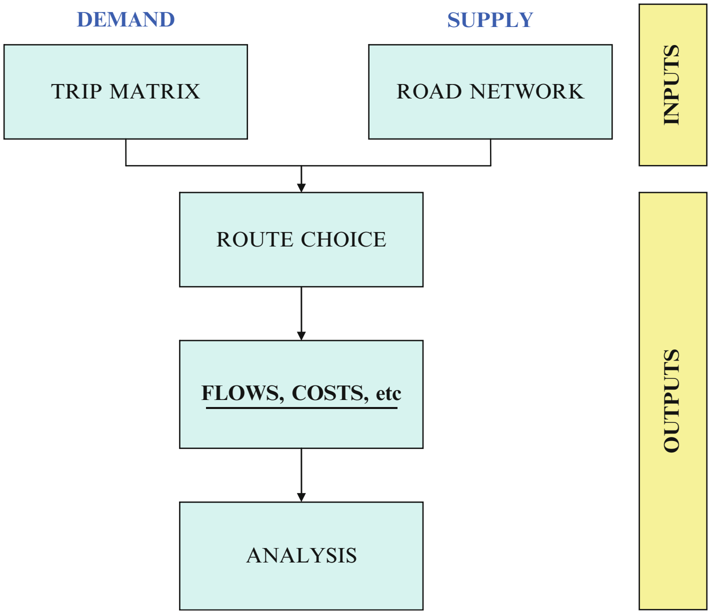

Fig. 6.5 Main structure of a typical assignment model

6.3.1 MT.MODEL

MT.MODEL is a user friendly and totally integrated system of mathematical models for decision support to the traffic and transport planning.

MT.MODEL allows to analyze the existing situation of a traffic system and, answering to questions as "what if?" (what would happen if . . .?), allows to estimate new suggestions of the area reorganization. The mathematical models that constitute its nucleus offer the opportunity to simulate the variations to the actual mobility and transport planning, previewing the effects that would derive from their realization.

In order to obtain a complete evaluation of the effects on the complete transport system, MT.MODEL allows:

- The analysis of the existing situation of demand, traffic supply and performances of the transport system
- The prediction of the mobility demand with regard to pre-assigned scenarios of socioeconomic and territorial evolution and pre-assigned configuration of traffic and transportation supply
- The valuation of the performances of transportation networks, according with these scenarios

The system is composed of:

- A data bank, that contains available information of demand and traffic supply
- Models of information management

- Models of demand and performance prediction of the transport system
- Current use and management software

MT.MODEL architecture is based on the general structure of a Decision Support System (DSS), proposed by Sprangue in 1986.

6.3.2 SATURN

SATURN (Simulation and Assignment of Traffic to Urban Road Networks) is an assignment model and as such it is mainly used for investigating traffic management strategies. It was developed in the Institute for Transport Studies of Leeds University (Hall et al. 1980; Van Vliet 1980) and is now widely used commercial simulation software for a variety of applications (Van Vliet et al. 1987; Matzoros et al 1987; Gulliver and Briggs 2005).

The main functions of SATURN are:

- Combined traffic simulation and assignment model for the analysis of road-investigated schemes ranging from traffic management over relatively localised to larger road networks.
- "Conventional" assignment model for the analysis of very large road networks.
- Simulation model for individual junctions.
- Network editor, database and analysis system.
- Matrix manipulation package.
- Trip matrix demand model covering basic elements of trip distribution modal split, etc.

There are two functions that are of interest within the framework of IN-SAFETY: the "conventional" assignment model and the network editor. The function of the assignment model assigns traffic, performing trips from an origin to a destination within the simulated road network, to different routes, based on a number of principles. The function of the network editor allows and can be applied for the analysis of network-based data which need not be in any way related to traffic assignment problems. As an example data related to accident rates per link, road resurfacings stored, etc., may be input and analysed.

SATURN offers a wide range of assignment methods, including generalised-cost, all-or-nothing, Wardrop equilibrium, etc. It employs the main structure of a typical assignment model which is illustrated in Fig. 6.5.

For the application of the traffic assignment, there are two main input elements that represent the demand and the supply of trips in a road network: the trip matrix Tij, which describes the number of trips from zone i to zone j that will take place, and the network, which describes the physical structure of roads, upon which the trips will be accommodated. The trip matrix and the road network are then input to a "route choice" model, which allocates trips to routes through the network. The result of this initial allocation is the development of traffic flows on the defined routes, based on which the corresponding network "costs" are estimated and the traffic assignment run by SATURN (according to pre-set user preferences) initiates. Last, within the analysis function the results of the assignment are estimated in the form that the user has defined and are provided to the user as an output of the program.

Part of the SATURN operation is the estimation of a cost for each route, based on which traffic is assigned into different routes. The cost is a function of the travel-time on the route and its distance (length of the route), and the corresponding formula for its estimation follows:

$$Cost = PPM * Time + PPK * Dis\tan ce + \sum_i PPU(i) * DATA(i), \qquad (6.1)$$

where PPM and PPK are the weight factors of time and distance respectively and PPU (pence per unit) are those attributed to other data inputs (DATA). Hence, SATURN model allows the user to introduce further parameters in the cost estimation; for example DATA(1) might be a link route familiarity index and PPU(1) a weight to convert route familiarity value into monetary values. The required values of PPU(i) are provided by the user on a specific record, and may differ for different user classes. By definition, all DATA values are fixed, independent of flows.

6.4 Model Applications for Safety Assessment of Proposed Scenaria

The following sections give some insight into the application and the possible results that the models described above can provide. Of course, only few examples can be given here. However, they give insight into the complex issue of pre-evaluation of safety enhancement scenarios and new technologies. Such pre-evaluations are needed for further investigations, like cost-benefit analyses, for the planning of large-scale tests, e.g. field operational tests (FOTs) or also for system design. In the latter case, the models can be integrated in the feedback loop, when designing and evaluating a traffic safety system by yielding the results of a concrete design of a system.

6.4.1 Example Applications of a Microscopic Simulator

6.4.1.1 Adaptive Cruise Control (ACC)

This section gives insight on how to evaluate and estimate the impact of Advanced Driver Assistance Systems (ADAS) on the example of Adaptive Cruise Control (ACC). Such a system influences driver behaviour and is therefore a good example for the application of a microscopic simulator. The focus here is on the adaptation of the simulator to cover vehicles which are equipped with such a system. The results are only exemplary because a micro-simulator can produce many parameters of interest. Thus, any traffic related parameter, be it speed, volume or their relationships, can be easily obtained. Here we present results that require more detailed analyses and are of interest to a wider community, as they include both emissions and safety related results. In the beginning, a more detailed description of the implementation is given, in order to show the potential of a simulator, which allows for changes to the driver behaviour by varying parameters.

The ACC system functionality was modelled directly in VISSIM as a new "driver behaviour". VISSIM allows defining arbitrary parameter settings for the pre-defined behaviour in the state diagram as shown in Fig. 6.2. The available parameters to determine driver- or system-behaviour are according to the VISSIM manual:

CC0 (Standstill distance) defines the desired distance between stopped cars. It has no variation.

CC1 (Headway time) is the time (in s) that a driver wants to keep. The higher the value, the more cautious the driver is. Thus, at a given speed v [m/s], the safety distance dx_safe is computed to: dx_safe = CC0 + CC1 * v.

The safety distance is defined in the model as the minimum distance a driver will keep while following another car. In case of high volumes this distance becomes the value with the strongest influence on capacity.

CC2 ('Following' variation) restricts the longitudinal oscillation or how much more distance than the desired safety distance a driver allows before he/she intentionally moves closer to the car in front. If this value is set to e.g., 10 m, the following process results in distances between dx_safe and dx_safe +10 m. The default value is 4.0 m, which results in a quite stable following process.

CC3 (Threshold for entering 'Following') controls the start of the deceleration process, i.e. when a driver recognizes a preceding slower vehicle. In other words, it defines how many seconds before reaching the safety distance the driver starts to decelerate.

CC4 and **CC5** ('Following' thresholds) control the speed differences during the 'Following' state. Smaller values result in a more sensitive reaction of drivers to accelerations or decelerations of the preceding car, i.e. the vehicles are more tightly coupled. CC4 is used for negative and CC5 for positive speed differences. The default values result in a fairly tight restriction of the following process.

CC6 (Speed dependency of oscillation): Influence of distance on speed oscillation while in following process. If set to 0, the speed oscillation is independent of the distance to the preceding vehicle. Larger values lead to a greater speed oscillation with increasing distance.

CC7 (Oscillation acceleration): Actual acceleration during the oscillation process.

CC8 (Standstill acceleration): Desired acceleration when starting from standstill (limited by maximum acceleration defined within the acceleration curves).

CC9 (Acceleration at 80 km/h): Desired acceleration at 80 km/h (limited by maximum acceleration defined within the acceleration curves).

The parameters modified for simulating the ACC system were:

- Desired distance: it was assumed that the drivers keep a fairly large standstill distance of 2 s plus 1 m as the minimum headway time during following. Thus, the relevant VISSIM parameters were set to CC0 = 1.0 and CC1 = 2.00.
- Oscillations during following: the system can perform a much "tighter" following than a human driver. "Tighter" meaning that differences in relative speed are better perceived. The parameters CC4 and CC5 were set to 0.5. Furthermore, CC6 was set to 1.00.
- Acceleration during following: the system can keep a speed much better than a human driver. It was therefore assumed that the oscillations during following are performed at only CC7 = 0.1 m/s^2.

Other parameters were not changed. Especially the overtaking behaviour remained unchanged – which may not be so in reality. However, statistically representative data for the network, with pre-dominant weaving manoeuvres as causes for lane-changes were not available, so as to adapt this parameter too.

The network chosen was one that represents reality: a heavily loaded motorway junction in the Rhine-Main-Area, close to Wiesbaden, was chosen. Figure 6.6 shows the VISSIM representation of this network around the junction. The sections, especially north and south of the junction were much longer than displayed. The two motorways BAB A3 and BAB A66 intersect here, both carrying long-distance as well as commuter traffic. In this network weaving actions, which may possibly be dangerous and through traffic are combined. This was considered a very appropriate application for tests with ACC. The specific reaction of vehicles cutting in represents a demanding task for the system. Here, safety effects of this comfort application may arise.

Fig. 6.6 Simulation Network, Motorway Junction BAB A3 and BAB A66, near Wiesbaden, Germany

For the scenarios to be simulated, the traffic volumes that entered the network on both ends of the north–south directed A3 were each 1,800 (low), 3,000 (medium) and 5,000 (high) vehicles per hour; in all cases 10% of all vehicles were trucks. This traffic then splits up into the possible directions at the junction, according to shares derived from the real shares found in the morning peak period.

The share of equipped vehicles was 0 (base case), 10, 25, 50, 75 and 100% of all passenger cars. Each of these 18 cases, 6 penetration rates and 3 traffic volumes, was simulated 5 times with different random number seeds, to get a statistically sound basis for evaluation (Anund et al. 2007). As a first example for the results, the emissions of NOx are presented here in Fig. 6.7. The data shown relate to all vehicles, equipped and un-equipped. It becomes obvious, that the introduction of ACC vehicles has a positive effect on these emissions for all simulated traffic volumes. The three groups of bars reflect the three volumes simulated; within each group the bars of different colours indicate the rates of equipped vehicles between 0% (base case) and 100% (potential when all vehicles are equipped).

In order to indicate the possibilities to also evaluate safety related effects from microscopic simulation, results from a similar study by Benz (2008) are presented. Here, too, the effects of ACC were evaluated, however, in a different study design. The volumes were varied into more than three cases, in order to cover all possible situations. Especially, the range close to capacity was thoroughly modelled. By doing so, data for all volumes could be retrieved.

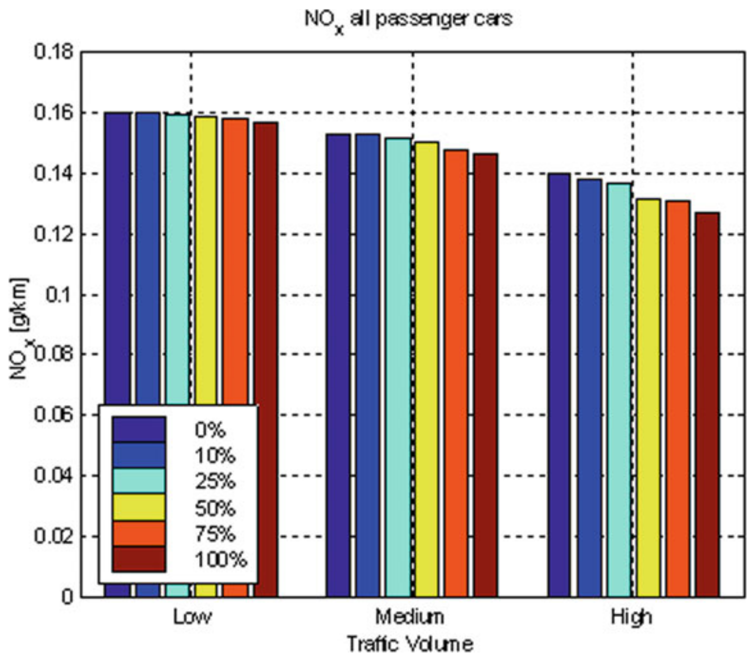

Fig. 6.7 NOx emissions

The safety effects were established by investigating time-to-collision (TTC) and the share of small headways. The two diagrams in Fig. 6.8 show the share of headway below 2 s (above) and below 1 s (below). These data were collected at a simulated cross-section. The lines in the diagrams relate to the base case (black), a low penetration rate (red line, 4% of passenger cars) and a high penetration rate (blue line, 13% of passenger cars).

It becomes obvious that the share of headways below 2 s is nearly independent of the presence of equipped vehicles; headways below 1 s, however, are less frequent with ACC vehicles in the network. Thus, ACC seems to reduce the very critical headways (Fig. 6.8).

6.4.1.2 Collision Avoidance System (CAS) and Lane Change Assistant (LCA)

Following the same scenarios design (Anund et al. 2007) (in terms of traffic volumes, penetration rates, etc.), another ADAS-related application was evaluated within IN-SAFETY. The aim of the application was to investigate the safety and traffic efficiency impacts of ADAS equipped vehicles, in several different penetration rates, on the same road and under the same circumstances. The network that has been simulated was a highway, including an intersection. The types of ADAS that were analysed were the Collision Avoidance System (CAS) and the Lane Change Assistant (LCA).

Following the structure of the VISSIM model, certain vehicle types and respective vehicle classes needed to be defined. Each of them represents a different group of vehicles with different characteristics. For the needs of the application in question, five different vehicle types/classes were defined, namely:

- PKW, including passenger cars, not equipped with any ADAS.
- LKW, including trucks, not equipped with any ADAS.
- ADASth, including passenger cars, equipped with the specific ADAS, following the theoretical behaviour parameters that the use of this equipment would imply (i.e. if the CAS warns the driver when TTC $\leq$ 2 s then we estimate that all drivers keep a min TTC of 2 s).
- ADASb, ADASc, including passenger cars equipped with the specific ADAS, following behaviour parameters, deriving from previous real tests with the ADAS in question (i.e. we consider different behavioural adaptations of drivers with CAS, such as different min TTC as measured in past tests with real users).

The driver behaviour parameters that were influenced in each category and their specific values are described in the relevant chapter.

In order to successfully simulate the behaviour of equipped vehicles in the network, certain default set parameters of driving behaviour needed to be changed, according to the expected effect of each ADAS. In VISSIM, there are several default parameters set, both for longitudinal and lane change behaviour, whose values determine the behaviour of the vehicle and whose differentiation could lead to different effects.

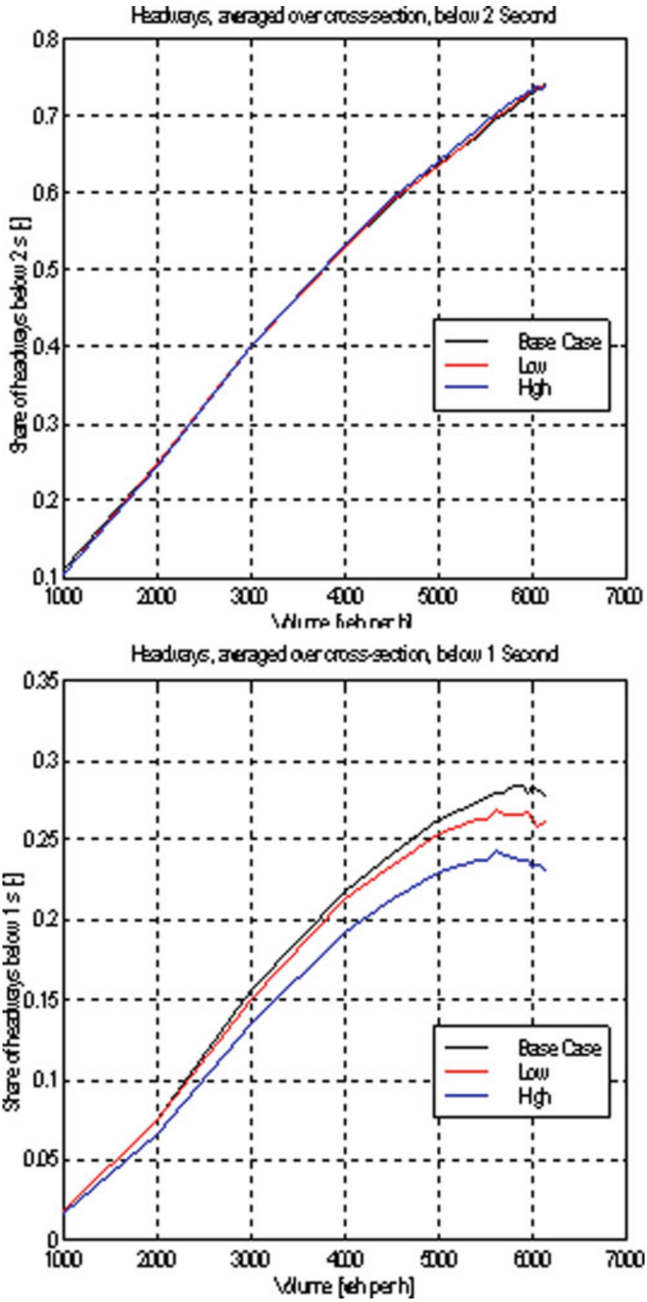

Fig. 6.8 Share of Small Headways depending on Volume
Source: Benz 2008

Longitudinal Behaviour Modelling of Selected ADAS

The longitudinal driving behaviour in the VISSIM micro-simulation traffic model is based on the "following" driving mode, as developed by (Wiedemann 1974, 1991). According to this approach, two different sets of parameters are included, defining the behaviour of the vehicle on the road. In terms of the study on the influence of the CAS, the parameter that has been influenced is the CC1, defining the time headway that the driver allows from the preceding vehicle. More specifically, in the case of CAS, the default value for time headway, as set in the Wiedemann 99 model, was 0.9 s. This value was changed to 1.0 s for the ADASth vehicle class, as is the theoretical value for the time headway used by the CAS. Moreover, in the case of ADASb and ADASc vehicle classes, which represent the behaviour from real tests, different values have been set for the CC1 parameter. More specifically, for the ADASb the value set was CC1 = 1.2 s and for ADASc, CC1 = 0.8 s, according to relevant on road tests results (Brouwer and Hoedemaeker 2006).

Lateral Behaviour Modelling of Selected ADAS

The VISSIM model includes a separate set of parameters ruling the lane change behaviour of the vehicles. Among them, the ones that were influenced during the performed study were:

- Min headway.
- Safety distance reduction factor.
- Max deceleration for cooperative braking.

The aim was to create a situation where the driver, influenced by the relevant ADAS, would be led to make more (or less) lane changes than in the default situation. However, as described in the results chapter, it was not possible to come up with a set of values that would create the desired effect, so as to simulate the behaviour of equipped vehicles' drivers.

The results indicated the influence of ADAS-equipped vehicles in the traffic composition over the total network.

Average Speed with Ideal (Theoretical) CAS

The overall average speed in the network changes in different terms as the CAS equipped vehicles penetration rate increases, depending on the traffic volume. At low traffic volume (1,800 veh/h) the average speed for all vehicles slightly decreases, with a max speed at 25% penetration rate and the min at 100%. The speed for the CAS equipped vehicle class shows a peak at 25% penetration rate but it generally decreases, with its minimum at 50%. At medium traffic volume (3,000 veh/h) the average speed for the whole network decreases at 10% penetration rate and then increases until 50%, where it has its max value, to decrease again until the minimum at 100%.The CAS equipped vehicle class gives two peaks at 25 and 75% penetration rates. On the other hand, the non-equipped vehicles have higher speeds at 25 until 50%, which decrease to reach the minimum at 75%. Finally, for the higher traffic volume (5,000 veh/h) all vehicle classes give lower speeds at 10, 50 and 75% penetration rates and the highest at 25%, while at 100% the speed is almost the same as at 0% (Fig. 6.9).

Noticing the high peaks at the diagram for high traffic volume (which however corresponds to very small absolute differences), one way analysis of variants (ANOVA) has been performed, to investigate the statistical significance of these differences. The result of the analysis (F(2, 6) = 9.916, $p = 0.06$) shows that the differences have no statistical significance.

Travel Time (Per Vehicle): With Ideal (Theoretical) CAS

As far as travel time is concerned, at low traffic volume the travel time for the whole of the network increases as the penetration rate of CAS equipped vehicles becomes higher. For CAS equipped vehicles the travel time is lower for penetration rates of

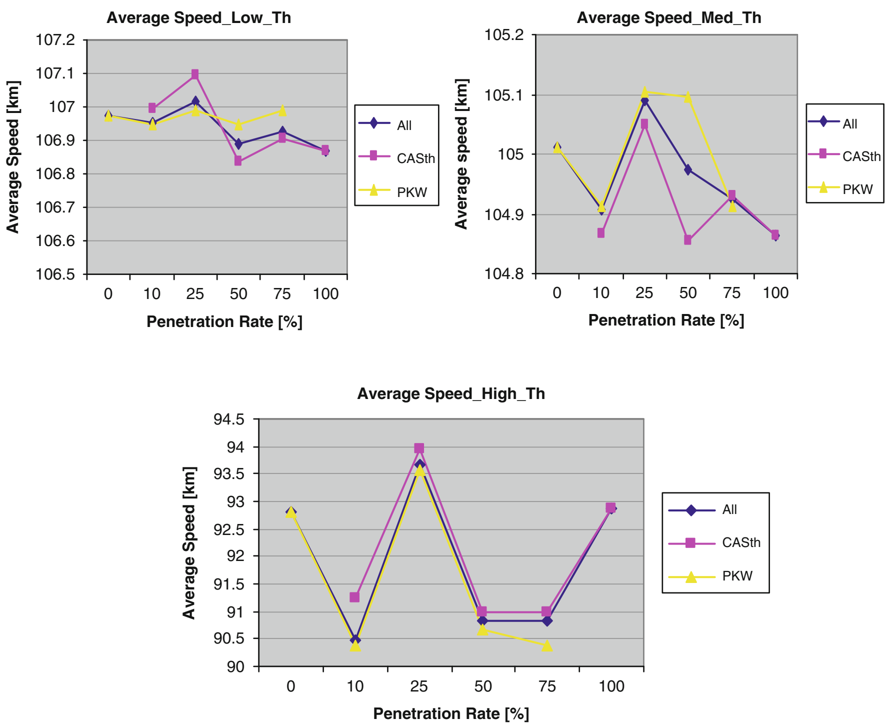

Fig. 6.9 Average speed at different traffic volumes with ideal CAS in different ADAS penetration rates

25% and 75% and higher for 50 and 100% penetration, while for the non-equipped vehicles it decreases until 50%, to increase at 75%. For medium traffic volume, travel time per vehicle at the network generally increases with penetration rate, only decreasing at 25%. The travel time for equipped vehicles is max at 10% penetration and min for 25%. For non-equipped vehicles the travel time generally decreases, having the minimum at 10% penetration. In the case of high traffic volume, travel time generally increases (max at 10%) with an exception at 25% penetration rate, where it decreases significantly and then increases again at 50%, to slightly decrease until 100% (Fig. 6.10).

Also in this case, ANOVA analysis has been performed to investigate the statistical significance of the variations noted in the "high" traffic volume diagram. The result ($F(2, 6) = 5.642$, $p = 0.056$) showed no significance.

Average Speed with Actual (Practical) CAS

A general remark on the average speed is that the speeds of the CASb and CASc classes are higher that the total, whereas the speed of the CASth and the PKW

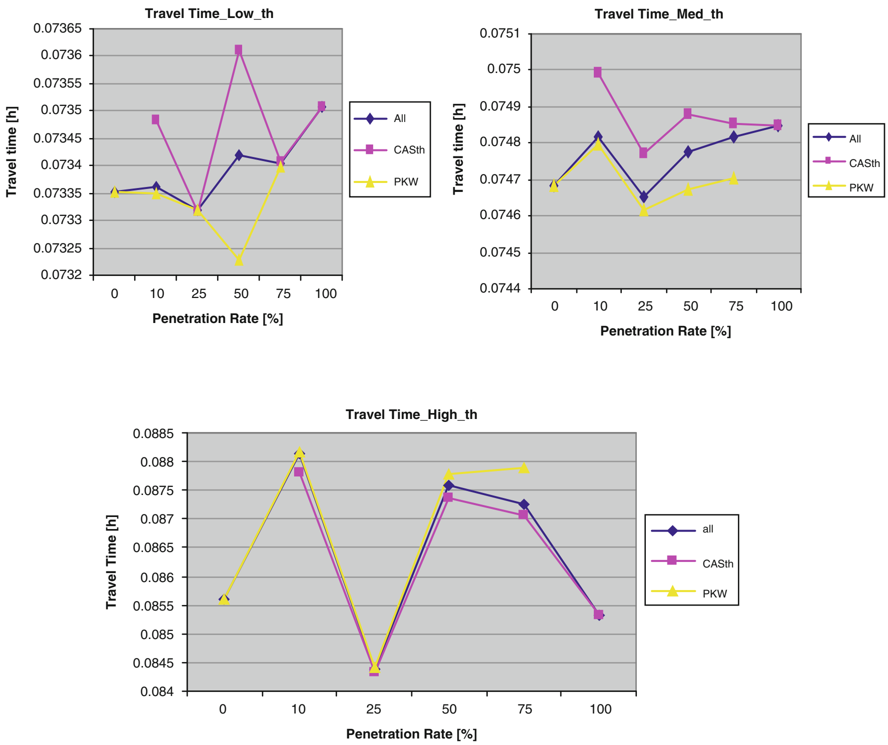

Fig. 6.10 Travel time per vehicle at different traffic volumes with Ideal (theoretical) CAS at different ADAS penetration rates

(non-equipped) vehicles are lower. The average speed on the network for low traffic volumes is slightly increasing. This is mainly due to the higher average speeds of the two classes of equipped vehicles (CASb and CASc), which are however decreasing as the penetration level is rising up. For the non-equipped vehicles the speed is decreasing, whereas for the third equipped vehicles' class (CASth) it is decreasing at 25% but then increases again until 75% penetration rate. For the medium traffic volume, the average speed for all vehicles is almost constant, with a slight increase. For all three equipped vehicles classes, as well as for the non-equipped, the speed is generally reducing. At high traffic volume the speed is decreasing in all cases, reaching the minimum at 75% penetration level (Fig. 6.11).

The results of the ANOVA analysis performed for the case of "high" traffic volume ($F(4,12) = 35.77$, $p < 0.001$) showed that there is statistical difference between some of the values. More specifically, CASb is significantly different from CASth and PKW, with CASb ($M = 99.57$) being significantly bigger than CASth ($M = 97.55$; $p = 0.022$) and PKW ($M = 97.44$; $p = 0.021$).

Also, in the case of "low" traffic volume, some statistically significant differences have been detected. ANOVA gave the result $F(4,12) = 18.88$, $p < 0.001$, which means that PKW is significantly different from CASb and CASc, with PKW ($M = 106.83$) being significantly smaller from CASb ($M = 107.534$; $p = 0.04$) and CASc ($M = 107.50$; $p = 0.05$).

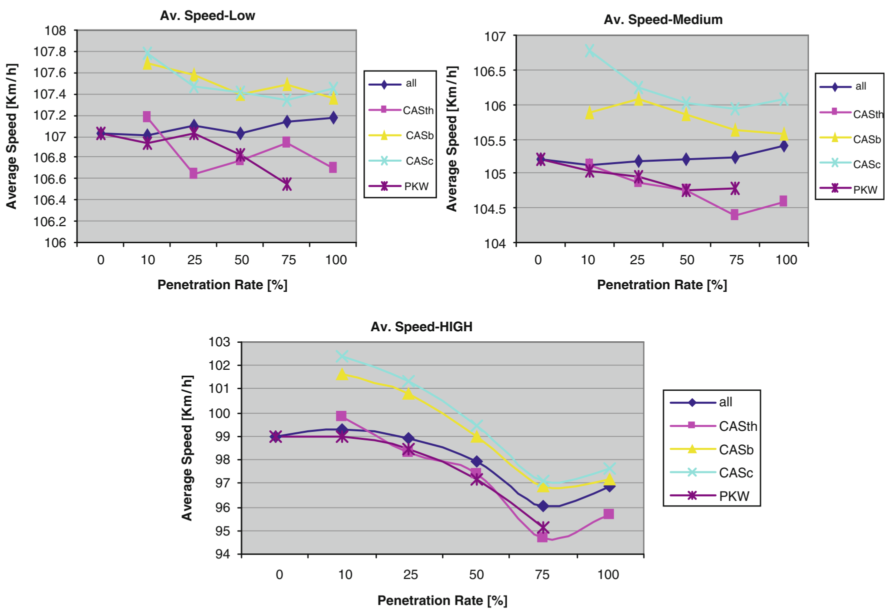

Fig. 6.11 Average speed (practical runs) at different traffic volumes with actual CAS in different ADAS penetration rates

Travel Time with Actual CAS

Regarding the travel time at the network per vehicle, at low traffic volume and for the total of vehicles, it is rather decreasing, except for the 50% penetration rate. The situation for the different vehicle classes is diverse, but generally the travel time tends to increase in all cases. In the case of medium traffic volumes, the travel time is generally not significantly changing for all vehicles. However, it is mostly increasing for all the separate vehicle classes. Finally, at high traffic volume, the travel time in all cases is clearly increasing, reaching its maximum at 75% penetration rate (Fig. 6.12).

In this case, ANOVA was also performed for the "low" and "high" traffic volumes. The result for the "low" was $F(4,12) = 6.03$, $p < 0.01$, indicating that the CASth ($M = 0.734$) values are significantly higher than the CASb ($M = 0.0731$) and CASc ($M = 0.0730$; $p < 0.05$ for both comparisons). Also, for the "high" traffic volume, the result ($F(4,12) = 44.12$, $p < 0.01$) indicates that CASth ($M = 0.0808$) is significantly different from CASb ($M = 0.0792$) and CASc ($M = 0.0788$; $p = 0.05$ for both comparisons). In addition, PKW ($M = 0.0809$) is significantly different from CASb ($M = 0.0788$) and CASc ($M = 0.0809$; $p < 0.05$ for both comparisons).

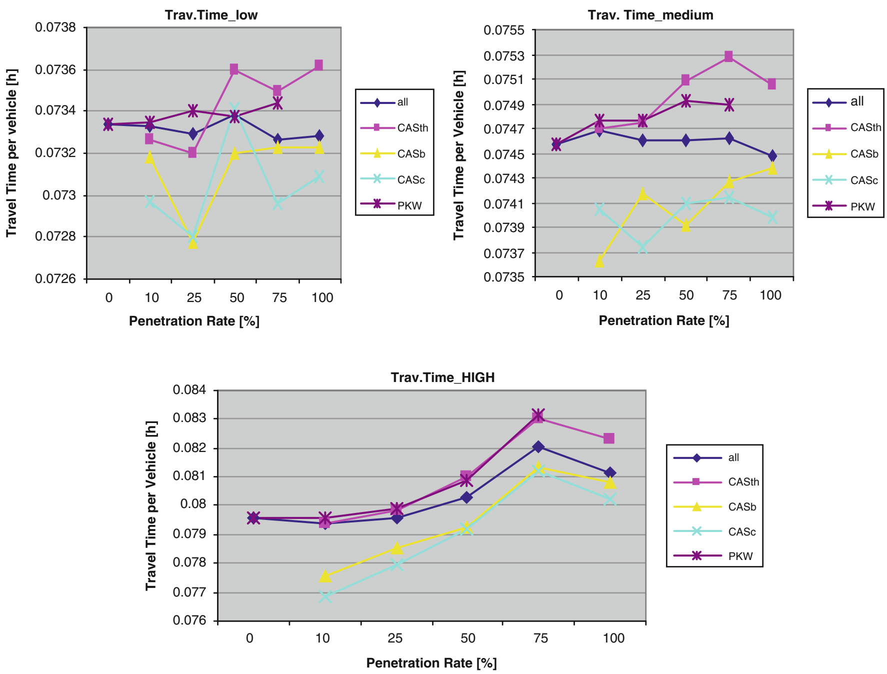

Fig. 6.12 Travel time per vehicle (practical runs) at different traffic volumes for actual CAS at different penetration rates

LCA Model Simulations

As stated above, different values were tested in the available lane change parameters, in order to investigate the influence of LCA in lane changing behaviour. However, no significant conclusion could be drawn from the results of the model, as the number of lane changes did not seem to be influenced. This fact was not in line with relevant results from real tests which have shown specific differentiation. Therefore, certain modifications should be considered for the lateral and lane change parameters of the model, in order for the model to be able to simulate reliably the actual driver behaviour, as affected in terms of lane changing.

6.4.2 Example Application of a Macroscopic Simulator

For the macroscopic simulation, an IVIS has been selected; namely route guidance. For its evaluation, a scenario of localized events has been examined, that expects local perturbations due to accidents. For this scenario three simulations have been made:

- All users are not guided
- 5% of Users are guided, 95% are unguided
- All users are guided

Tests have been made using the traffic simulation model on the road network of Turin, with its mobility demand. In the scenario, accidents are homogeneously positioned on primary roads, used by a big number of paths, and cause a big delay on the interested road sections, influencing both capacity and speed. On all the other links, it has been assumed that there were no changes and that therefore the road features were identical to those historical averages. Figure 6.13 shows the links with accidents.

The scenario considers the benefits which the "guided" users can obtain, if they avoid roads with accidents. In this case the total decrease has been evaluated on the hypothesis that all the users chose their usual path, using also the roads affected by accidents. The average travel time for the OD pairs, weighed with the volume of the OD pair, in the case without accidents, is equal to 9.7 min; the presence of unknown events involves an increase by 39% (13.5 min) of the weighed average travel time. In this situation it is obvious that, though events exist only on few links, to avoid such congestion is very important: in the case of 5% "guided" users, they improve their travel time compared with the "unguided" by 27% (9.9 min). In case these 5% of the users are "guided", also the "unguided" users improve their travel times: in fact the reduction of the 5% of congestion in the critical points improves the travel times of those who travel there. The total weighted average travel time for the "unguided" users becomes 12.9 min. Taking into account all the users together, the total average travel time on the network is equal to 12.8 min (Table 6.1).

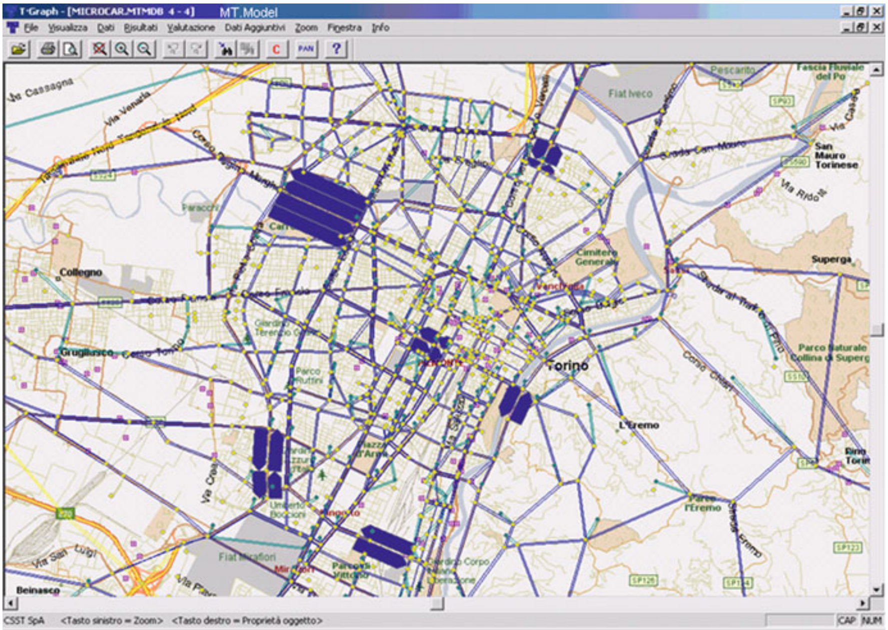

Fig. 6.13 Simulated accidents in the Torino network (Anund et al. 2007)

Table 6.1 Average travel time for the different scenario cases

Average travel time		Average travel time (weighted)
No accidents	All users are “unguided”	9.7
Localized accidents	All users are “unguided”	13.5
	5% of Users are “guided”	9.9
	95% of Users are “unguided”	12.9
	Scenario 5% “guided” + 95% “unguided”	12.8
	All users are “guided”	9.9

Figure 6.14 represents the flow distributions (the link thickness is proportional to the vehicular flow quantities on the link): the links with disturbance are represented with red colour. It is obvious that when the users are “guided”, the roads with accidents are not used, while the parallel and neighbouring roads increase their flows. The “not-guided” traffic, instead, does not know about the accidents and therefore chooses paths blocked by accidents.

6.5 Into the Future

The use of simulation models in the traffic safety domain opens wide possibilities for different applications. In the current state of model development, it is already

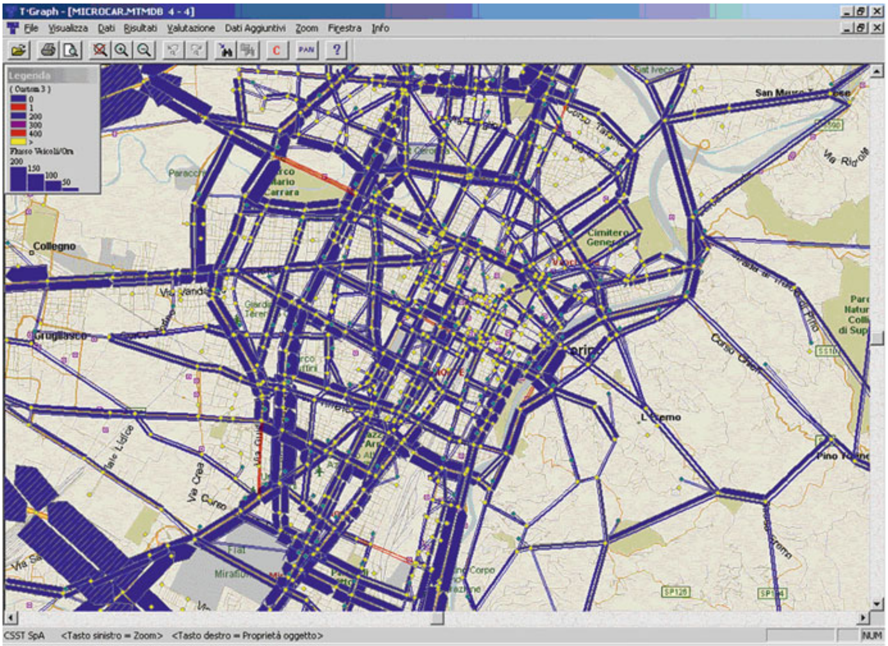

Fig. 6.14 Flow distribution when 5% of users are “guided”

possible to model some applications of Intelligent Transport Systems and evaluate their effects, even if the models do not yet treat safety as such. Macroscopic models have been applied to determine the network-wide effects of driver information about safety levels on network parts; thus it was possible to establish the overall consequences for drivers with and without such a system.

Microscopic models are suitable to investigate such ITS applications that directly change the movement of vehicles. The ITS application is modelled either by adapting the driver behaviour or by including the system behaviour explicitly in the model. The results of a simulation run then reveal all changes to the traffic flow: macroscopic changes to the volume-speed-density relationships, changes in environmental aspects via a suitable environmental model and also changes to the overall safety level. Although current microscopic models do not include mechanisms for safety critical situations, they can provide indications about safety via so-called surrogate parameters, which allow an estimation of the safety level. It should, however, be noted that the reliability of results of the model depends highly on the driving behaviour parameters included in the model and the values selected for them by the researcher.

Further research will provide new insights into the processes that ultimately govern the occurrence of accidents. Including such processes into micro-simulations will allow investigating such critical situations in much more detail. This will not only lead to an improved ITS assessment but also to the design of improved safety relevant ITS measures. Especially in the case of LCA, the VISSIM microsimulation model, at its present state, does not seem to provide a reliable simulation of the effect of such a system in the lane change behaviour. Thus, there is need for the inclusion of adequate parameters, which would allow the model to effectively simulate such behaviours. As far as route choice is concerned (S-Paramics) the results of the different indicators do not all point in the same direction. The significance of the different indicators for research into route choice requires more attention. What is more, it is important to examine whether the indicators in the micro simulation provide a result that conforms to reality. The indicators for the safety of a route only comprise the safety of car drivers using a route. The indicators should be extended to the safety of all users (also cyclists and pedestrians) of a route. At the same time, a method should be developed for optimizing the safety of all (main) routes in the network. For planning applications the method should be integrated in existing planning models. For traffic management applications the safety criteria should be built into the choice algorithms of route planners.

Moreover, regarding the RUTSIM macrosimulation model, future research would include analysis of traffic effects of the individual driver results. These results include changes in driving performance due to driver fatigue and rumble strips on two-lane highways. In addition, further research on the relation between simulation-based safety indicators and accident risks is needed, in order to facilitate more accurate safety analysis using traffic simulation models.

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