# UNIVERSITY OF PALERMO

**Department of Civil, Environmental, Aerospace, Materials Engineering**


**PhD IN CIVIL AND ENVIRONMENTAL ENGINEERING**

**Transportation Infrastructures Engineering and Geomatics**

**CICLE XXVI – S.S.D. ICAR/04**

**PhD THESIS**

# *Traffic fundamentals for A22 Brenner freeway by microsimulation models.*


**PhD Candidate**
*Ing. Sandro Chiappone*

**Coordinator**
*Prof. Eng. Orazio Giuffrè*

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**JANUARY 2016**

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Sandro Chiappone

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# I. FOREWORD

## I.1 GENERALITIES

Road traffic microsimulation models are one of the latest generation of available traffic models and became very popular for the development and evaluation of a broad range of road traffic management and control systems. They model the movements of individual vehicles, traveling around road networks by using car following, lane changing and gap acceptance rules; hence, traffic microsimulation models try to replicate the behavior of individual drivers. However, the "realism" sought by the representation of individual drivers introduces a level of complexity into the modeling process which must be taken into account from the stage of model calibration. Traffic microsimulation models typically include a very large number of parameters, representing various characteristics of travelers, vehicles and road system, that must be calibrated before the model is applied as a prediction tool of traffic performances (Hollander and Liu, 2008).

Microsimulation models are the ones closer to reality in the reproduction of the traffic system opening a wide range of traffic scenarios in which precise descriptions of traffic control and traffic management schemes can be explicitly included.

Microsimulation traffic models can produce visual outputs by which lay and technical people can discuss the respective merits of traffic and transport proposals. The models can represent road and transport networks and their operation and the behaviour of vehicles and travelers in more detail, and broaden the range of applications. The visual representation of problems and solutions in a format understandable to lay people, project managers and modellers is a useful way to gain more widespread acceptance of complex strategies.

## I.2 THE AIMS OF THIS PHD THESIS

In this work of PhD Thesis a methodology to find fundamentals diagrams by microsimulations will be presented.

As it is know from scientific literature, the fundamental diagram relates two of the three variables: average speed (v), flow (q) and density (k) to each other. If two of these variables are known, the third can be derived using the relation $q = kv$. Therefore, if only one variable is known, and the fundamental diagram is known, the traffic state can be determined. The fundamental relationship is largely used in road infrastructure engineering, e.g. in the level-of-service evaluation of basic freeway or multilane segments.

The present work of PhD thesis starts by introducing the fundamental diagram using Edie's definitions and the use of speed- density diagrams. Another objective will be to analyzed a method that include an automated technique based on genetic algorithm (GA) for automating the process of calibration of the parameters in order to reproduce the fundamentals diagrams of the A22 Brenner freeway.

A further important objective will be to evaluate the impact of heavy vehicle on the quality of flow of the A22 Brenner freeway by calculating the Passenger Car Equivalents Factor (PCEs) between heavy vehicles and cars based on the results obtained in microsimulation. The calculation of PCE (Passenger Car Equivalents) will be done in general terms in order to compare the results with those published in the Highway Capacity Manual (HCM, 2010) resulting from experimental studies.

## I.3 ORGANIZATION OF THE THESIS

The present PhD thesis consists of four chapters that illustrate the work of study and research that has been developed during the PhD course. The chapter one is a background that describes the traffic modeling techniques available in the scientific literature with particular attention to microscopic simulation models. In particular it will be explained the benefit and the advantage of using Traffic Microsimulation Models for freeways.

In the second chapter a statistical approach based on observed and simulated speed-density relationships will be applied in the calibration process to measure the closeness between empirical data and simulation outputs. The comparison established between the $\ln S\text{-}D^2$ linear regressions (where S is for Speed and D is for density) for all simulated values and the corresponding linear regressions for the empirical data will allow to evaluate the quality of the calibration of the traffic microsimulation model. Furthermore, a statistical approach including hypothesis testing using t-test and confidence intervals will be used.

In the third chapter, the most important models for the analytical calculation of PCEs (Passenger Car Equivalents) will be presented and the Aimsun software performance will be tested. After that, the results of microsimulations in Aimsun will be evaluated in order to obtain the relevant parameters for the estimation of the PCEs and their comparison with those proposed by HCM.

Finally, the last chapter will show the first results obtained by applying a genetic algorithm in the microsimulation traffic model calibration process. The calibration will be formulated as an optimization problem in which the objective function was defined to minimize the differences of the simulated measurements from those observed in the speed-density diagram.

# I. TRAFFIC SIMULATION MODELS

Simulation is a process based on building a computer model that suitably represents a real or proposed system which enables the extraction of valid inferences on the behavior of the modeled system, from the outcomes of the computer experiments conducted on its model. Simulation has become, in recent years, one of the most used and powerful tools for systems analysis and design, by its proven ability to answer "what if" questions helping the system designer to find solutions for building new systems, or assess the impact of proposed changes on an already existing system. A simulation model is always a simplified representation of a system that addresses specifically those aspects of the studied system relevant for the purposes of the analysis from the point of view of the system analyst. A simulation model is therefore specific, both for the problem and for whoever tries to use the model for finding solutions to the problem. A simulation study has usually the objective of helping to achieve a better understanding on how a system behaves, evaluating the impact of changes in the system, or in values of the parameters governing the system, or of decisions on the policies controlling the system.

Mathematical modelling of traffic flow behaviour is a prerequisite for a number of important tasks including transportation planning, traffic surveillance and monitoring, incident detection, systematic control strategy design, simulation, forecasting and, last but not least, more recently in evaluating energy consumed by transportation systems, environmental impacts due to transportation systems, and in assessing vehicle guidance systems (Barce1ò et al., 1995a, 1995b).

Furthermore, traffic modelling plays an important part in the assessment of a range of traffic schemes, whether these are new road schemes, junction improvements, changes to traffic signal timings or the impact of transport telematics. There is a wide range of alternative modelling approaches now available based on macro- or micro-simulation methods. Micro-simulation models differ significantly from traditional transport models in terms of their methodology and supporting algorithms.

The management of a road network often requires the forecasting of the impacts of implementing various traffic management measures. These measures include, for example, signal coordination, high occupancy vehicle (HOV) lanes, one-way systems, different types of intersection control (priority sign, signal or roundabout), signal priority, driver information systems and incident management. Apart from road vehicles, trams, light rails, pedestrians and cyclists can also be simulated

Traffic modelling techniques can be broadly classified into the following four types:

a) **Analytical modelling** – this technique relates directly to traffic flow theory and is often a set of equations governing driver behaviour such as gap acceptance, lane changing, car– following, or platoon dispersion. The combination of analytical models can constitute a more complex analytical model for traffic analysis. Individual sets of analytical equations can also act as sub-models in other modelling techniques. Analytical modelling is sometimes also known as microscopic modelling.

b) **Microscopic Simulation -** the movement of a vehicle in a microscopic simulation is traced through a road network over time at a small time increment of a fraction of a second. A detailed simulation of vehicle-road interaction under the influence of a control measure is therefore possible. This technique is useful for a wide range of applications but requires more computational resources. Random number generators are involved and the calibration of these models requires more effort, and it is difficult to optimise model parameters.

c) **Macroscopic Simulation** - vehicles in a macroscopic simulation are no longer simulated individually. Vehicle movements are often simulated as packets or bunches in a network with a time step of one or several seconds. An analytical model such as the platoon dispersion model is used to govern the movement of a vehicle platoon along a road link. A macroscopic simulation is deterministic by nature and is useful for network design and optimization.

d) **Mesoscopic simulation –** this technique combines a detailed microscopic simulation of some key components of a model (e.g. intersection operations) with analytical models (e.g. speedflow relationships for traffic assignment). This technique is sometimes known as mesoscopic simulation and provides more detail to what is normally an assignment only model. It is also possible to interface a microsimulation model with a real-time signal control system such as SCATS - an area of active research and development at RTA NSW (Millar et al. 2006).

In recent years, Intelligent Transport System (ITS) measures such as adaptive signal control algorithms, incident management strategies, active bus/tram priority and driver information systems have been introduced to freeways and arterial roads. These are complex traffic processes and traffic flow theories are often unable to accurately predict the impacts in terms of delay, queue length, travel times, fuel consumption and pollutant emissions. Computer models equipped with advanced graphical facilities have been developed in recent years to meet the needs of a road manager.

Computer software has long been developed to simulate traffic management processes amongst road authorities in Australia (e.g. Cotterill et al. 1984; Tudge 1988). Past research also includes the development of car-following and lane changing algorithms for microsimulation (Gipps 1981 and 1986), the review of eight small area traffic management models, and the comparison of macroscopic and microscopic simulations (Luk and Stewart 1984; Ting et al. 2004). More recent research includes the assessment and further development of car-following and lane changing algorithms (Hidas 2005; Panwai and Dia 2004). A key finding is that microscopic simulation models require careful calibration to produce meaningful results, especially in the lane changing behaviour in congested conditions.

## I.1 BENEFITS OF MICROSCOPIC TRAFFIC SIMULATION MODELS

Micro-simulation models have the ability to model each individual vehicle within a network. In theory, such models should provide a better representation of actual driver behavior and network performance, particularly when networks are approaching capacity and vehicle interactions become far more important in determining the outturn operational performance. They are the only modelling tools available with the capacity to examine certain complex traffic problems (e.g. junctions, shockwaves, effects of incidents, interaction with pedestrian traffic etc.). In addition, there is the appeal to users of the powerful graphics offered by most micro-simulation packages. Whilst this can provide decision makers and consultee's graphical representation of the performance of a scheme it should never be the only reason for using micro-simulation.

Microsimulation can potentially offer benefits over traditional traffic analysis techniques in three areas: clarity, accuracy and flexibility as follows:

- *Clarity* - a comprehensive real-time visual display and graphical user interface illustrate traffic operations in a readily understandable manner. The animated outputs of microsimulation modelling are easy to understand and simplify checking that the network is operating as expected, and whether driver behaviour is being modelled sensibly. With microsimulation, what you see is what you get. If a microsimulation model does not look right, then it probably is not right, and vice versa;
- *Accuracy* - by modelling individual vehicles through congested networks, the potential exists for more accurate modelling of traffic operations at complex and simple intersections or merges. Individual drivers of vehicles make their own decision on speed,

lane changing and route choice, which could better represent the real world than other modelling techniques. For examples, analytical and macrosimulation models often use fixed value of saturation flows and all vehicles are assumed to behave in the same manner. In contrast, microsimulation models represent individual vehicles and detailed networks. A parameter such as the saturation flow can actually be an output of the model;

- *Flexibility* - a greater range of problems and solutions can be assessed than with conventional methods, e.g. vehicle-activated signals, demand dependent pedestrian facilities, queue management, public transport priorities, incidents, toll booths, road works, signalised roundabouts, shock waves, incidents or flow breakdown, or slip road merges.

Dowling et al. (2002) lists the following as study conditions where micro simulation models are desirable:

- Conditions that violate one or more basic assumptions of independence required by HCM models
    - Queues spill back from one intersection to another
    - Queues overflow turn pockets
    - Queues from city streets back up onto freeways
    - Queues from ramp meters back up onto city streets

- Conditions not covered well by available HCM models
    - Queue spill-back
    - Multi-lane with traffic signals or stop signs
    - Truck climbing lanes
    - Short through lane adds or drops at a signal
    - Boundary points between different signal systems operating at different cycle lengths
    - Signal pre-emption (e.g., railroad crossings and fire stations)
    - HOV lane entry options or design options for starting or ending an HOV lane
    - Two lanes turning left (however, currently no commercially available micro simulation software can model this)
    - Roundabouts
    - Tight diamond interchanges
    - Incident management options (Because HCM and macroscopic models assume a steady-state condition within each analysis period, they are not well suited to accurately track the build-up and dissipation of congestion related to random transitory conditions caused by incidents.)

In this regard, Transport of London (2003) lists the following issues as being suitable for microscopic simulation models:

- Complex traffic operation schemes (e.g., bus priority, advanced signal control, incident management, different modes of toll collection);
- Significant conflicts among different road users (e.g., pedestrians, cyclists, buses);
- Major traffic movement restrictions (e.g., lane closures, one-way system, toll plazas);
- Politically sensitive projects that could benefit from visualization;
- Planning and design of high-value projects with potential large savings if detailed microscopic simulation models are prepared;
- Emulation of the operation of a dynamic signal control system, with a simulated network driven directly by the control system and with significant saving in signal timing preparation and optimization;
- Town center studies;
- Tram and light rail operations.

However, there are some limitations to consider in microsimulation models. In this respect, it is always beneficial to restate Dr. May's observations regarding the use of micro simulation (May 1990):

- There may be easier ways to solve the problem; consider all possible alternatives;
- Micro simulation can be time-consuming and expensive; do not underestimate time and cost;
- Micro simulation packages require considerable input characteristics and data, which may be difficult or impossible to obtain;
- Micro simulation applications or models require calibration, validation and verification, or auditing, which if overlooked could make the model useless;
- Development of simulation models requires knowledge in a variety of disciplines, including traffic flow theory, computer programming and operation, probability, decision-making, and statistical analysis;
- Micro simulation is difficult unless the model developer fully understands the software platform;
- The micro simulation package may be difficult for non-developers to use because of lack of documentation or unique computer facilities;
- Some users may apply micro simulation packages and treat them as black boxes and really do not understand what they represent;
- Some users may apply simulation models and not know or appreciate model limitations and assumptions.

The scale of application of microsimulation models depends on the size of the computer memory and on the computer power available. Models that have not been built to run simulations on large networks but rather to achieve highly specific objectives have a small scale of application, typically less than one hundred vehicles. The scale of application ranges tipically varies from about 20 km, 50 nodes, and one thousand vehicles, to a large application of 200 nodes and many thousands of vehicles.

With the increasing application of micro-simulation models, there is a need for advice on their development and application, particularly in the context of the motorway and trunk road network. Key issues to be addressed include how well and under what conditions or constraints micro-simulation works and offer the greatest benefits. The calibration, validation and subsequent performance of any model are fundamental and, sometimes, contentious issues. The variables that are taken into account in micro-simulation models have lead to questions as to the validity of the results obtained and the degree to which confidence can be placed on the modelling.

## I.2 IMPROVING DECISION-MAKING BY USING MICROSIMULATION MODELS

In reality, there are a large number of situations where micro simulation led to better investment decisions and more effective designs. There are likely to be situations where simulation models provided faulty predictions, but these projects were not included in the web survey. It is probably safe to assume, however, that a properly calibrated and validated microscopic simulation model will more often than not lead to more effective designs and investment decisions because it can more closely replicate what is likely to occur in the real world.

Suggesting that a design is better or more effective is either a subjective opinion or it requires some basis of comparison. In most of the cases reported in the web survey, the assessment was based on a comparison to prior studies using traditional models or HCM calculations. For example, an intersection designed as an all-way stop using traditional traffic engineering calculations did not perform as expected in the real world. A microscopic simulation was then used to confirm the observed behavior and develop a more effective design for the intersection. The evaluation led to the decision that traffic would be better served if the intersection was configured as a round-about.

Micro simulation modeling has also proved useful in situations that are outside the bounds of traditional techniques. These can include odd or complex intersection configurations or heavily congested arterials. For example, a heavily congested arterial with two cross streets 120 feet apart could not be designed using traditional stop sign or signalization calculations. A round-about option was modeled using micro simulation with the software providing guidance on the appropriate diameter for the round-about, whether it required a single or dual lane circle, and how queuing on minor approaches would be eliminated. In addition, the model was able to show that driveways for existing businesses around the proposed round-about would be too close to the traffic circulating. The tool provided the data needed to relocate the driveways a safe distance from the round-about. In fact, there are a large number of studies and real cases that show the benefits of micro simulation for improved decision-making.

## I.3 TRAFFIC SIMULATION WITH AIMSUN

Aimsun by Ferrer and Barcelò (1993) is a software tool able to reproduce the real traffic conditions on an urban network which may include both expressways and arterial routes. It is based on a microscopic simulation approach. The behavior of each single vehicle which is present in the network is continuously modeled throughout the simulation time period, according to several driver behavior models (car following, lane changing, gap acceptance). Having outgrown the stated aim of the original Aimsun acronym 'advanced interactive microscopic simulator for urban and non-urban networks' (Ferrer and Barceló, 1993; Barceló et al., 1994, 1998a), the software now includes macroscopic, mesoscopic and microscopic models and is simply known as 'Aimsun' (Aimsun, 2008). Expanding in response to practitioners' requirements, Aimsun has come to encompass a collection of dynamic modelling tools. Specifically, these include mesoscopic and microscopic simulators and dynamic traffic assignment models based on either user equilibrium or stochastic route choice. From a practitioner's standpoint, macroscopic modelling plays an increasingly important role in the area of demand data preparation. The primary areas of application for Aimsun are offline traffic engineering and, more recently, online (real-time) traffic management decision support. In either case, the use of Aimsun, or Aimsun Online, aims to provide solutions to short and medium term planning and operational problems for which the dynamic and disaggregate models described in this chapter are extremely well suited. Strategic planning is an adjacent realm for which more aggregate and/or static models continue to be very suitable. There are important interfaces between those two realms at the level of methodology (effect on demand of lasting changes to the effective capacity) and technology (importing from and exporting data to strategic planning software) and these will be commented upon further in the following sections.

### I.3.1 Model building principles in Aimsun

Building a transport simulation model with Aimsun is an iterative procedure that comprises three steps:

- Model building, that is, the procedure of gathering and processing the inputs to create the model;

- Verification, calibration and validation, that is the process of confirming that implementation of the model logic is correct; setting appropriate values for the parameters and comparing the outputs of the model to correspond with realworld measurements in order to test its validity;

- Output analysis, explores the outputs of model in line with the overall objectives of the modelling study.

In the next section, some key elements of the Aimsun Traffic Microsimulation model will be focused upon.

### I.3.2 MODEL VERIFICATION, CALIBRATION AND VALIDATION

Before starting to modify the model parameters in order to calibrate the model, the user must be sure that there are no specification errors that affect the model logic and therefore simulation results. Verification consists in assuring that the model has been correctly edited in Aimsun, checking network geometry, control plans, management strategies and traffic demand, and verifying that the model description corresponds to the objectives of the study. Aimsun provides a tool that can automatically detect errors in supply definition, such as a section where not all the lanes at the beginning or at the end are connected or an OD pair with trips but no feasible path. Verification of traffic demand is carried out through a manual comparison with traffic counts wherever possible; for example the total trips generated and attracted by a zone must be compared with the counts of the sections to which the corresponding centroid is connected. An important check is to verify that the model is suitable for the objectives of the study; the model must include all the area that might be influenced by future changes being modelled; the boundaries must be free of congestion; if rerouting strategies are simulated, then alternative paths must be possible in the network being modelled; OD matrices should be time sliced so as to reproduce traffic demand dynamics correctly and the study time frame must extend beyond (earlier than) the peak hour to avoid starting the simulation in an oversaturated condition. Calibration is an iterative process that consists of changing model parameters and comparing model outputs with a set of real data until a predefined level of agreement between the two data sets is achieved. Which output needs to be generated depends on the type of model (macro, meso or micro), the objective of the study and the type of network. The most significant measures for a highway model are the relationship between speed/flow/density, lane utilization and congestion propagation.

### I.3.3 Aimsun Core Model: Car following and lane changing

The core models in Aimsun deal with individual vehicles, each vehicle/driver having behavioral attributes assigned to them when they enter the system; those attributes remain constant during the whole trip. The difference between the core models at the mesoscopic and microscopic levels relates to the level of abstraction and to the process employed to update each vehicle's status. Accordingly, in what follows, two sets of fundamental core models: microscopic behavioral models and mesoscopic behavioral models are described separately.

In the Aimsun micro-simulator, during a vehicle's journey along a route in the network, its position is updated according to two driver behavior models termed 'car following' and 'lane changing'.

The premise behind the models is that drivers tend to travel at their desired speed in each road section but the environment (i.e. preceding vehicle, adjacent vehicles, traffic signals, signs, blockages, etc.) conditions their behavior. Simulation time is split into small time intervals called simulation cycles or simulation steps. At each simulation step, the position and speed of every vehicle in the system is updated according to the algorithm of the lane changing and car following model.

Once all vehicles have been updated for the current simulation step, vehicles scheduled to arrive during this cycle are introduced into the system and the next vehicle arrival times are generated.

### I.3.4 MICROSCOPIC CAR FOLLOWING MODEL

The car-following model implemented in Aimsun is based on the model proposed by Gipps (Gipps, 1986). It can actually be considered an evolution of this empirical model, in which the model parameters are not global but determined by the influence of local parameters depending on the type of driver (speed limit acceptance of the vehicle), the road characteristics (speed limit on the section, speed limits on turnings, etc.), the influence of vehicles on adjacent lanes, etc. The model consists of two components: acceleration and deceleration. The first represents the intention of a vehicle to achieve a certain desired speed, while the second reproduces the limitations imposed by the preceding vehicle when trying to drive at the desired speed.

This model states that the maximum speed to which a vehicle (n) can accelerate during a time period *(t, t+T)* is given as:

$$V_a(n, t+T) = V(n,t) + 2{,}5 \cdot a(n) \cdot T \cdot \left(1 - \frac{V(n,t)}{V^*(n)}\right) \cdot \sqrt{0{,}025 + \frac{V(n,t)}{V^*(n)}}$$

where:

- V(n,t) is the speed of the vehicle n at time t;
- a(n) is the maximum acceleration for the vehicle n;
- T is the reaction time;
- V*(n) is the desired speed of the vehicle (n) for current position.

On the other hand, the maximum speed that the same vehicle (*n*) can reach during the same time interval (*t*, *t+ T*), according to its own characteristics and the limitations imposed by the presence of the lead vehicle (*n*−1), is:

$$V_b(n,t+T) = d(n)\cdot T + \sqrt{\begin{matrix} d^2(n)\cdot T^2 - d(n)\{2\left[x(n-1,t) - s(n-1) - x(n,t)\right] + \\ - V(n,t)\cdot T - \dfrac{V^2(n-1,t)}{d'(n-1)}\} \end{matrix}}$$

Where:

- d(n) is the maximum deceleration desired by vehicle n;
- x(n, t) is the position of the vehicle n at time t;
- x(n–1, t) is the position of the preceding vehicle (n−1) at time t;
- s(n–1, t) is the effective length of the vehicle (n−1);
- d(n–1) is an estimate of the vehicle (n−1) desired deceleration.

The speed of the vehicle (n) during time interval (t, t+T) is the minimum of the two expressions above:

$$V(n,t+T) = \min\left\{V_a(n,t+T); V_b(n,t+T)\right\}$$

Then, the position of the vehicle n inside the current lane is updated taking this speed into the movement equation:

$$x(n, t + T) = x(n, t) + V(n, t + T) \cdot T$$

The car-following model is such that a leading vehicle, i.e. a vehicle driving freely without any vehicle affecting its behavior, would try to drive at its maximum desired speed. Three parameters are used to calculate the maximum desired speed of a vehicle while driving on a particular section or turning; of these, two are related to the vehicle and one to the section or turning. Specifically:

- Maximum desired speed of the vehicle $i$: $v_{max}(i)$
- Speed acceptance of the vehicle $i$: $\theta(i)$
- Speed limit of the section or turning $s$: $S_{limit}(s)$

The speed limit for a vehicle $i$ on a section or a turning $s$, $s_{limit}(i, s)$, is calculated as follows:

$$S_{limit}(i, s) = \theta(i) \cdot S_{limit}(s)$$

Then, the maximum desired speed of the vehicle $i$ on a section or a turning $s$, $v_{max}(i, s)$, is calculated as follows:

$$V_{max}(i, s) = \min[S_{limit}(i, s); V_{max}(i)]$$

This maximum desired speed $v_{max}(i, s)$ is the same as that referred to above, in the Gipps' car-following model, as $V*(n)$.
The car-following model proposed by Gipps is a one-dimensional model that considers only the vehicle and its leader. However, the implementation of the car following model in Aimsun also considers the

influence of adjacent lanes. When a vehicle is driving along a section, we consider the influence that a certain number of vehicles driving slower in the adjacent right-side lane – or left-side lane when driving on the left – may have on the vehicle. The model determines a new maximum desired speed of a vehicle in the section, which will be used in the car following model, considering the mean speed of vehicles driving downstream of the vehicle in the adjacent slower lane and allowing a maximum difference of speed.

### I.3.5 LANE CHANGING MODEL

The lane-changing model can also be considered as a development of the Gipps lane-changing model (Gipps, 1986). Lane change is modelled as a decision process, analysing the necessity of the lane change (such as for turning manoeuvres determined by the route), the desirability of the lane change (to reach the desired speed when the leader vehicle is slower, for example), and the feasibility conditions for the lane change that are also local, depending on the location of the vehicle in the road network.

The lane-changing model is a decision model that approximates the driver's behaviour in the following manner: each time a vehicle has to be updated, we ask the following question: Is it necessary or desirable to change lanes? The answer to this question will depend on the distance to the next turning and the traffic conditions in the current lane. The traffic conditions are measured in terms of speed and queue lengths. When a driver is going slower than he wishes, he tries to overtake the preceding vehicle. On the other hand, when he is travelling fast enough, he tends to go back into the slower lane. If we answer the previous question in the affirmative, to successfully change lanes, we must first answer two further questions:

- "*Is there benefit to changing lane?*" Check whether there will be any improvement in the traffic conditions for the driver as a result of lane changing. This improvement is measured in terms of speed and distance. If the speed in the future lane is fast enough compared to the current lane, or if the queue is short enough, then it is beneficial to change lanes;
- "*Is it feasible to change lanes?*" Verify that there is sufficient gap to make the lane change with complete safety. For this purpose, we calculate both the braking imposed by the future downstream vehicle to the changing vehicle and the braking imposed by the changing vehicle to the future upstream vehicle. If both braking ratios are acceptable, then the lane change is possible.

In order to achieve a more accurate representation of the driver's behaviour in the lane-changing decision process, three different zones inside a section are considered, each one corresponding to a different lane-changing motivation. These zones are characterized by the distance up to the end of the section, i.e., the next point of turning (see Fig. 1.1).

- *Zone 1*: This is the furthest distance from the next turning point. The lane-changing decisions are mainly governed by the traffic conditions of the lanes involved. The necessity of a future turning movement is not yet taken into account. To measure the improvement that the driver will achieve by changing lanes, we consider several parameters: desired speed of driver, speed and distance of current preceding vehicle, speed and distance of future preceding vehicle in the destination lane;

- *Zone 2*: This is the intermediate zone. It is mainly the desired turning lane that affects the lane-changing decision. Vehicles not driving in valid lanes (i.e. lanes where the desired turning movement can be made) tend to get closer to the correct side of the road from which the turn is allowed. Vehicles looking for a gap may try to adapt to it but do not yet affect the behaviour of vehicles in the adjacent lanes.
- *Zone 3*: This is the shortest distance to the next turning point. Vehicles are forced to reach their desired turning lanes, reducing speed if necessary, and even come to a complete stop (gap forcing) in order to make the change possible. Within this zone, vehicles in the adjacent lane may also modify their behaviour (courtesy yielding) in order to provide a gap big enough for the vehicle to succeed in changing lanes.

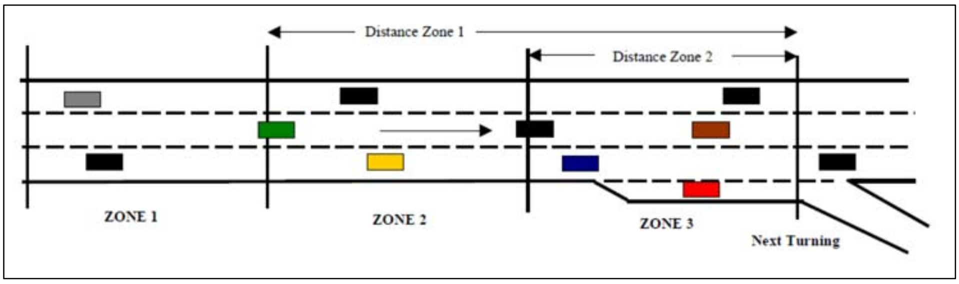


**Figure 1.1** Lane-changing zones

The lane changing of each vehicle *i* at section *s* could be summarized with the following elements:

- Lane Changing zone distance calculation;
- Target Lanes calculation;
- Vehicle behaviour considering the target lanes;
- Gap Acceptance model;
- Target Gap and Cooperation.

The "*Lane changing zones*" are defined by two parameters, at level of turning, Distance to Zone 1 and Distance to Zone 2. These parameters are defined in time (seconds) or distance (metres), depending on the user preferences. When these parameters are defined in time, the conversion to physical distance is calculated as:

$D_m = D_T \bullet S_{\lim it}(s)$

Where:

$D_m$: Distance in metres;

$D_T$ : Distance in seconds;

$S_{\lim it}$ : Speed limit of the section s.

The perception of Distance to Zone 1 and Distance to Zone 3 for each vehicle could be varied using the Distance Zone Variability defined at level of Experiment.

The "*Target Lane calculation*" implies that once each vehicle has a perception of all distance zones, the lane changing process starts calculating the valid target lanes according to the traffic conditions of the current position and including the traffic conditions and the feasible lanes for reaching the turning movements determined in its path plan and all possible obstacles. The output of this process is a set of valid lanes for zone 3 (TL3) and a set of valid lanes for zone 2 (TL2).
Receiving as input the valid target lane per zone (TL2 and TL3), the vehicle computes the type of behaviour according its current lane as:

- If the vehicle's current lane is not within the subset of valid lanes determined by Zone 3, the vehicle's behaviour is determined by Zone 3;
- If the vehicle's current lane is within the subset of valid lanes determined by Zone 3 but outside of the subset of valid lanes

determined by Zone 2, the vehicle's behaviour is determined by Zone 2;

- If the vehicle's current lane is within the subsets of valid lanes of both Zone 3 and 2, the vehicle's behaviour is determined by Zone 1.

The main idea is every vehicle tries to reach the set of valid lanes defined by zone 2 and 3, and once the current lane of a vehicle is inside of the set of valid lanes then the behavior is determined by Zone 1, that means overtaking maneuvers inside zone 2 and zone 3.
When the current lane of a vehicle is in the a valid lane determined by zone 2 and 3, in general the behavior is modeled as Zone 1, but there is an exception when its leaders is affected by an obstacle (turning movement, incident, lane closure, etc.) that is closer than its obstacle, then there is the evaluation to overtake the leader using a lane that can be outside of the subset of lanes given by Zone 2.

The "*Gap acceptance model for lane changing*" used in version 8 of Aimsun has been revisited and there is a full consistency with the car following model, in order to avoid artificial break down situations:

$$V_n(t+T) = d_n \cdot T + \sqrt{\begin{array}{l}(d_n \cdot T)^2 + d_n \cdot \{2 \cdot \left[x_l(t) - x_n(t) - s_l - s_n\right] + \\ - V_n(t) \cdot T - \dfrac{V_l^2(t)}{d_l}\}\end{array}}$$

$$\mathrm{Gap}(t) = [x_l(t) - x_n(t) - s_l - s_n] =$$
$$= \frac{V_l^2(t)}{2 \cdot d_l} - \frac{V_n^2(t+T)}{2 \cdot d_n} + [0{,}5 \cdot V_n(t) + V_n(t+T)] \cdot T$$

The Gipps car following model is stable (i.e. does not require the use of decelerations above the maximum desired deceleration (where $d_n$ is an estimation of vehicle leader desired deceleration, and $\alpha$ is a parameter of aggressiveness set to 1 as a default and takes the value defined inside the vehicle type as "Sensitivity for Imprudence Lane Changing" if there is a Imprudence Lane Changing) when:

$$V_n(t+T) \geq \max[0\,;\ V_n(t) + \alpha \cdot d_n \cdot T]$$

This is achieved when:

$$\mathrm{Gap}(t) \geq \frac{V_l^2(t)}{2 \cdot d_l} + 0{,}5 \cdot V_n(t) \cdot T +$$
$$+ \max\left[ -\frac{V_n^2(t)}{2 \cdot d_n} + (1 - 0{,}5 \cdot \alpha) \cdot \alpha \cdot d_n \cdot T^2 + (1 - \alpha) \cdot V_n(t) \cdot T \right]$$

The Gipps car following model is crash free when the Gap remains positive throughout the deceleration process. This gives an additional constrain:

$$\mathrm{Gap}(t) \geq \max\left\{ 0\,;\ \frac{V_l^2(t)}{2 \cdot d_l} + 0{,}5 \cdot V_n(t) \cdot T + \right.$$

$$+\max\left[-\frac{V_n^2(t)}{2\cdot d_n}+(1-0{,}5\cdot\alpha)\cdot\alpha\cdot d_n\cdot T^2+(1-\alpha)\cdot V_n(t)\cdot T\right]\Bigg\}$$

This condition must be fulfilled to apply the Gipps car following model with a new leader when a vehicle changes lane (i.e. selection of possible leader and gap acceptance).

It is possible to evaluate the speed and position of all vehicles at time *t+dt* if the vehicle changes lane:

- For the vehicles that are already updated, we take their current speed and position;
- For the others, we compute the speed and position assuming that the vehicle changes lane at time *t+dt;*

In particular, the Gap is acceptable if the physical quantities at time *t+dt* fulfill the three following requirements:

- the gaps are positive;
- the computed speeds are positive;
- the decelerations imposed are smaller than $\alpha$**DecelMaxDeseada*.

Using the previous equations this can be achieved with one condition at time t that needs to be fulfilled for both the upstream and downstream gaps.

$$\mathrm{Gap}_{dw}(t) \geq \max\left\{0\,;\ \frac{V_{dw}^2(t)}{2\cdot d_{dw}} + 0{,}5\cdot V_{lc}(t)\cdot T + \right.$$

$$\left. + \max\left[0\,;\ -\frac{V_{lc}^2(t)}{2\cdot d_{lc}} + (1-0{,}5\cdot\alpha_{lc})\cdot\alpha_{lc}\cdot d_{lc}\cdot T^2 + (1-\alpha_{lc})\cdot V_{lc}(t)\cdot T\right]\right\}$$

$$\mathrm{Gap}_{up}(t) \geq \max\left\{0\,;\ \frac{V_{lc}^2(t)}{2\cdot d_{lc}} + 0{,}5\cdot V_{up}(t)\cdot T + \right.$$

$$\left. + \max\left[0\,;\ -\frac{V_{up}^2(t)}{2\cdot d_{up}} + (1-0{,}5\cdot\alpha_{up})\cdot\alpha_{up}\cdot d_{up}\cdot T^2 + (1-\alpha_{up})\cdot V_{up}(t)\cdot T\right]\right\}$$

Furthermore, it is possible modifying the acceptance of the gap in the lane changing model by defining the following parameters:

- Percentage for Imprudent Lane Changing Cases: This parameter defines the probability to one vehicle apply a lane changing with a non-safe gap (reducing the gap until the length of the vehicle);
- Sensitivity for Imprudent Lane Changing Cases: This parameter determines the deceleration of the upstream vehicle in order to estimate the gap necessary to apply an Imprudent Lane Changing. If this parameter is greater than 1, it overestimates the deceleration of the vehicle upstream assuming a non-realistic gap.

# II. STATISTICAL APPROACH FOR CALIBRATING THE MICROSIMULATION MODEL FOR A22 FREEWAY

As already discussed in the previous chapter, simulation is a sampling experiment on the real system through its model (Pidd, 1992). This means that the evolution over time of the system model should be able to imitate properly the evolution over time of the modeled system, and conclusions on the system behavior can be drawn by examining samples of the observational variables of interest through statistical analysis techniques. Thus a traffic simulation model has to represent the system behavior with sufficient accuracy so that the model can be used as a substitute for the actual system for experimental purposes. Road traffic microsimulation models, first commercially introduced in the 1990s, are one of the latest generation of available traffic models and became very popular for the development and evaluation of a broad range of road traffic management and control systems. They model the movements of individual vehicles, traveling around road networks by using car following, lane changing and gap acceptance rules; hence, traffic microsimulation models try to replicate the behavior of individual drivers. However, the "realism" sought by the representation of individual drivers introduces a level of complexity into the modeling process which must be taken into account from the stage of model calibration. Traffic microsimulation models typically include a very large number of parameters, representing various characteristics of travelers, vehicles and road network, that must be calibrated before the model is applied as a prediction tool of traffic performances (Hollander and Liu, 2008). Calibration of a traffic microsimulation model is an iterative process that consists of changing and adjusting numerous model parameters and comparing model outputs with a set of empirical data until a predefined level of agreement between the two data sets is achieved (Barcelo, 2011). Since no single model can be equally accurate for all possible traffic conditions or can include the whole universe of variables affecting real-world traffic conditions, every microsimulation software has a set of user-adjustable parameters which enable the analyst to calibrate the model to match locally observed conditions.

In order to reproduce the mechanism of a single decision made by an individual driver (e.g. the decision to change lane or to use a gap in the opposing stream to enter an intersection), every traffic microsimulation model consists of several sub-models each of which includes several parameters. Direct measurement of these parameters is complex, because many of them represent features difficult to isolate, or extensive data collection is required. Thus, in the calibration process, aggregate data, which do not describe the behavior of individual drivers, are often used; however, when a model is calibrated using aggregate data, the result can limit behavioral power (see Hollander and Liu, 2008). Another question concerns which parameters have to be considered in the model calibration process. Some studies focus on the calibration of driver behavior parameters only, while assuming the others are given (see e.g. Hourdakis et al., 2003; Kim and Rilett, 2003); other studies introduce driving behavior in a broader problem, including the calibration of a route choice model and/or an o-d matrix (see e.g. Dowling et al. 2004a). There are also differences among calibration studies in terms of variation in the number of parameters that must be calibrated before the model can be used as a tool for prediction. In the case of a small number of parameters, the calibration process can be developed through a manual procedure; thus some parameters are calibrated often through multiple retries (Toledo et al., 2003). In the case of a longer number of parameter subsets, the calibration process normally uses automated algorithms, which should allow a closer approach to the optimal solution; anyway automated procedure makes it harder to follow changes in the value of each parameter (Menneni et al., 2008). However, the selection of calibration parameters is often considered in relation to the purpose of the calibration problem. The achievement of calibration targets, i.e. when the model outputs are similar to empirical data, can be influenced by the simplification of which microsimulation models are fixed. This concerns some technical characteristics of micro-simulation models such us the transport system update mechanism, the representation of randomness, traffic generation, allocating driver/vehicle characteristics, vehicle interactions, etc. A further question concerning microsimulation is whether this process produces a valid model for the system in general, or the model gives only a representation of the specific set of input data. In this regard it should be noted that to gain a valid model, two independent data sets are necessary: the first set of data should be used for the calibration of the model parameters; the second set should be used for the running of the calibrated model so that the resulting model output data can be compared to the second set of system output data. The comparison part is referred to as the validation of the calibrated model; it represents the process of checking to what extent the model built replicates reality (see e.g. Toledo and Koutsopoulos, 2004). The objective of this chapter is to present a methodology which uses speed-density relationships in the microsimulation calibration process, stated that they represent the traffic flow phenomenon in a wide range of operational conditions and they well summarize all the information that may be collected in the field (or following a run of the microsimulation model) on two of the three key variables of traffic flow. The matching of speed-density relationships from the field with the simulation was evaluated using statistical analysis as technique of pattern recognition. A freeway segment under uncongested traffic conditions was selected as case study and reference will be made to it in the following. Based on traffic data observed at A22 Brenner Freeway, Italy, statistical regressions between the variables of traffic flow were investigated. Analogous relationships were obtained using the Aimsun microscopic traffic simulator software, reproducing the in field conditions and varying some selected parameters until a good matching between field and simulation was achieved.

## II.1 THE A22 BRENNER FREEWAY

The Brennero Freeway (A22) connects Italy to Central Europe inside the European freeway corridor E45 (Göteborg-Gela). At present it features two lanes in each direction, starting from the Brennero Austrian border (A13 – Innsbrück-Brennero – interchange) and passes through the Bolzano, Trento, Verona, Mantova and Reggio Emilia provinces with an overall length of 314 km. There are 21 toll-houses, at an average distance of 15 km, while the junctions are with the A4 (Milano-Venezia) and the A1 (Milano-Roma), at Verona Nord and Campogalliano. For its function and geographical position, the Brenner freeway is continuosly occupied, along its whole route, by heavy traffic flows and dominated by intense seasonal tourist flows. These tourist flows are predominantly directed to Lake Garda, Trentino and Alto Adige resorts and to the Adriatic Riviera.

The most severe operating conditions of the infrastructure are related to the tourist flow peaks and so during these periods poor level of service or oversaturation conditions can be recorded. Together with these characteristics, we notice that A22 traffic is, in all its components, systematically growing consistent with the national freeway network trend. The Fig. 2.1 shows the S. Michele section of the A22 Freeway studied in this research.

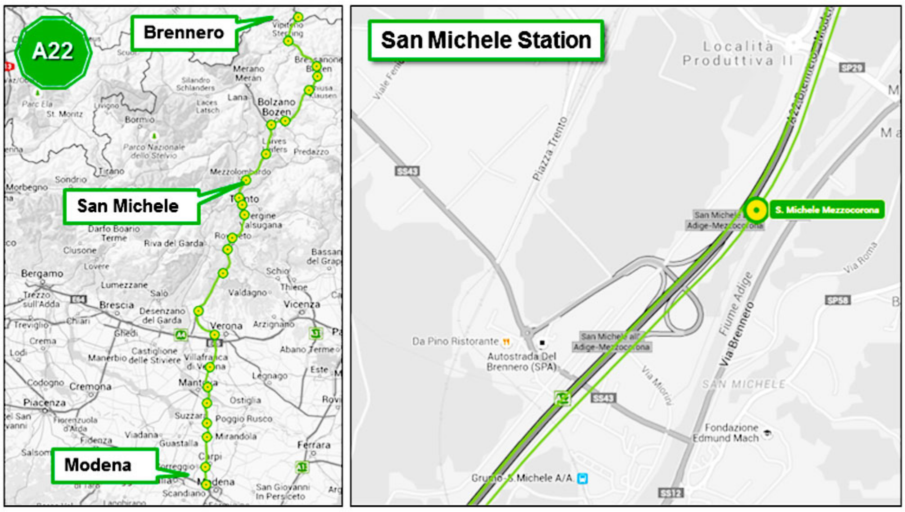


Fig. 2.1. Italy A22 Brenner Freeway- S. Michele Section

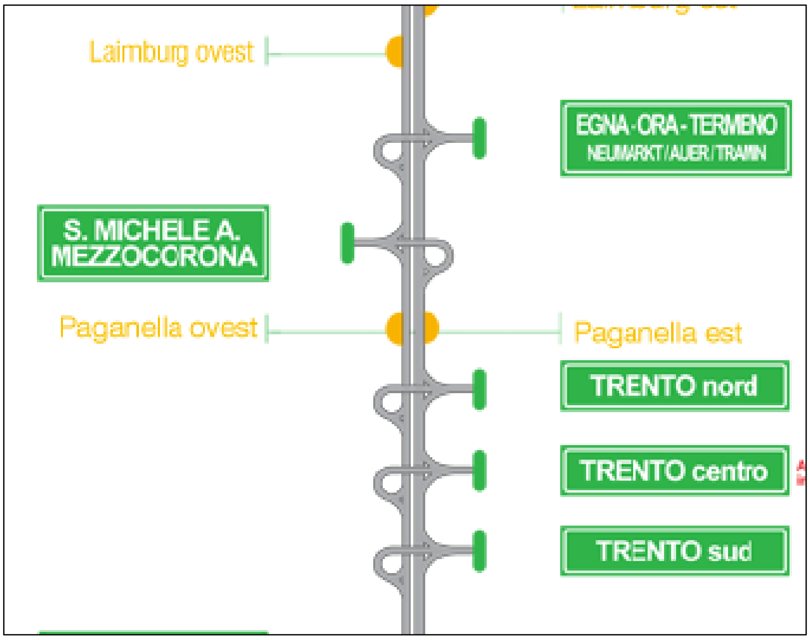


Fig. 2.2. Analyzed section "S. Michele" at A22 Brenner Freeway

| **A22 Freeway sections** | **↓km↓** | **↑km↑** | **City** |
|---|---|---|---|
| Modena Nord | 0 | 315 | MO |
| Campogalliano – Modena | 3 | 311 | |
| Area Servizio "Campogalliano" | 5 | 309 | |
| Carpi | 11 | 303 | |
| Reggiolo | 28 | 286 | RE |
| Pegognaga | 37 | 277 | MN |
| Area Servizio "Po" | 47 | 267 | |
| Mantova Sud | 49 | 265 | |
| Mantova Nord | 57 | 257 | |
| Nogarole Rocca | 71 | 243 | VR |

| | | | |
|---|---|---|---|
| Area Servizio "Povegliano" | 74 | 240 | |
| Verona Sud | 86 | 228 | |
| Verona Nord | 88 | 226 | |
| Area Servizio "Garda" | 97 | 208 | |
| Affi – Lago di Garda Sud | 98 | 207 | |
| Area Servizio "Adige" | 119 | 186 | |
| Ala – Avio | 135 | 179 | TN |
| Rovereto Sud – Lago di Garda Nord | 147 | 167 | |
| Area Servizio "Nogaredo" | 154 | 160 | |
| Rovereto Nord | 156 | 158 | |
| Trento Sud | 174 | 140 | |
| Trento Nord | 182 | 132 | |
| Area Servizio "Paganella" | 185 | 129 | |
| San Michele dell'Adige – Mezzocorona | 193 | 121 | |
| Egna – Ora | 212 | 102 | BZ |
| Area Servizio "Laimburg Ovest" | - | 99 | |
| Area Servizio "Laimburg Est" | 218 | - | |
| Bolzano Sud | 229 | 85 | |
| Bolzano Nord | 237 | 77 | |
| Area Servizio "Sciliar Ovest" | - | 69 | |
| Area Servizio "Isarco Est" | 250 | - | |
| Chiusa – Val Gardena | 261 | 53 | |
| Bressanone – Zona Industriale | 266 | 48 | |
| Area Servizio "Plose" | 272 | 42 | |
| Bressanone – Val Pusteria | 276 | 38 | |
| Area Servizio "Trens" | 294 | 20 | |
| Vipiteno – Barriera del Brennero | 298 | 16 | |

| | | | |
|---|---|---|---|
| Area Servizio “Autoporto Sadobre” | 298 | 16 | |
| Ponticolo | - | 7 | |
| Terme di Brennero | - | 5 | |
| Innsbruck – Confine di Stato – Austria | 315 | 0 | - |

Table 2.1. Sections of the A22 Freeway

The infrastructure has a total length of about 313 km, has 2 lanes for each direction, each of a width of 3.75 m, hard shoulders of 2.50 m. The figure 2.3 below shows the road section of the A22 Freeway.

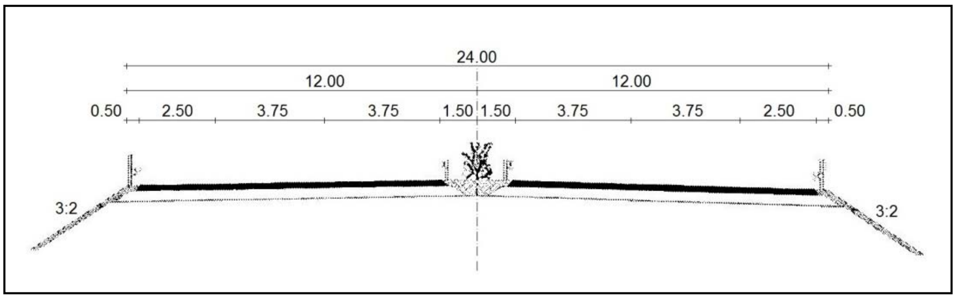


Fig. 2.3. Road section of A22 freeway.

The most severe operating conditions experiencing low Service Levels or congested situations. Table 2.2 illustrates the traffic for the A22 wich exhibits systematic growth in accordance with the trend of the national highways.

The Average Annual Daily Traffic AADT (in Italian TGMA- Traffico Giornaliero Medio Annuo) is defined as the ratio between the number of vehicles traveling in a year and the number of days of the same.

| ANNO | TGMA TOT | | | | | | |
|---|---|---|---|---|---|---|---|
| | Km 0-57 | Km 57-98 | Km 98-135 | Km 135-156 | Km 156-193 | Km 193-229 | Km 229-313 |
| 2004 | 19541 | 23277 | 20678 | 19988 | 23117 | 19775 | 11565 |
| 2005 | 19845 | 24985 | 21069 | 20657 | 23692 | 20139 | 12040 |
| 2007 | 30371 | 38237 | 32244 | 31617 | 36258 | 30821 | 18426 |
| 2008 | 40894 | 51485 | 43415 | 42566 | 48821 | 41499 | 24811 |
| 2011 | 38315 | 48238 | 40678 | 39882 | 45742 | 38882 | 23246 |
| 2012 | 36841 | 46383 | 39113 | 38348 | 43983 | 37387 | 22352 |

Tab. 2.2. $TGMA_{tot}$ of A22 Freeway Northbound (Modena- Brennero)

| ANNO | TGMA TOT | | | | | | |
|---|---|---|---|---|---|---|---|
| | Km 0-85 | Km 85-121 | Km 121-158 | Km 158-179 | Km 179-217 | Km 217-257 | Km 257-313 |
| 2004 | 12178 | 19047 | 23002 | 19744 | 20511 | 22144 | 19111 |
| 2005 | 12249 | 20038 | 23649 | 20465 | 20965 | 24772 | 19356 |
| 2007 | 19766 | 29844 | 36108 | 31219 | 31658 | 37343 | 29664 |
| 2008 | 27096 | 40075 | 47978 | 42315 | 43284 | 50048 | 39997 |
| 2011 | 25387 | 37548 | 44952 | 39647 | 40555 | 46892 | 37474 |
| 2012 | 24411 | 36104 | 43223 | 38122 | 38995 | 45088 | 36033 |

Tab. 2.3. $TGMA_{tot}$ of A22 Freeway Southbound (Brennero- Modena)

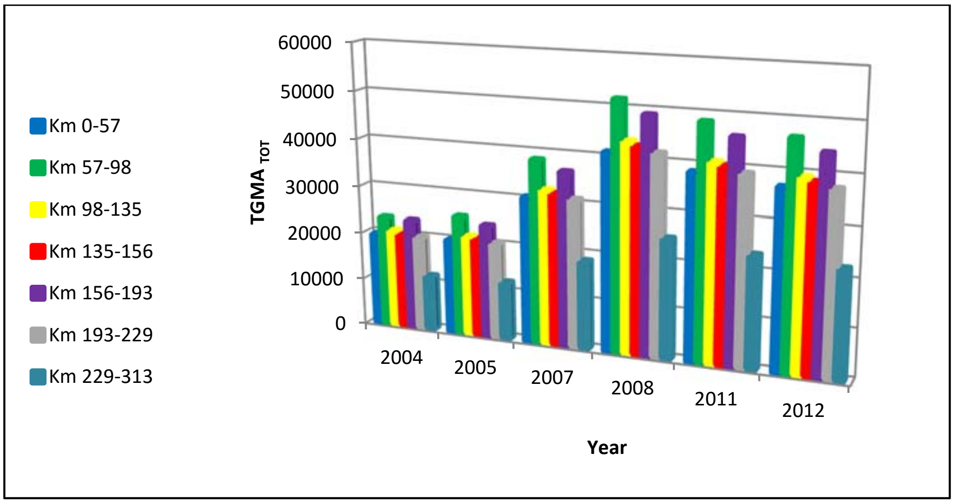


Fig.2.4. TGMA$_{tot}$ of A22 Freeway Northbound (Modena- Brennero)

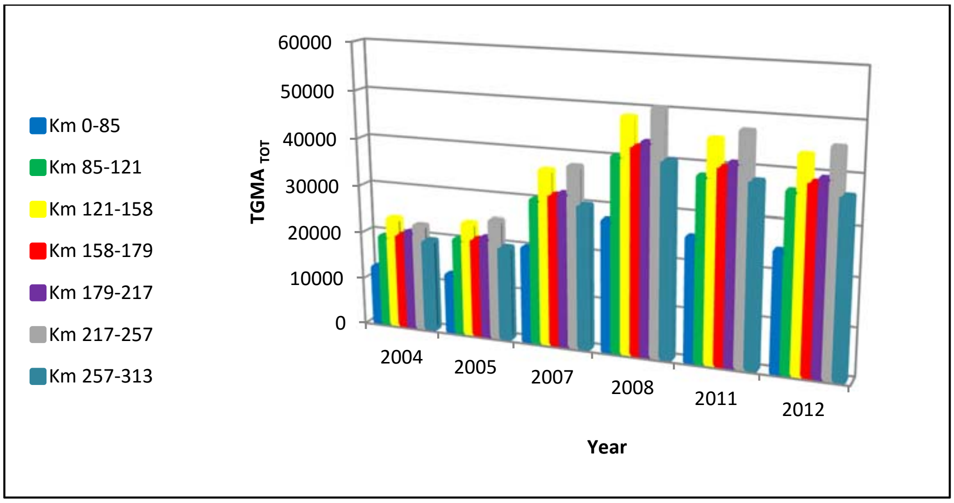


Fig. 2.5. TGMA$_{tot}$ of A22 Freeway Southbound (Brennero- Modena)

In addition, forecast of the traffic in the year 2014 was estimated (Tab. 2.4, 2.5 and Fig. 2.6).

| ANNO | TGMA TOT | | | | | | |
|---|---|---|---|---|---|---|---|
| | Km 0-57 | Km 57-98 | Km 98-135 | Km 135-156 | Km 156-193 | Km 193-229 | Km 229-313 |
| 2014 | 46157 | 58507 | 49024 | 48150 | 55168 | 46857 | 28091 |

Tab. 2.4. Prevision of $TGMA_{TOT}$ in the year 2014 (Modena- Brennero)

| ANNO | TGMA TOT | | | | | | |
|---|---|---|---|---|---|---|---|
| | Km 0-85 | Km 85-121 | Km 121-158 | Km 158-179 | Km 179-217 | Km 217-257 | Km 257-313 |
| 2014 | 30949 | 45165 | 54096 | 47902 | 48882 | 56943 | 45151 |

Tab. 2.5. Prevision of $TGMA_{TOT}$ in the year 2014 (Brennero- Modena)

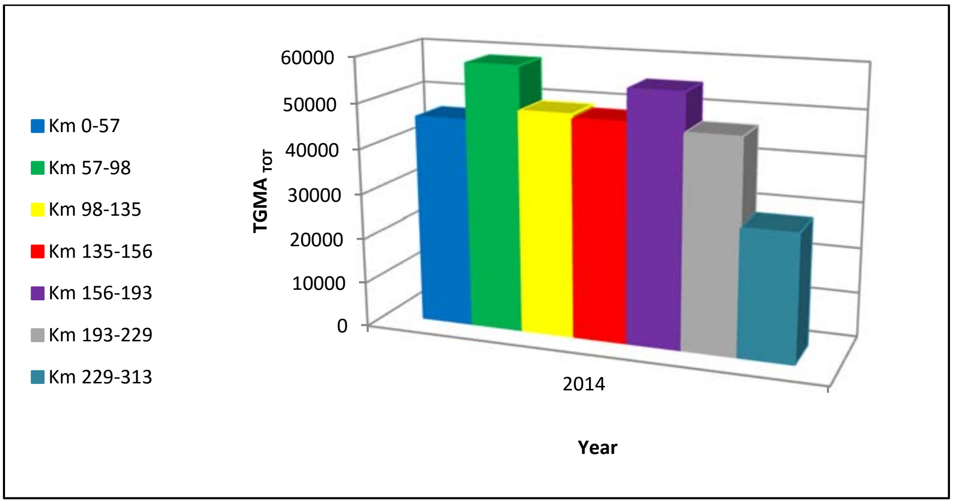


Fig. 2.6. Prevision of $TGMA_{TOT}$ in the year 2014 (Modena- Brennero)

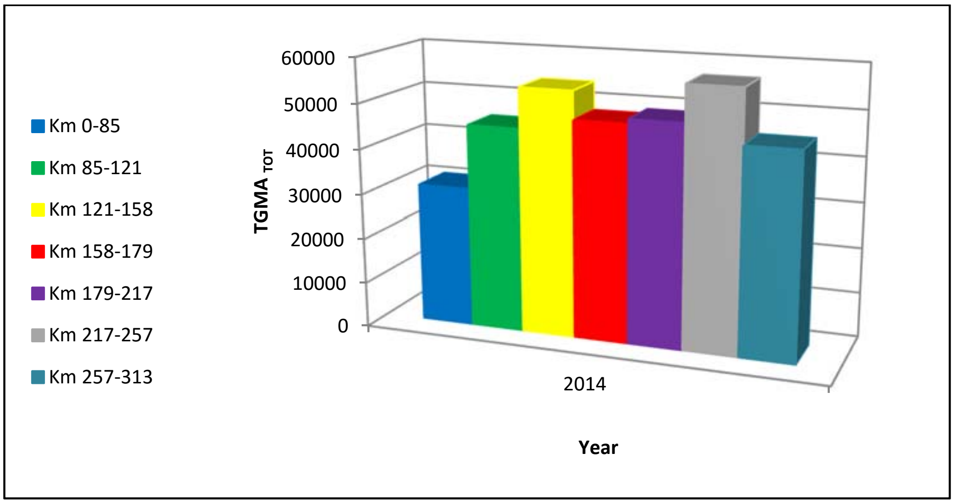


Fig. 2.7. Prevision of $TGMA_{TOT}$ in the year 2014 (Brennero- Modena)

## II.2 OVERWIEW OF THE CALIBRATION METHODOLOGIES

Before discussing in detail the recommended approach to the calibration and validation of micro-simulation models it is useful to state what exactly comprises "calibration" and "validation":

- Model calibration is the process of tuning and refining the input data and parameters within the model in order to agree with real observed data, and thus provide a tool which is reliable for forecasting;

- Model validation is a process of comparing the results of the model with independent observed data.

In the transportation literature various methodologies for calibrating and validating traffic microsimulation models have been discussed in several publications (Barceló et al. (2010); Kim et al. (2005); Ma and Abdulhai (2002); Toledo et al. (2004); Park and Qi (2005); Abdalhaq and Baker (2014)).

Kim and Rilett (2003) applied a methodology that used a single measure, whereas other authors used more than one measure by executing sequences of calibration sub-processes, each one of which included different traffic measures for calibrating separate groups of parameters. Dowling et al. (2004b) proposed a three step methodology structured as follows: i) the calibration of the driving behavior parameters, performed by comparing capacities; ii) the calibration of the route choice parameters, performed by comparing flows; iii) and finally calibration completed by comparing travel times and queue lengths. Hourdakis et al. (2003) compared simulated and observed flows to calibrate global parameters such as maximum acceleration and other vehicle characteristics; then they compared simulated and observed speeds to calibrate local parameters and, finally, they proposed an optional calibration stage by comparing any measure chosen by the user. In order to find a set of model parameters that make the model outputs as close as possible to the field-measured capacities, Dowling et al. (2004a) proposed that the capacity calibration was one of the steps in microsimulation calibration process. The calibration of the model to capacity consisted of the global calibration phase, performed to identify the appropriate network-wide value of the capacity parameters best reproducing on-field conditions, and the fine-tuning phase, performed so that the link-specific capacity parameters were adjusted to match more accurately the capacity measurements at each bottleneck. Queue discharge flow rate can be also used for the estimation of a numerical value for capacity, but loss of information can derive since the capacity should be expressed by a distribution of capacity values and not by a single numerical value only. In this regard, Brilon et al. (2007) introduced the stochastic approach for highway capacity analysis; thus, the capacity of a highway facility was regarded as a random variable instead of a constant value.

However, basing the capacity calibration process on a single numerical value, matching the means of the capacity distribution could not give very certain results, since other important properties of a distribution, or other traffic parameters characterizing capacity as speed or density, could be neglected (Menneni et al. (2008)). In any case, it should be noted that in the calibration process, the main target should be to maximize the information suitable for replicating real system performances. Generalized relationships among speed, density, and flow rate can allow us to determine the required capacity information; these relationships can also provide information regarding free-flow and congested regions which cannot be gained from a single numerical value or a distribution of capacities. Based on speed-flow, speed-density, or flow-density relationships which provide information about the free-flow, congested, and queue discharge regions, a calibration procedure could replicate the whole range of traffic behavior and not just the peak period. For model calibration purposes, only a proportion of one of the three graphs mentioned above, instead of the entire graph, could be used (Menneni et al. (2008)). In any case, the amount of information available in fitting empirical/simulated data is very important, and more information can be obtained by using speed-flow, speed-density, or flow-density graphs; as a consequence, a higher number of parameters can be submitted to the calibration process, resulting in a better fine-tuned simulation model. The calibration through speed-flow, speed density, or flow-density graphs could be considered as the first step, necessarily followed by route-choice and the system performance calibration. Despite the potential benefits in the calibration process, the use of the fundamental relationships of traffic flow in the microsimulation calibration process remains still marginal. Wiedemann (1991) replicated field speed-flow relationships and used them to demonstrate closeness of field and simulated data; Fellendorf and Vortisch (2001) demonstrated the ability of a simulation model to replicate speed-flow graphs from real-world freeways. Menneni et al (2008) developed an objective function based on minimizing the dissimilarity between speed-flow graphs. Thus the dissimilarity of two graphs by calculating the amount of area that is not covered by the other was measured. Since speed and flow measurements were represented as point sets, discretization to convert point information to area was necessary. Moreover, considering that the information derived from the field and simulation was often just partial and not a complete speed-flow graph, the comparison was only made over the space occupied by the field graph. Differently from the approaches mentioned above, Mauro et al. (2014) developed the calibration methodology based on speed-density relationships in the microsimulation calibration process, stated that they represent the traffic-flow phenomenon in a wide range of operational conditions and well summarize all the information that may be collected in field (or following a run of the microsimulation model) on two of the three key variables of traffic flow. The matching of speed-density relationships from field and simulation was evaluated using statistical analysis as a technique of pattern recognition.

## II.3 THE FUNDAMENTAL DIAGRAM OF TRAFFIC FLOW FOR THE A22 FREEWAY

Experimental surveys carried out at observation sections on the A22 Brenner Freeway, Italy, have allowed the relationships between the fundamental variables of traffic flow (namely the speed-flow-density relationships) to be modelled for a traffic flow of cars only (Mauro 2003, 2005, 2007). Data were collected over different locations and multiple days and combined to show a complete graph between the pairs of traffic flow variables. The aforesaid relationships between flow and density, speed and density, speed and flow were developed for the right lane, the passing lane and the roadway, through the treatment and the processing of traffic data measured at specific observation sections (San Michele, Rovereto and Adige) on the A22 Freeway (Mauro 2003, 2005, 2007). A procedure for the estimation of the passenger car equivalent factors was also developed and reported in (Mauro 2003, 2005, 2007). For the same reference framework, under uninterrupted flow conditions an exploratory study proposed a criterion for predicting the reliability of freeway traffic flow by observing speed stochastic processes (see Mauro et al., 2013).

First the relationship between speed and density was searched. This choice was motivated by the following: considering the real traffic flow phenomenon, the speed-density relationship is a monotonically decreasing function and implies a mathematical relation simpler than the flow-density and speed-flow relationships; furthermore, the function *V=V(D)* represents in a direct way the interaction between vehicles in a traffic stream, where users, through the mutual spacing among vehicles, perceive the density and to it adapt their speed. The main speed-density models as proposed by literature, were taken into account (e.g. Greenshield, 1935; Greenberg, 1959; Underwood, 1961; Edie, 1965; May, 1990). The single-regime models were selected; among these, May's model (May, 1990) was chosen since it appeared as the best in interpreting the available data and the traffic flow phenomena at the observed sections, particularly the maximum values of density under congested traffic conditions. According to May's model (May, 1990), the relationship between speed and density was expressed mathematically as follows:

$$V = V_{FF} \cdot \exp\left[-0.5 \cdot \left(\frac{D}{D_c}\right)^2\right] \tag{2.1}$$

where $V_{FF}$ is the free flow speed and $D_c$ is the critical density, namely the density to which is associated the reaching of the capacity achieved *C*. Equation 1 can be converted into linear form by using the logarithmic transformation:

$$\ln(V) = \ln(V_{FF}) - \frac{1}{2 \cdot \mathrm{D}_\mathrm{c}^2} \cdot D^2 \quad \text{or else} \qquad V_1 = a + b \cdot D_1 \tag{2.2}$$

where $V_1$ is $ln(V)$, $a$ is $ln(V_{FF})$, $b$ is $-\frac{1}{2 \cdot D_c^2}$ and $D_1$ is $D^2$, with $V_{FF}$ and $D_c$ as previously defined. Starting from the above equation, by means of the fundamental relation between flow $Q$, density $D$ and speed $V$, $Q = D \cdot V$, it was possible to obtain $Q$ as follows:

$$Q = V \cdot \sqrt{\frac{\ln\left(\frac{D}{D_c}\right)^2}{0.5 \cdot D_c^2}} \qquad (2.3)$$

$$Q = V_{FF} \cdot D \cdot \exp\left[-0.5 \cdot \left(\frac{D}{D_c}\right)^2\right] \qquad (2.4)$$

that allowing the speed-flow relationship, $V = V(Q)$, and the flow-density relationship, $Q = Q(D)$. To be obtained and thus complete specification of the relationships between the parameters $V_{FF}$ and $D_c$ shown before were estimated. Traffic flow models were calibrated for the right lane, the passing lane and the roadway at the sections under examinations, by using the values of $Q$, veh/h, and $V$, km/h, and calculating the density $D$, veh/km/lane, from $D = Q/V$; then, for every value of speed $V$, corresponding to each lane and the roadway, the natural logarithm, $lnV$, was calculated to derive from each of the available pairs ($D, V$) the corresponding pair of variables ($D^2, lnV$). For every observation section, based on the corresponding scatter plot ($D^2; lnV$), according to equation 2.2, a least squares estimation was performed; then, the model calibration parameters ($V_{FF}$ and $D_c$) were calculated for all observation sections (see Mauro 2003, 2005, 2007). Thus, the relationships between the fundamental variables of traffic flow were specified for all observation sections by using equations 2.1, 2.3 and 2.4; estimations of capacity $C$ and speed $V_c$, corresponding to $C$, were then performed. For all cases, moreover, values of $R^2$ corresponding to ($V; Q$) and ($Q; D$) relationships are never found to be lower than 0.7. In order to calculate the speed-flow-density relationships for the right lane, the passing lane and the roadway for the A22 Freeway (Italy), the homologous determinations of $V_{FF}$ and $D_c$, corresponding to the three observation sections were averaged. Using the $V_{FF}$ and $D_c$ values the speed-flow-density relationships for the freeway under examination were obtained (see Fig. 2.8, 2.9, 2.10). In the following sections, however, empirical data, which were taken as a reference in the calibration of the microsimulation model, are those corresponding to the S. Michele observation section (southbound), chosen as the case study; for this research.

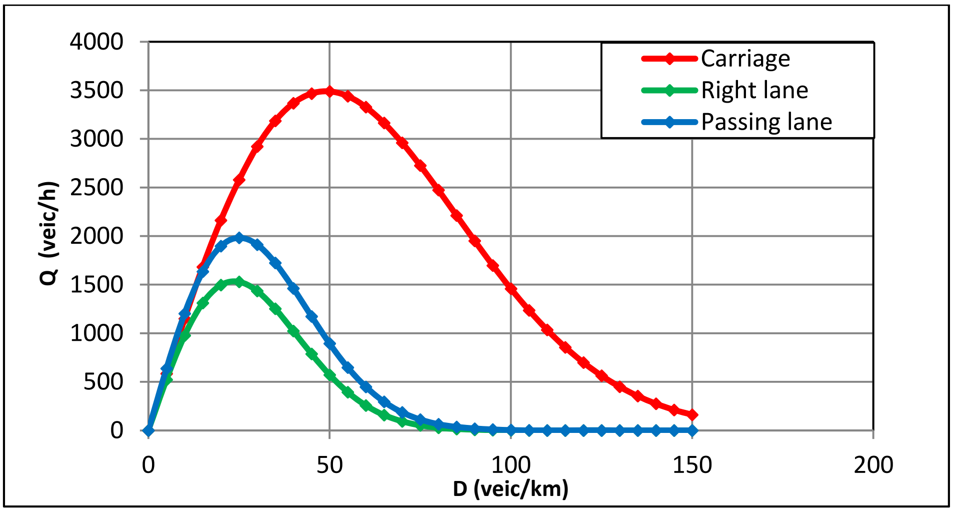


Fig.2.8. Flow (Q) vs. Density (D) for carriage, right lane, passing lane

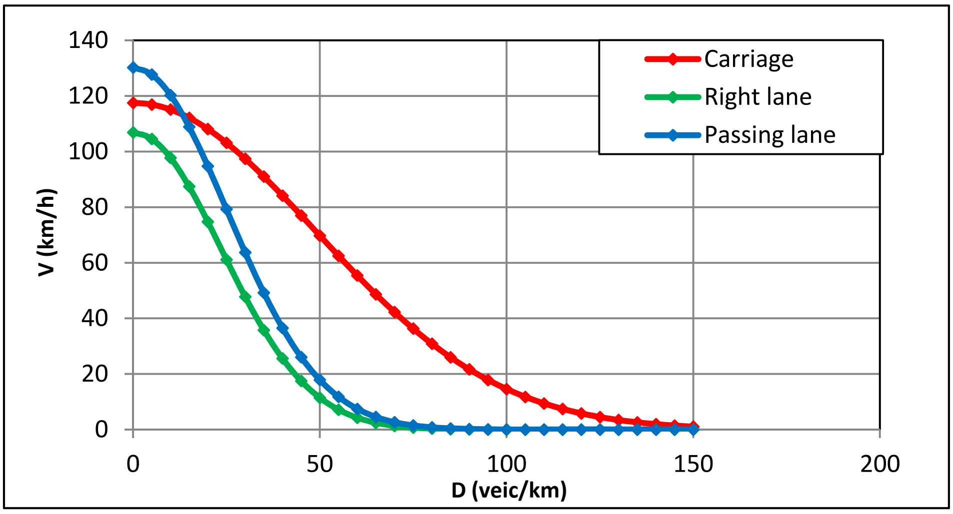


Fig.2.9. Speed (V) vs. Density (D) for carriage, right lane, passing lane

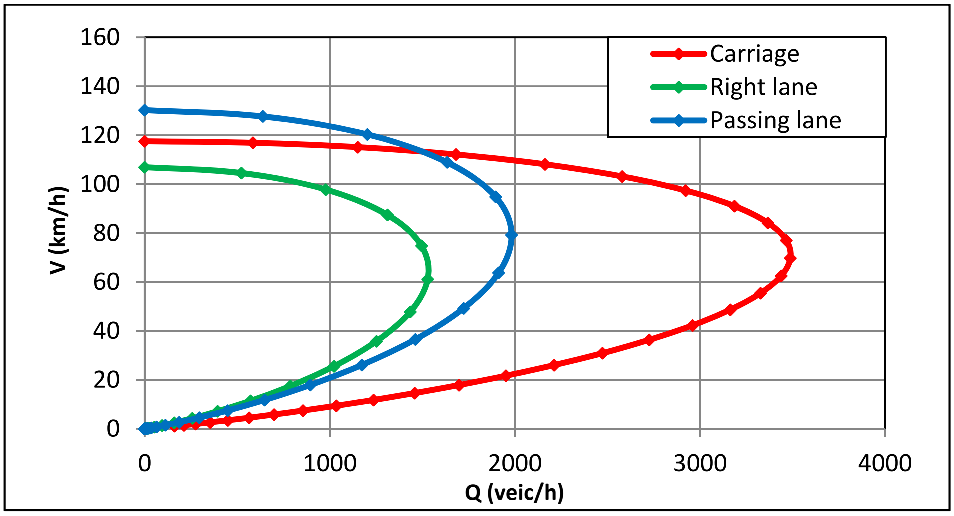


Fig.2.10. Speed (V) vs. Flow (Q) for carriage, right lane, passing lane

Table 2.6 shows the values of $V_{FF}$ (Free flow speed), $D_C$ (Critical density), C (Capacity) and $V_C$ (critical speed) related to the speed-flow-density relationship showed in Fig. 2.8, 2.9, 2.10.

| | $V_{FF}$ | $D_C$ | C | $V_C$ |
|---|---|---|---|---|
| **Right lane** | 106.95 | 23.65 | 1534.00 | 64.86 |
| **Passing lane** | 130.28 | 25.09 | 1983.00 | 79.02 |
| **Carriageway** | 117.55 | 48.95 | 3490.00 | 71.30 |

Tab.2.6. Parameters of speed-flow-density relationships for the A22 Freeway.

Taking into account the parameters of tab.2.6, the equations (2.1), (2.4) give the following equations which represent the relationship for the A22 Freeway:

- Inside lane (Right lane):

$$V = 106.95 * \exp\left[-0.5 * \left(\frac{D}{23.65}\right)^2\right] \quad (2.5)$$

$$Q = 106.95 * D * \exp\left[-0.5 * \left(\frac{D}{23.65}\right)^2\right] \quad (2.6)$$

- Passing lane:

$$V = 130.28 * \exp\left[-0.5 * \left(\frac{D}{25.09}\right)^2\right] \quad (2.7)$$

$$Q = 130.28 * D * \exp\left[-0.5 * \left(\frac{D}{25.09}\right)^2\right] \quad (2.8)$$

- Carriageway:

$$V = 117.55 * \exp\left[-0.5 * \left(\frac{D}{48.95}\right)^2\right] \quad (2.9)$$

$$Q = 117.55 * D * \exp\left[-0.5 * \left(\frac{D}{48.95}\right)^2\right] \quad (2.10)$$

## II.4 CALIBRATION PARAMETERS

Traffic simulation for the freeway facility was performed with Aimsun micro-simulator. As for any other microsimulation software program, Aimsun comes with a set of user-adjustable parameters for the purpose of calibrating the model to local conditions, i.e. to minimize the difference between the empirical and the simulated values of the variables of interest. The Aimsun micro-simulator updates the vehicle position which moves along the network, basing on two driver behavior models named “car following” and “lane changing” (Barcelo, 2011). As already mentioned, the car-following model implemented in Aimsun is an evolution of the empirical model proposed by Gipps (1981; 1986), in which the model parameters are determined by the influence of local parameters, depending on the type of driver, the road characteristics, the influence of vehicles driving in the adjacent lanes, etc. Very briefly the model consists of two components: acceleration, representing the intention of a vehicle to achieve a certain desired speed, and deceleration, reproducing the limitations imposed by the preceding vehicle when trying to drive at the desired speed. The car-following model proposed by Gipps considers only the vehicle and its leader; the implementation of this model in Aimsun also includes the influence of certain vehicles driving slower in the adjacent lane on the vehicle driving along a section of road. The model determines a new maximum desired speed of a vehicle in the section, considering the mean speed of vehicles driving downstream of the vehicle in the adjacent slower lane as well as allowing a maximum difference of speed (Barcelo, 2011). The lane-changing model can be considered an evolution of the lane changing model proposed also by Gipps (1986), according to which the lane change is modeled as a decision process analyzing the desirability of a lane change.

This in the sense that the benefits of a lane change resulting from the attainment of the desired speed when the leading vehicle is slower, and the feasibility conditions for a lane change depending on the location of the vehicle in the road network are accomodated. For the list of the car following and lane-changing model parameters for freeways the reader is referred to Barcelo (2011).

In order to find the set of parameter values for the model that best reproduces local traffic conditions at the A22 Freeway, the default values for the model parameters were used in trial simulation runs for checking any coding error. However, the outcomes of the comparison between simulation and empirical data showed that the default parameters provided simulation outputs which did not emulate properly the existing traffic flow characteristics. The fine-tuning process involved the iterative adjustment of some parameters and simulation replications until the simulated pairs of speed and density, as closely as possible, matched the corresponding pairs observed in the field. Due to unrealistic simulation results in comparison to field observations when Aimsun default parameters were used, some parameters were changed, based on engineering knowledge and best practices. These parameters included the minimum headway, representing the time in seconds between the leader and the follower vehicle. The reaction time, or the time in seconds it takes a driver to react to speed changes in the preceding vehicle, and the minimum distance between vehicles or the distance, in metres, that a vehicle manteins between itself and the preceding vehicle when stopped.

After having explored different combinations of values for the parameters, a value of 1.70s was used for the minimum headway parameter instead of the default value of 2.10s, whereas a value of 0.8s was used for the reaction time parameter instead of the default value of 0.7s; for the minimum distance between vehicles a values of 1m was used instead of the default value of 1.10m, see table 2.7.

| Parameter | Default | Used | Levels | | |
|---|---|---|---|---|---|
| Minimum headway (seconds) | 2.10 | 1.70 | 1.70 | 1.90 | 2.10 |
| Minimum distance between vehicles (meters) | 1.10 | 1.00 | 1.00 | 5.00 | 10.00 |
| Reaction time – (seconds) | 0.70 | 0.80 | 0.70 | 0.80 | 1.00 |

Tab.2.7. Calibration parameters.

The calibration process also included the adjustments of the desired speeds, namely the maximum speed, in km/h, that a certain type of vehicle can travel at any point in the network. For example, a “car” vehicle type can be defined in Aimsun having as default values, a mean desired speed of 110km/h and a deviation of 10km/h; desired speed for each vehicle of this type is sampled from a truncated Normal distribution (10km/h, 110km/h). According to observational data for A22 Freeway and what was reported by Uddin and Ardekani (2002), the desired speeds on the inside lane were assumed to be lower than those in the passing lane; moreover, it was noted that the desired speed was sensitive to flow rate, tending to decrease as flow rate values became consistent (see Table 2.8).

| **Flow rate [pcu/h]** | **Desired speed (mean) [km/h]** | | |
|---|---|---|---|
| | **Inside lane** | **passing lane** | **roadway** |
| <1500 | 110 | 140 | 125 |
| 2000 | 100 | 140 | 115 |
| 2500 | 95 | 140 | 115 |
| >3000 | 90 | 130 | 115 |

Tab. 2.8. Adjustments for the desired speed.

In the simulation process, a 2km long freeway segment centered on the S. Michele observation section (southbound) was used, having the cross section of A22 Brenner Freeway (Italy) and a grade equal to 0.09%; the aforesaid length was chosen so that all vehicles introduced into the segment exited at the end of the segment and no traffic entered and exited in the middle. For the freeway segment, 10 simulation replications were performed for 7 different values of traffic flow, increasing with incremental steps of 500 veh/h from 500 veh/h to 3500 veh/h during a time interval of 4 hours; values of traffic variables generated during the first half-hour, namely the warm up period, were excluded, because they were considered related to a motion condition not fully operational, and therefore unreliable. A fleet of cars only was used, choosing them within the range of cars that Aimsun allows to select. With regard to traffic generation, in the Aimsun micro-simulator different headway models may be selected as interval distributions; the exponential distribution is the default distribution among different headway models and it was chosen to model time intervals between two consecutive arrivals of vehicles. The simulation data were collected by placing virtual detectors at exactly the same locations as detectors in the field. Furthermore, the simulated values were verified against the empirical values as indicated in the speed-density diagrams, where the plots of empirical and simulated data for S. Michele section (southbound) are shown in Figure 2.11, 2.12, 2.13; lnV-D$^2$ regression lines for observed and simulated data for S. Michele section (southbound) will be shown in the next section, in which issues on implementing the methodology for calibrating the traffic microsimulation model will be introduced.

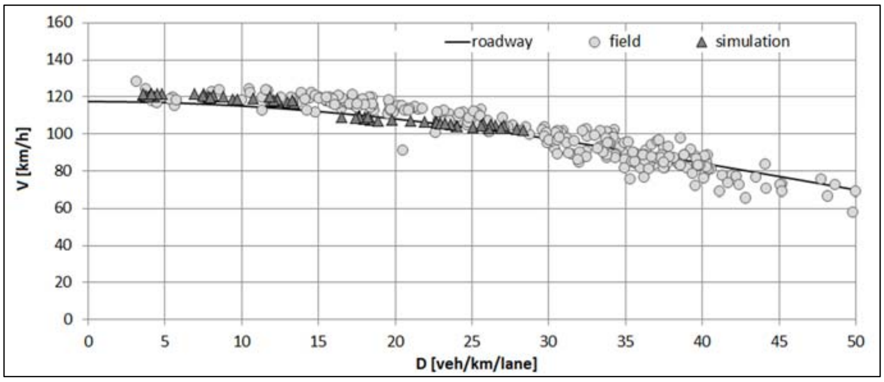


Fig. 2.11. Speed- density graph for carriageway with plot of field and simulated data.

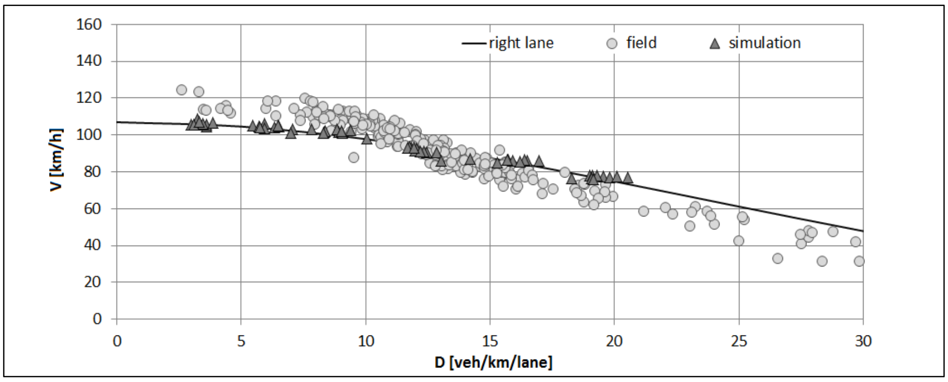


Fig. 2.12. Speed- density graph for the inside lane with plot of field and simulated data.

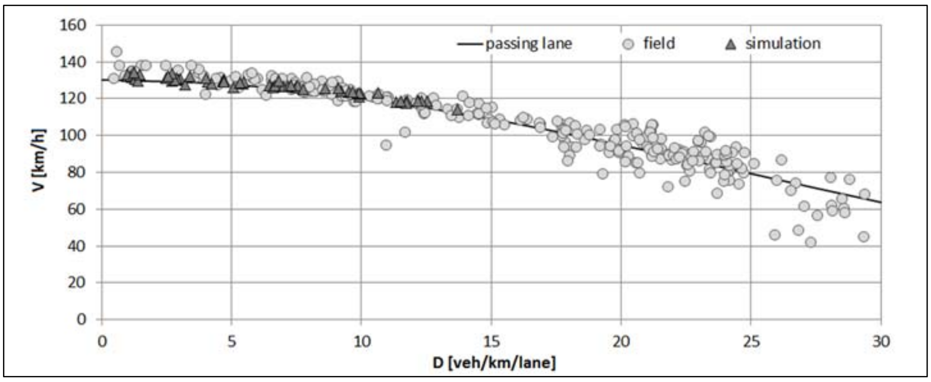


Fig. 2.13. Speed- density graph for the passing lane with plot of field and simulated data.

The GEH index, widely used in the case of microscopic simulation models, was calculated as an indicative criterion for acceptance (or otherwise rejection) of the model. The GEH statistic is used to represent goodness-of-fit of a model. It takes into account both the absolute difference and the percentage difference between the simulated and the observed flows.

The GEH statistic calculates the index for each counting station as follows:

$$GEH_i = \sqrt{\frac{2(x_i - y_i)^2}{x_i + y_i}}$$

where:

$x_i$ = the *i*th simulated speed;

$y_i$ = the *i*th observed speed.

For comparison purposes, each observed speed value was calculated from the speed-density equations in Table 2.6, as specified for the carriageway, the inside lane and the passing lane, by using the simulated values of density. The index is usually interpreted in the following terms: if the deviation of the simulated values with respect to the measurement is smaller than 5% in at least 85% of the cases, then the model is accepted. The fact that for the three case in Fig. 2.11, 2.12, 2.13 (i.e in the carriageway, the inside lane and the passing lane), each GEHi resulted less than 5 (and equal to 1) would lead to the conclusion that the model could be accepted as significantly close to the reality.

## II.5 HYPOTESIS TEST FORMULATION

A statistical approach based on observed and simulated speed-density relationships was applied in the calibration process to measure the closeness between empirical data and simulation outputs. The comparison established between the lnV-$D^2$ linear regressions for all simulated (speed/density) values and the corresponding linear regressions for the empirical data allowed the quality of the calibration of traffic microsimulation model to be evaluated. Thus, a statistical approach including hypothesis testing, using t-test and confidence intervals, was used as described briefly below. Suppose we observe, for i = 1,...,n, the measured variable $Y_i$ ($\ln V_i$) corresponding to certain values of the input variables $x_i$ ( $D_i^2$) and we want to use them with the objective of estimating the regression parameters ($\alpha$ and·β) in a simple linear regression model. If A and B are the estimators that we are searching for, then ($A + Bx_i$) is the estimator of the response variable corresponding to the input variable $x_i$. In order to get the distribution of the estimators A and B, additional assumptions necessarily have to be made. As a starting point the estimators A and B are usually assumed to be independent, normally distributed with zero mean and constant variance $\sigma$^2. Consequently, if for i = 1, 2, ..., n, the measured variable $Y_i$ is the response given to the input variable xi, we will assume that $Y_1, Y_2, \ldots, Y_n$ are independent and and $Y_i \sim N(\alpha+\beta x_i, \sigma^2)$.

Starting from the above proposition, a statistical test and confidence intervals for the regression parameter β were constructed. As it is well known the hypothesis to be tested is that β = 0 (the response does not depend on the input variable, i.e. there is no correlation between the two variables). It can be demonstrated that the statistic for the test here considered has a t distribution with n-2 degrees of freedom:

$$\sqrt{\frac{(n-2)\cdot S_{xx}}{SS_R}}\,\mathrm{B} \qquad \sim t_{n-2} \tag{2.11}$$

where $S_{xx}$ is $\sum_i x_i^2 - n\bar{x}^2$ and $SS_R$ is the sum of squared residuals. So, to test H0 : β = 0 against H1 : β ≠ 0, at the γ significance level, we have to:

reject $H_0$, if $\sqrt{\frac{(n-2)\cdot S_{xx}}{SS_R}}\,|\mathrm{B}| > t_{\frac{\gamma}{2},n-2}$

accept $H_0$ otherwise.

Thus an interval containing $\beta$, at the $1\text{-}\gamma$ confidence level, is the following:

$$\left(B - t_{\frac{\gamma}{2},n-2}\cdot\sqrt{\frac{SS_R}{(n-2)\cdot S_{xx}}},\, B + t_{\frac{\gamma}{2},n-2}\cdot\sqrt{\frac{SS_R}{(n-2)\cdot S_{xx}}}\right) \tag{2.12}$$

The determination of the confidence intervals and statistical tests for the regression parameter $\alpha$ was obtained as for $\beta$. So, the confidence interval at the 1- $\gamma$ level is given by:

$$A \pm t_{\frac{\gamma}{2},n-2} \cdot \sqrt{\frac{SS_R \cdot \sum_i x_i^2}{n(n-2)S_{xx}}} \qquad (2.13)$$

Table 2.9 shows the coefficient estimates and goodness-of-fit for lnV-$D^2$ regression lines (observed and simulated) for S. Michele section (southbound), for the carriageway, the inside lane and the passing lane; on each set of data, statistical inference on the regression parameters (intercept and slope) was performed by means of a t-test at the significance level of 5%. GEH index was calculated again for each pair ($V_{obs}$, $V_{sim}$) obtained from the regressions in Table 2.9; only under saturated conditions (D<Dc) were considered. In all the cases we obtained GEH = 100%. A $\chi^2$ test was also performed considering the percentage of occurrence of a class of speed both for the field case and for the simulated one in Table 2.9. In all the cases (i.e. the carriageway, the inside lane and the passing lane) the test showed that the two populations (observed and simulated) did not differ significantly at the 0.05 level of confidence:

- carriageway (50 degree-of-freedom)

$\chi^2 = 11.48 < \chi^2_{cr} = 67.5$;

- inside lane (25 degree-of-freedom)

$\chi^2 = 0.93 < \chi^2_{cr} = 37.7$;

- passing lane (25 degree-of-freedom)

$\chi^2 = 16.33 < \chi^2_{cr} = 37.7$;

| **Road** | | | **Parameter estimate (s.e.)** | **t (t pr.)** |
|---|---|---|---|---|
| Roadway | field | $\beta_0$ | 4.7726 (0.0100) | 477.26 (<.001) |
| | | $\beta_1$ | -0.0002139 (0.000004) | -53.47 (<.001) |
| | sim | $\beta_0$ | 4.7972 (0.00362) | 1325.19 (<.001) |
| | | $\beta_1$ | -0.00024417 (0.00000951) | -25.67 (<.001) |
| Inside lane | field | $\beta_0$ | 4.6540 (0.0109) | 426.97 (<.001) |
| | | $\beta_1$ | -0.00084291 (0.0000185) | -45.56 (<.001) |
| | sim | $\beta_0$ | 4.6744 (0.00431) | 1084.56 (<.001) |
| | | $\beta_1$ | -0.00088134 (0.0000219) | -40.24 (<.001) |
| Passing lane | field | $\beta_0$ | 4.8789 (0.0112) | 435.62 (<.001) |
| | | $\beta_1$ | -0.00082173 (0.0000160) | -51.36 (<.001) |
| | sim | $\beta_0$ | 4.8819 (0.00183) | 2667.71 (<.001) |
| | | $\beta_1$ | -0.0007380 (0.0000248) | -29.76 (<.001) |

Table 2.9. Coefficients estimates and goodness-of-fit for S. Michele section.

Comparing the two regression lines (observed and simulated), including statistical confidence areas, a significant overlapping of the regression curves can be seen as shown in Fig. 2.14.

It is worthwhile to note that the simulated data resided almost entirely within the confidence band of the regression line fitted to the observed data. Thus the microsimulation model was able to reproduce the real phenomenon of traffic flow within a wide sufficiently range of operations, from the free flow conditions until reaching almost the critical density. At the same time we argue that the methodology has showed that, if only one regime of traffic flow (for example, the congested flow conditions) had been considered, we would not have had any assurance of the ability of the model to reproduce, just as well, the real operations at different regimes of traffic flow. It should be emphasized the exploratory nature of the analysis carried out in this study in which, among all models analyzed, only the single-regime model was considered having the accuracy and consistency to interpret the experimental data which covered the three traffic regimes (i.e., free-flow, congested, and queue discharge), and to represent the operating conditions for each lane and the entire roadway.

Nevertheless, in order to improve the calibration process, one can hypothesize that modelling separately of the inside lane and the outside lane is preferable and a further survey should be conducted to relax the single-regime assumption.

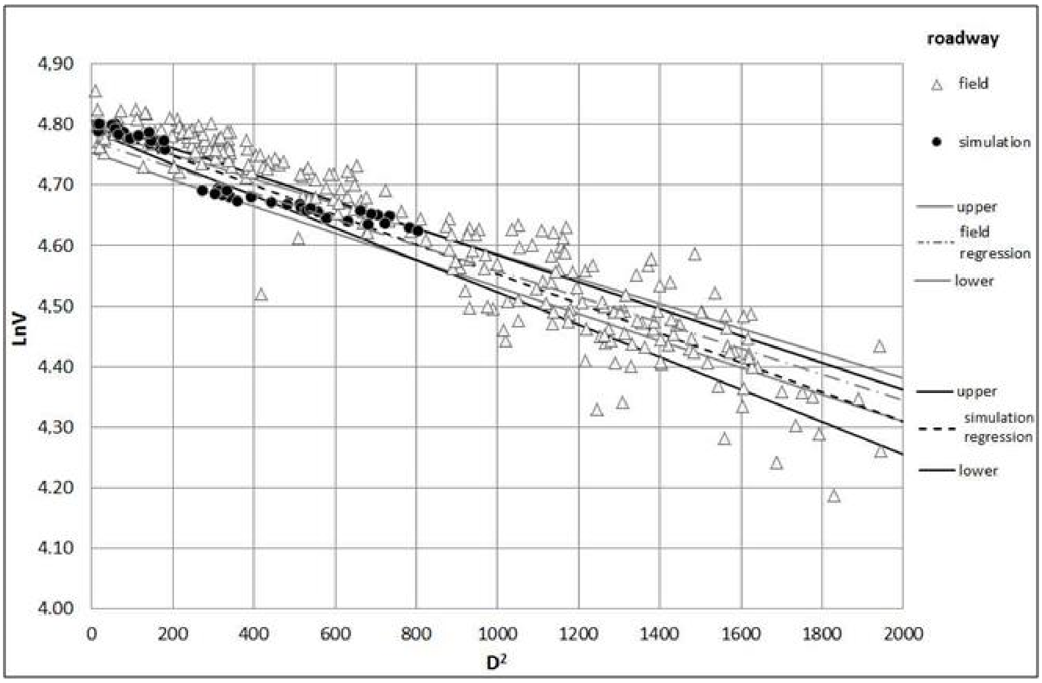


Fig. 2.14. Roadway- S. Michele section (southbound): plots of field and simulated data.

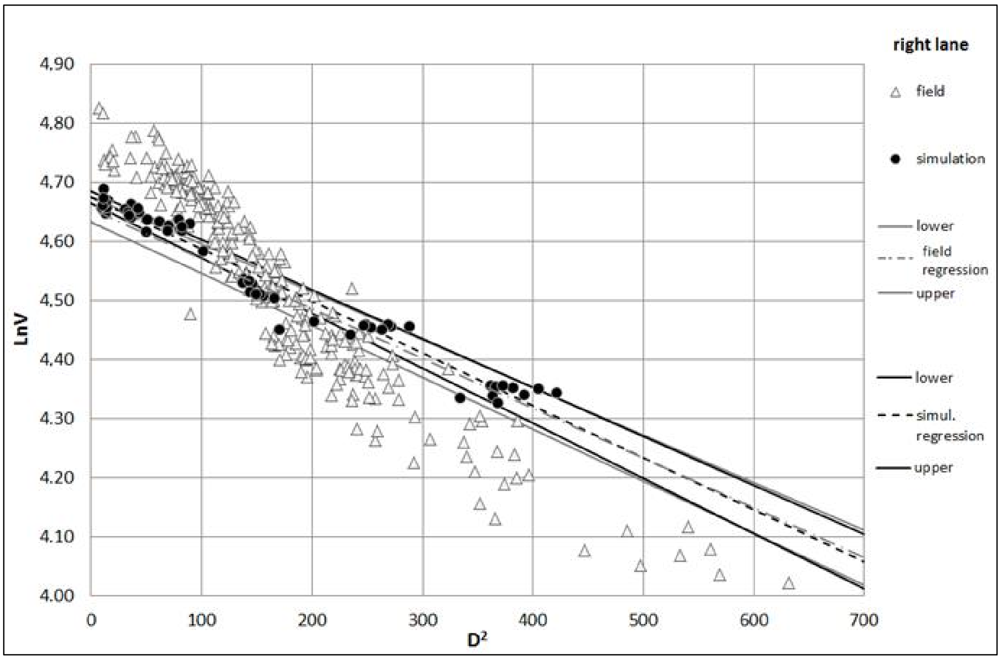


Fig. 2.15. Inside lane- S. Michele section (southbound): plots of field and simulated data.

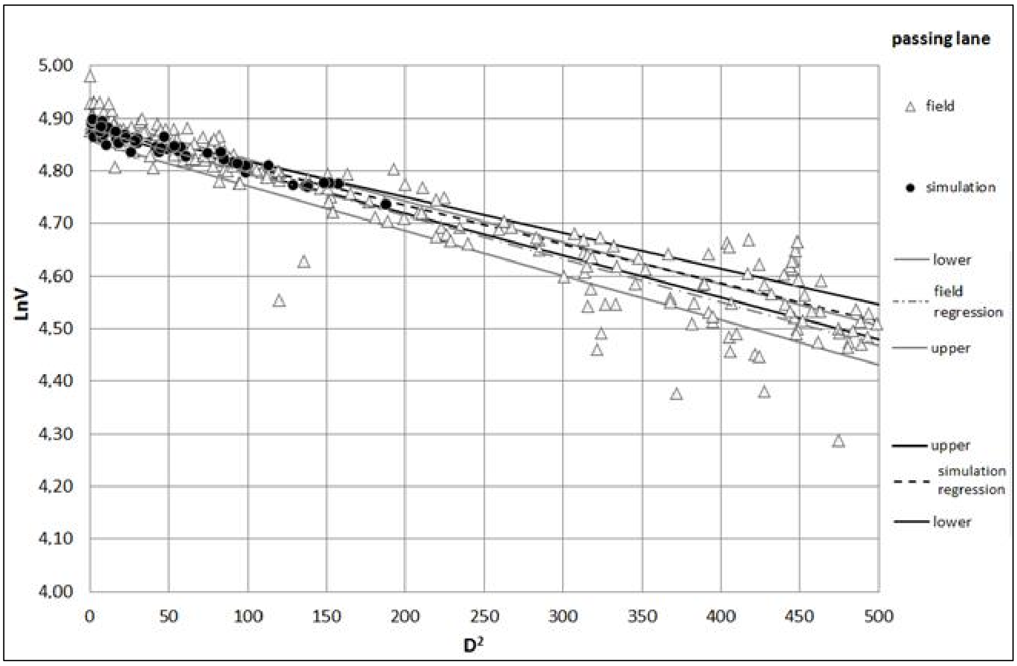


Fig. 2.16. Passing lane- S. Michele section (southbound): plots of field and simulated data.

## II.6. DISCUSSION AND CONCLUSION

In this chapter a methodology using speed-density relationships in the microsimulation calibration process is described. Statistical analysis technique of pattern recognition was used to evaluate the match of speed-density relationships from field and simulation. Traffic patterns were implemented developing relationships between the variables of traffic flow for empirical and simulated data: for the former we referred to traffic data observed at A22 Freeway (Italy); for the latter, Aimsun software was applied to test freeway segment in uncongested traffic conditions for a fleet of cars only. Different to the methodologies referred in the technical literature on this topic, this research proposed a measure of the closeness between empirical data and simulation outputs was achieved through a statistical approach which included hypothesis testing and confidence intervals. Encouraging results were obtained from the comparison of the observed and simulated data; indeed, a substantial overlapping of the regression lines was obtained and the simulated data resided almost entirely within the confidence band of the regression line fitted to the empirical data. Thus we stated that the microsimulation model was able to reproduce the real phenomenon of traffic flow within a wide range of operations (from free flow conditions until sufficiently reaching almost the critical density). Conversely, the proposed methodology showed that, if only one regime of traffic flow (free flow or congested conditions) had been considered, we would not have had any assurance on the ability of the model to reproduce, as well, the real operations at different regimes of traffic flow. Finally, the deepening of the model calibration as presented in this work has led the authors to develop an approach which considers a much wider landscape summarized in the following: i) first, although the results of the calibration process may seem satisfactory, the analyst does not have any guarantee of his/her work: he/she may have changed (or, in the extreme, forced) some parameters, and may have neglected other parameters that are even more important. However, it must be said that this risk can be contained when information for the calibration process is derived from the speed-flow, speed-density, or flow-density graphs, since a higher number of parameters can be submitted to the calibration process, resulting in interrelated and improvement on the fine-tuning of a simulation model. Moreover, the above relationships provide information about the free-flow, congested, and queue discharge regions, which cannot be achieved from a single numerical value or a distribution of capacities; ii) secondly, although the microsimulation model gave us data that, on the whole, belong to the population of the observed data, some doubts could relate to what was developed for the inside lane. One single model which fits the empirical data both for the inside lane and the passing lane, as well as for the entire carriageway, does not always represent the best choice. The empirical observations have gradually led to consider that modeling the speed-density relationship (and the associated fundamental diagram) could be improved differentiating by each lane; for example, this can be achieved with regard to the capability of the model (single or multi regime) to fit empirical data reasonably well over the entire range of a traffic variable (i.e. flow, speed or density). The inability of single regime models to perform well over the entire range of density may prompt thinking about fitting the data at intervals through multiple equations; iii) thirdly, another question to be investigated further relates to the traffic generation. Starting the simulation run, the system is empty; based on the input volumes and an assumed headway distribution, vehicles enter the network from centroids. Although in microsimulation one may choose among different headway models (exponential, uniform, normal, constant, etc.), the default distribution is usually preferred. However, the choice of the distribution should not be so automatic, instead it should depend on how much complexity is desired to interpret traffic behavior. Indeed, Poisson distribution for vehicle counts and negative exponential distribution for time headways are only applicable when no interaction between the vehicles occurs, thus enabling them to move at random (i.e. traffic flows are light). However as traffic becomes heavier the interaction between vehicles increases, therefore vehicles are restricted in their driving freedom; moreover, the exponential distribution provides nonzero probabilities even for very small values of headways. In order to improve the capability of microsimulation models to replicate the real traffic phenomenon, distributions different from the exponential should be used; where poor agreement between the frequencies of observed headways and those predicted by the negative exponential distribution (as well as theoretical considerations precluding very short headways). It follows that in microsimulation the use of one of the default headway distributions can produce inappropriate choices in traffic generation, and a user-defined program can be required to feed the network with vehicles not without further computational effort and time.

# III. DEVELOPING PASSENGER CAR EQUIVALENTS BY MICROSIMULATION

Passenger car equivalents (PCEs) for heavy vehicles are used to convert a mixed vehicle flow into an equivalent flow composed exclusively of passenger cars. In transportation engineering their calculation is relevant to capacity and level of service determinations, since incorporating the impact of heavy vehicles on freeway operations make the performance analysis of a specific road infrastructure more accurate. Heavy vehicles, indeed, differ from passenger cars for size and acceleration/deceleration abilities; these different (physical and operational) characteristics can result in different driving behaviour depending on the vehicle class in a traffic stream where the distribution of vehicles among the classes is, in any case, influenced by location in the network and time of day. Due to their larger size and manoeuvring difficulties, heavy vehicles also impose a psychological and practical impact of drivers in adjacent lanes (Anwaar et al., 2011; Roess et al. 2014). The impact of heavy vehicles on freeway operations has been a topic of interest since the first edition of the Highway Capacity Manual (HCM). The recent versions of the HCM (2000, 2010) provide different values of passenger car equivalents for heavy vehicles depending on the percentage of heavy vehicles, different grades, and grade length for freeways and highways. Addressing the heavy vehicles effect on different types of highway facilities, passenger car equivalents are intended for use in level-of-service (LOS) analyses. However, assuming the values of passenger car equivalents as the HCM (2010) suggests, both underestimation or overestimation of the effect of heavy vehicles on the quality of the traffic flow may occur.

Various methodologies have been used to calculate the passenger car equivalents for heavy vehicles for different types of facilities. Definitions of equivalency based on the heavy vehicle effect on different parameters have been proposed. The determination of passenger car equivalents, indeed, include methods based on flow rates and density (John and Glauz, 1976; Huber, 1982; Krammes and Crowley, 1987; Sumner et al., 1984; De Marchi and Setti, 2003; Webster and Elefteriadous, 1999), headways (Werner and Morrall, 1976; Anwaar et al., 2011), queue discharge flow (Al-Kaisy et al., 2002), speed (Hu and Johnson, 1981), delay (Craus et al., 1980; Cunagin and Messer, 1983), volume/capacity ratio (Linzer et al., 1979), platoon formation (Elefteriadou et al. 1997; Van Aerde and

Yagar, 1984; Al-Kaisy et al. 2002) and travel time (Keller and Saklas, 1984). However, significant differences can be found among the values of PCE factors from different methods especially in heterogeneous traffic environment; see e.g. Adnana (2014). Only a few studies have been based on field data; most current published studies and research used traffic simulation to obtain equivalent flows for a wide combination of flows and geometric conditions.

In operational analysis of freeways PCEs calculations should be based on density, since it is used to define LOS for freeways (HCM, 2010). In this regard, Huber (1982) proposed a framework for PCEs derivation based on finding a flow rate of a base stream of passenger cars only and a flow rate of a mixed stream $Q_M$ containing $Q_M \cdot p_T$ heavy vehicles and $Q_M \cdot (1 - p_T)$ cars, having the same level of a measure of impedance. Huber (1982), indeed, used some measure of impedence as a function of traffic flow to relate one traffic stream of heavy vehicles mixed with passenger cars and another traffic stream of passenger cars only. PCE values were related to the ratio between the volumes of the two streams at some common level of impedance (i.e. the density of both streams). A different approach from Huber (1982), was adopted by Sumner et al. (1984) who measured the impedance by the number of vehicle-hours in the base and mixed streams, which is equivalent to density as a measure of impedance. They used microscopic simulations to expand the Huber procedure to calculate the PCE of each type of vehicle in a mixed traffic stream taking into account the different types of heavy vehicles, in addition to passenger cars. Webster and Elefteriadou (1999), in turn, expanded the work of Sumner et al. (1984) by including a wide range of freeway conditions and derived PCEs based on density. It is noteworthy that the HCM (2010) utilizes PCEs to estimate the effect of heavy vehicles on traffic stream behaviour under free-flow or undersaturated conditions. Moreover, these factors have been used to conduct analyses for all traffic conditions (from free-flow to through congested-flow conditions). A growing body of recent empirical evidence suggests that the PCEs for undersaturated conditions can underestimate the effect of heavy vehicles after the onset of congestion (Al-Kaisy et al., 2005). One must say that the acceleration and deceleration cycles, as normally experienced during congestion or stop-start conditions, impose an extra limitation on the performance of heavy vehicles. In this regard, few studies have been conducted to explore the effect of heavy vehicles also for forced-flow conditions (Ahmed, U., 2010). Al-Kaisy et al. (2002) derived PCEs using queue discharge flow as the equivalency criterion; however, they are still far from a generalization in the results, albeit these findings were consistent with field observations as experienced by Yagar and Richard (1996).

This research proposes the steps of the methodological approach to estimate the PCEs in terms of their effects on the operations of a basic freeway section. There are two detailed objectives for this research: i) to investigate the influence of a range of traffic, road design, and vehicle characteristics on PCEs; ii) to propose a set of PCE values to be used in analyzing the operation of basic freeway sections. Since the variation of the traffic quality had to be evaluated including different percentages of heavy vehicles in the traffic demand, a simulation model has been used to isolate traffic conditions difficult to observe in the field, to replicate them to generate a significant amount of data, and to quantify the fundamental variables of traffic flow, namely the speed, flow, density, for a test freeway segment. Using Aimsun software it was possible to account for the wide range of traffic conditions on the freeway segment selected as case study. The process of finding the best model parameters was accomplished by a calibration procedure that used traffic data observed at A22 Brenner Freeway (Italy). In order to check to what extent the model replicated reality, the validation of the calibrated model was also addressed. Simulated data were then used to develop the relationships among the variables of traffic flow and to calculate the passenger car equivalents for heavy vehicles by comparing a fleet of passenger cars only with a mixed fleet, having different percentages of heavy vehicles.

## III.I CALCULATION OF PCEs: A LITERATURE REVIEW

As already mentioned in the introduction, various methodologies have been used to calculate the passenger car equivalents for heavy vehicles. Particularly, the transportation literature proposes several different methods to calculate PCEs throughout the evolution of highway capacity analysis. These methods have been applied for different cases and situation such as for two lane highways and multilane highways or freeways.

### III.1.1 PCEs IN THE 1965 HCM

In the 1965 HCM, which was the second edition of the HCM, is introduced the concept of LOS and the definition of PCE. In the 1965 HCM, PCE was defined as "The number of passenger cars displaced in the traffic flow by a truck or a bus, under the prevailing roadway and traffic conditions" (Elefteriadou et al, 1997). The 1965 HCM used relative speed reduction to define PCEs for two lane highways and quantified this by the relative number of passings known as the Walker method. For multilane highways, PCEs were based on the relative delay due to trucks.

The relative delay due to trucks was calculated using the Walker method for two-lane highways in conjunction with gradability curves and field observations. Gradability curves relate speed distribution to grades of specific length and percent. Steeper grades and longer grades result in a more drastic speed reduction. Cunagin and Messer (1983) suggested that the gradability curve used to calculate PCEs in the 1965 HCM. was based on a truck with a weight to power ratio of 198 kg/kW (325 lb/hp), which was considered typical for trucks of the time. However, Roess and Messer (1984) emphasized that the normal truck assumed in the 1965 HCM was of 122 kg/kW (200 lb/hp). Regardless of which truck was assumed, the gradability curve was eventually considered obsolete for vehicle performance calculations and was updated in subsequent years. PCEs for multilane highways based on relative delay may be found as:

$$E_T = \frac{(D_{ij} - D_B)}{D_B} \tag{3.1}$$

where $D_{ij}$ is the delay to passenger cars due to vehicle type i under condition j and $D_B$ is the base delay to standard passenger cars due to slower passenger cars.

PCEs in the 1965 HCM were reported for grades of specific length and percent, proportion of trucks, and LOS grouped as A through C or D and E. As expected, the highest PCE was reported for the longest and steepest grade with the highest proportion of trucks and the lowest LOS. However, in many cases the PCE for a given grade and LOS decreased with increasing proportion of trucks. This result has been obtained by many other researchers, as mentioned below.

### III.1.2 PCEs BASED ON DELAY

In 1983, it was used an extension of the 1965 HCM method to calculate PCEs for multilane highways based on relative delay. In their approach, they used a combination of the Walker method of relative number of passings and the relative delay method. They recognized that on multilane highways, passing vehicles or overtaking vehicles are inhibited only by concurrent flow traffic. PCEs were calculated as:

$$E_T = \frac{(OT_i/VOL_i)[(1/SP_M)-(1/SP_B)]}{(OT_{LPC}/VOL_{LPC})[(1/SP_{PC})-(1/SP_B)]} \qquad (3.2)$$

where $OT_i$ is the number of overtakings of vehicle type i by passenger cars, $VOL_i$ is the volume of vehicle type i, $OT_{LPC}$ is the number of overtakings of lower performance passenger cars by passenger cars, $VOL_{LPC}$ is the volume of lower performance passenger cars, $SP_M$ is the mean speed of the mixed traffic stream, $SP_B$ is the mean speed of the base traffic stream with only high performance passenger cars, and $SP_{PC}$ is the mean speed of the traffic stream with only passenger cars.

Since at low traffic volumes faster vehicles will not likely be impeded in overtaking other vehicles, equation (3.2) was used omitting the bracketed expression. However at higher traffic volumes, such as near capacity, slower overtaking vehicles will impede faster vehicles. This results in queue formation in the passing lane. In their research, Cunagin and Messer (1983) applied a linear combination of equation (3.2) with and without the bracketed expression for intermediate volumes.

The authors examined three different grade conditions, flat, moderate, and steep. In addition, they examined proportion of trucks and volume levels corresponding to each of the five LOS categories. The PCEs developed, increased relative to the proportion of trucks and volume levels in flat and moderate grade conditions. However, in steep grade conditions, the PCEs decreased for increasing proportion of trucks.

### III.1.3 PCEs IN THE TRB CIRCULAR 212

The TRB Circular 212 titled "Interim Materials on Highway Capacity" was published in 1980, as an effort to summarize the current knowledge in highway capacity and to identify needs for immediate research before the completion of the planned third edition of the HCM (HCM, 2000). PCEs reported in TRB Circular 212 were developed based on the constant v/c method. Linzer et al. (1979) describes the constant v/c method, whereby PCEs are calibrated such that the mixed traffic flow will produce the same v/c ratio as a passenger car only flow.

The design chart relates the percent grade, mixed vehicle flow, and percent reference trucks to percent capacity (equivalent to v/c ratio). The PCE is formulated as:

$$E_T = \frac{q_B - q_M(1-P_T)}{q_M \times P_T} \qquad (3.3)$$

where $q_B$ is the equivalent passenger car only flow rate for a given v/c ratio, $q_M$ is the mixed flow rate, and $P_T$ is the proportion of trucks in the mixed traffic flow.

St John and Glauz (1976) introduced the concept of percent reference trucks to account for the variability of truck performance characteristics by truck type. This was accomplished by aggregating all truck types into a single reference truck. The Ohio Department of Transportation provides an excellent copy of the most common vehicle classification scheme on their website. The Federal Highway Administration (FHWA) also follows this vehicle classification scheme whereby trucks are considered to be vehicle types 5 through 13; the FHWA vehicle classification scheme is also available online. For any given truck population, they derived weighting factors to compute the percent reference trucks. The derived weights were based on the performance of each truck type relative to the slowest speed truck. The higher the weight factor, the worse performing the subject truck is compared to the slowest speed truck. The following equation for percent reference trucks is:

$$\textit{Percent reference trucks} = P_T(3.16p_{10} + 1.41p_9 + 0.14p_8 + 0.06p_7)$$

where $P_T$ is the total proportion of trucks and $p_i$ is the proportion of index truck type i out of the total proportion of trucks.

The typical truck used in calculation of PCEs for the TRB Circular 212 by Linzer et al (1979) was of 183 kg/kW (300 lb/hp), slightly lower than the 198 kg/kW (325 lb/hp) truck used in the 1965 HCM, and reflecting the increased performance of trucks since the 1960's. In addition, a light truck of 91.4 kg/kW (150 lb/hp) and a heavy truck of 213.2 kg/kW (350 lb/hp) were used to calculate PCEs. Truck performance curves were used from research conducted by Pennsylvania State University, with initial truck speed of 88.5 km/h (55 mi/h). Since the research calculated PCEs for truck populations with a single weight to power ratio, the percent reference trucks method proposed by the MRI was used by assuming that only trucks of the given weight to power ratio existed.

Results of the constant v/c method for calculating PCEs indicated that PCEs did not alter significantly for changes in the v/c ratio or the freeway design speed. For this reason, PCEs reported in the TRB Circular 212 were given according to percent grade, length of grade, and percent trucks just as they had been in the 1965 HCM. In addition however, PCEs were calculated for freeways with six or more lanes as well as typical freeways with four lanes. The need to calculate PCEs for different freeway sizes (number of lanes) arose from cases of high proportion trucks and/or steep grades. PCEs developed by Linzer et al exhibit a decrease for increasing percent trucks.

### III.1.4 PCEs BASED ON SPEED

As an extension to his research on truck performance on upgrades, St John (1976) proposed a non-linear truck factor. This non-linearity addressed the successively smaller impact of trucks on the traffic stream as the proportion of trucks increased. He reasoned that as the proportion of trucks increases platoons may form and the interaction with cars may be reduced. In addition, he asserted that the effect of multiple truck types highlights the need for a non-linear truck factor. The truck factor was based on a speed flow relationship. He introduced the concept of equivalence kernel, which accounts for the incremental effect of trucks in a traffic stream and is used to calculate PCEs.

In a report published in 1981, Hu and Johnson (1981) described how to use the 1965 HCM to find PCEs based on speed. According to their report, PCEs are used to convert a mixed vehicle flow into a passenger car only flow with the same operating speed. They used equation (3.3) developed by Linzer et al to calculate the PCE. Operating speeds were based on the design charts obtained by research performed by the MRI, as described in the section on the TRB Circular 212. Hu and Johnson (1981) did not use specific grade adjustments, but rather developed their PCEs based on extended freeway segments.

Later, Huber (1982) derived equation (3.3) in a different functional form to relate PCE to the flow of a passenger car only traffic stream and a mixed vehicle traffic stream. The effect of trucks is quantified by relating the traffic flows for an equal LOS. Any equivalent LOS or impedance could be chosen for the equality. If for example, density was used to define the equal LOS criteria, the flow-density relationship could be used to relate the traffic flows at an equal density value. Huber’s basic equation is formulated as:

$$E_T = \frac{1}{P_T}\left(\frac{q_B}{q_M} - 1\right) + 1 \qquad (3.5)$$

where $P_T$ is the proportion of trucks in the mixed traffic flow, $q_B$ is the base flow rate (passenger cars only), and $q_M$ is the mixed flow rate. Huber used the assumption of statistically similar average travel time as the measure of LOS. Equal average travel time on a one-mile segment is equivalent to the inverse of the average speed. The consequence of his assumption of equal speed is that PCEs decrease as volumes increases. A slow moving truck will have a smaller impact on the average speed when the total volume is higher. Huber took this result objectionable and suggested that equal total travel time be used as a measure of LOS. He formulated equal total travel time as the volume in vehicles per hour multiplied by the average travel time in hours per mile. By this representation, equal total travel time is equivalent to equal density because it describes equal vehicle occupancy on the roadway in vehicles per mile. The calculation of PCE by equal density is discussed later.

Sumner et al (1984) calculate the PCE of a single truck in a mixed traffic stream, which includes multiple truck types. This calculation requires an observed base flow, mixed flow, and flow with the subject vehicles. The equal LOS or impedance measure would cut across all three flow curves. The relationship described is formulated as:

$$E_T = \frac{1}{\Delta P}\left(\frac{q_B}{q_s} - \frac{q_B}{q_M}\right) + 1 \tag{3.6}$$

where $\Delta P$ is the proportion of subject vehicles that is added to the mixed flow and subtracted from the passenger car proportion, $q_B$ is the base flow rate (passenger cars only), $q_M$ is the mixed flow rate, and $q_S$ is the flow rate including the added subject vehicles. The authors used total travel time in terms of vehicle hours as the equal measure of LOS. In this case total travel time was applied to urban arterial roads and measured in terms of vehicle hours, which is not equivalent to density.

Using the formulation in equation (3.6), Elefteriadou et al (1997) calculated PCEs for freeways, two-lane highways, and arterials based on equal speed. The researchers also examined the impact of prevailing traffic flow, proportion of trucks, truck type (by length and weight to power ratio), length and percent grade, and number of freeway lanes in their evaluation. Their analysis was based on specific truck types, and not truck populations. The results of the analysis indicated that PCEs remain mostly unchanged for increasing traffic flow on freeway segments while PCEs remain unchanged or slightly increase with increasing proportion of trucks. The report did not indicate the impact of the number of freeway lanes on the PCE.

In 1984, it was developed a methodology to calculate PCE based on relative rate of speed reduction (Van Aerde and Yagar, 1984). This PCE was intended for use in average speed analysis of capacity, which is unique to two lane highways. Field observations and known speed-flow relationships were used to calibrate a multiple linear regression model that estimates the percentile speed based on the free speed and speed reduction coefficients for each vehicle type. A linear speed-flow model was chosen because the speed-flow relationship within the bounds of practical operating volumes was found to be nearly linear. The multiple linear regression model is:

*Percentile speed = free speed +* $C_1$*(number of passenger cars) +* $C_2$*(number of trucks) +* $C_3$*(number of RVs) +* $C_4$*(number of other vehicles) +* $C_5$*(number of opposing vehicles)*

where coefficients $C_1$ to $C_5$ are the relative sizes of speed reductions for each vehicle type. Although this model was formulated for two lane highways with opposing traffic flow, it could be applied to multilane highways by setting the coefficient $C_5$ to zero. Using the speed reduction coefficients, the PCE for a vehicle type n is calculated as:

$$E_n = \frac{C_n}{C_1} \tag{3.7}$$

where $C_n$ is the speed reduction coefficient for vehilce type n and $C_1$ is the speed reduction coefficient for passenger cars.

### III.1.5 PCEs IN THE 1985 HCM

PCEs in the 1985 HCM were calculated for trucks of 61, 122, and 183 kg/kW (100, 200, and 300 lb/hp) with 122 kg/kW (200 lb/hp) being considered the normal truck population (Roess and Messer, 1984). The consideration of freeway size, introduced in the TRB Circular 212, was retained in the 1985 HCM. The shift of the typical truck from 183 to 122 kg/kW (300 to 200 lb/hp) was inspired by indications that the average truck population on freeways was between 76 and 104 kg/kW (125 and 170 lb/hp). Besides this change, the approach to calculating PCE based on v/c ratio in the TRB Circular 212 remained unchanged in the 1985 HCM.

### III.1.6 PCEs BASED ON V/C RATIO

After the publication of the 1985 HCM, the constant v/c method for calculating PCE subsided. The constant v/c method was most appropriate when LOS was defined primarily in terms of v/c ratio; however, since LOS is now defined primarily by density, the constant v/c method is no longer favorable. Traffic streams with an equal v/c ratio will not necessarily have equal density and speed and therefore LOS. However, this method was applied in 1989 to calculate PCEs for expressways in Singapore. He reasoned that although density was used to define LOS for freeways, capacity analysis performed with PCEs would still be desirable to be based on the v/c ratio. The functional form of his relationship was a multiple linear regression equation whereby the v/c ratio was related to the PCE multiplied by the observed flow of each vehicle type. The target v/c ratio to compute PCE was at 0.67 to 1.0, corresponding to LOS D or E. Fan pointed out that for capacity analysis it would be unimportant to calculate PCEs at v/c ratios well below capacity. The results of the research by Fan were PCEs for multiple vehicle types.

### III.1.7 PCEs Based on Headways

Headways have been used for some of the most popular methods to calculate PCEs. Therefore, Werner and Morrall (1976) suggested that the headway method is best suited to determine PCEs on level terrain at low levels of service. The PCE is calculated as:

$$E_T = \left(\frac{H_M}{H_B} - P_C\right)/P_T \qquad (3.8)$$

where $H_M$ is the average headway for a sample including all vehicle types, $H_B$ is the average headway for a sample of passenger cars only, $P_C$ is the proportion of cars, and $P_T$ is the proportion of trucks. In their study, they used the headway method for low speed trucks and the conventional speed method of the 1965 HCM for higher speed trucks. One question arises as to use of the headway method for low speed trucks when low speeds generally occur on upgrades rather than on level terrain. The results of the study replicated PCEs in the 1965 HCM for higher speed trucks. PCEs were categorized by percent grade, length of grade, and LOS grouped A and B, C, or D and E.

In 1982, it was revealed that the presence of trucks in the traffic stream of a freeway resulted in increased average headways (Cunagin and Chang, 1982). The largest headways involved trucks following trucks, and the headways increased for larger truck types. Seguin et al (1982) formulated the spatial headway method for calculating PCEs. This method defines the PCE as the ratio of the mean lagging headway of a subject vehicle divided by the mean lagging headway of the basic passenger car and is formulated as:

$$E_T = \frac{H_{ij}}{H_B} \tag{3.9}$$

where $H_{ij}$ is the mean lagging headway of vehicle type i under conditions j and $H_B$ is the mean lagging headway of passenger cars. The lagging headway is determined from the rear bumper of the lead vehicle to the rear bumper of the following vehicle and therefore includes the following vehicle's length.

The constant volume to capacity method, equal density method, and spatial headway method were compared in 1986 in an article by Krammes and Crowley (1987). The authors concluded that the spatial headway method was most appropriate for level freeway segments. Particularly the authors point out that the spatial headway method not only accounts for the accepted effect of trucks due to size and lower performance, but also the psychological impact of trucks on drivers of other vehicles. This impact is in the form of aerodynamic disturbances, splash and spray, sign blockage, off tracking, and underride hazard. So, spatial headway is considered a surrogate measure for density. Both of which reflect the freedom of maneuverability in a traffic stream. A modification to equation (3.5) put forth by Huber to calculate PCE based on flow rate allows the calculation of PCE based on headway. The equation uses the lagging headway because it is the following vehicle's perception of maneuverability that affects the PCE. Contradictory to the findings of Cunagin and Chang (1982), the lagging headway for trucks following trucks was found to be significantly lower than the lagging headway for cars following trucks. Therefore, contrasting the recommended equation (3.9), the authors suggest that PCE should be calculated as:

$$E_T = [(1 - P_T)H_{TP} + pH_{TT}]/H_P \tag{3.10}$$

where $P_T$ is the proportion of trucks, $H_{TP}$ is the lagging headway of trucks following passenger cars in the mixed vehicle stream, $H_{TT}$ is the lagging headway of trucks following trucks in the mixed vehicle stream, and $H_P$ is the lagging headway of cars following either vehicle type in the mixed vehicle stream. An improvement over equation (3.9) recommended by Seguin is that the proportion of trucks is considered in equation (3.10).

The authors believe that an increase in the proportion of trucks will result in higher PCEs because the opportunity for interaction between cars and trucks will increase.

A drawback of the headway method is that it must be assumed that drivers are exhibiting steady state, in lane behavior. It would be difficult therefore to separate the headways observed from drivers who are either not in steady state, or are not maintaining the lane (continuously following the same vehicle). Specific to multilane highways, it is less likely that cars will continue to follow trucks given the first opportunity to pass.

### III.1.8 PCEs Based on Queue Discharge Flow

In 2002, Al-Kaisy et al (2002) published a report describing the calculation of PCE using measurements of queue discharge flow. The hypothesis of their theory was that the effect of trucks on traffic is greater during congestion than during under saturated conditions. The congested condition is represented by queue discharge flow, where the v/c ratio is equal to one. A primary assumption of their work was that queue discharge flow capacity is constant except for the effect of trucks in the traffic stream. The authors used field observations and linear programming to determine the PCE. For the case studies in their analysis, they did not find a relationship between PCE and the proportion of trucks. However, the authors theorized that the PCE should decrease with increasing proportion of trucks because the interactive effect of trucks on trucks may be lower than the effect of trucks on passenger cars.

### III.1.9 PCEs BASED ON DENSITY

As already mentioned, Huber (1982) introduced the concept of using equal density to relate mixed flow rate and base flow rate for calculation of PCE in equation (3.5). The drawback of Huber's computation is that it assumes the mixed vehicle flow contains passenger cars and only one type of truck. However, the formulation in equation (3.6) allows the calculation of the PCE of a single truck in a mixed vehicle stream including multiple truck types. As applied to freeways, density is the most common equal measure of LOS, and Webster and Elefteriadou (1999) used this method to calculate PCEs for trucks in 1999. Their approach was to use simulation modeling to calculate the flow verses density relationships.

Again, the researchers examined the impact of prevailing traffic flow, proportion of trucks, truck type (by length and weight to power ratio), length and percent grade, and number of freeway lanes in their evaluation. The results of the analysis indicated that PCEs increase with increasing traffic flow on freeway segments and decrease with increasing proportion of trucks and number of lanes. The most important conclusion is that truck type, as defined by length and weight to power ratio, is critical for determination of PCEs.

Afterwards, De Marchi and Setti (2003) published an article describing the limitations of deriving PCEs for traffic streams with multiple truck types. In an algebraic derivation, they proved that PCEs developed for a single truck type in a mixed traffic flow containing multiple truck types using equation (3.6) do not fully account for the interaction between trucks. They reasoned that considered separately, "the PCE value for the subject vehicle is normally underestimated, because the marginal impact decreases as the proportion of subject vehicles in the stream increases." Conversely, the impact of trucks already in the mixed vehicle stream is overestimated because their actual proportion should be smaller than it is prior to addition of the subject vehicles.

The authors suggested that a different approach to avoid the errors associated with calculating the PCE for each truck separately is to calculate an aggregate PCE formulated as:

$$E_T = \frac{1}{\sum_i^n P_i}\left[\frac{q_B}{q_M} - 1\right] + 1 \qquad (3.11)$$

where $P_i$ is the proportion of trucks of type i out of all trucks n in the mixed traffic flow, $q_B$ is the base flow rate (passenger cars only), and $q_M$ is the mixed flow rate. This equation is basically equation (3.5) put forth by Huber and modified for multiple truck types in the mixed traffic stream. This approach, using an aggregate PCE, seems to have been adopted in the 1994, 1997, and 2000 editions of the HCM. PCEs in the

HCM 2000 are reported by percent grade, length of grade, and percent trucks. The PCEs exhibit a decrease for increasing proportion of trucks.

## III.2 DATA ANALYSIS AND SIMULATION ISSUES FOR A22 FREEWAY

Before explaining the study methodology used, study efforts, made both to develop the fundamental diagram of traffic flow for the A22 Brenner Freeway, and to tackle the issues associated with calibration and validation of the simulation model parameters, will be introduced.

### III.2.1 TRAFFIC DATA FOR A22 FREEWAY

The speed-flow-density relationships for a traffic flow of passenger cars only were developed following the field survey activities performed on the A22 Brenner Freeway, Italy (Mauro, 2007). These relationships were built after treating and processing of traffic data collected at specific observation sections. Focusing on the development of a criterion for predicting the reliability of traffic flow by observing speed stochastic processes on A22 Freeway, a study has already been done (Mauro et al., 2013). The specification of the speed-flow-density relationships is discussed by Mauro et al. (2014). Here it will be described briefly the May's model (1990), as expressed by the following equation 3.12:

$$V = V_{FF} \cdot \exp\left[-0.5 \cdot \left(\frac{D}{D_c}\right)^2\right] \tag{3.12}$$

where $V_{FF}$ is the free-flow speed and $D_c$ is the critical density (to which is associated the reaching of the capacity). Starting from equation 3.12, by means of the relationship between the fundamental parameters of traffic flow, flow values were obtained; the speed-flow and flow-density relationships were also derived. Traffic flow models were calibrated for the right lane, the passing lane and both lanes of the roadway; for each observation section, the $V_{FF}$ and $D_c$ values were calculated by using the logarithmic transformation of equation 3.12.

Table 3.1 shows $V_{FF}$ and $D_c$ values for the two lanes of the carriageway only. Note that for S Michele sections a fleet of cars only was observed; for the other observation sections, traffic flows were homogenized before the calibration of the May's model to consider the effects of passing heavy vehicles; for this purpose the passenger car equivalents calculated by Mauro (2007) were used.

| roadway | free flow speed [km/h] | critical density [veh/km/2-lanes] |
|---|---|---|
| S. Michele section – Southbound | 118.20 | 48.35 |
| S. Michele section – Northbound | 121.00 | 45.36 |
| Rovereto – Southbound | 114.30 | 49.61 |
| Adige – Southbound | 116.30 | 50.92 |
| Adige – Northbound | 112.60 | 39.20 |

Table 3.1. The May model parameters for the sections on A22 Freeway

## III.3 CALIBRATION AND VALIDATION OF THE MODEL

In the context of the activities developed in micro-simulation, calibration was searched by ensuring that Aimsun gave results close to empirical data. Thus the empirical measurements of speed, flow and density and simulated data as generated by Aimsun were compared. For the fundamental core models (i.e. car following and lane changing) as implemented in Aimsun for modelling microscopic vehicle movements, the reader is referred to the relevant literature (see e.g. Barcelo, 2011; Vasconcelos et al., 2009; 2014).

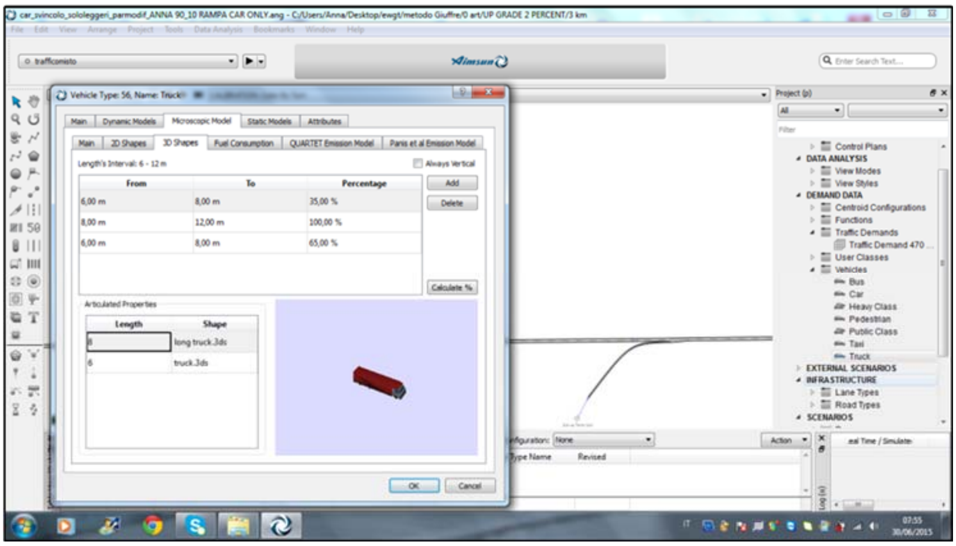

Fig. 3.1. View of the Aimsun window: choose of heavy vehicle type

The first step for executing Aimsun was to create a model network for the A22 Freeway such as to enable the geometric and functional representation of the freeway facility (having basic freeway segments, on- and off- ramps, etc.) and the related objects as traffic detectors at specific locations in the road network. Focus was then put on a basic freeway segment just a little over 2 kilometers and centered on the S. Michele observation section (Southbound); this basic freeway segment is characterized by the same cross section of A22 Freeway (Italy), having two traffic lanes, each 3.75 m wide, in each direction, and a slope of 0.09 percent. The previously mentioned freeway segment was chosen outside of the influence area of ramps so that so that uninterrupted flow conditions were guaranteed. In order to test the traffic microsimulation model validity, some model parameters were changed and adjusted until the model outputs were similar to empirical data. It is noteworthy that the calibration of a microsimulation model is an iterative process which can be stopped only when the model matches locally observed conditions (Barcelo, 2011). In a previous research a statistical approach including hypothesis testing using t-test and confidence intervals was used to measure the closeness between empirical data and simulation outputs for a test freeway segment under uncongested traffic conditions (Mauro et al., 2014). The lnV-$D^2$ regressions for simulated and empirical data were compared. Thus the microsimulation model was able to reproduce the real phenomenon of traffic flow within a wide enough range of operations, from the free flow speed conditions until almost to the critical density. However, in this study further considerations have been developed.

In order to reproduce local traffic conditions on A22 Freeway, some trial simulation runs were performed by using the default values for the model parameters; however, outputs from simulation runs were not quite right to represent the existing traffic conditions. Thus, the iterative changing of some parameters was done, different combinations of values were explored and many simulation replications were needed until the difference between the empirical and the simulated values of the variables of interest was minimized. Table 3.2 shows the parameter values (default and adjusted) that were used to replicate the field conditions. For calibration purposes, a maximum allowed speed (in km/h) for the vehicles travelling through the freeway roadway was introduced on each lane; moreover, the reaction time, namely the time it takes a driver to react to speed changes in the preceding vehicle was defined as fixed, that is the same as the simulation step. Global parameters in the two-lane car-following model were also considered for calibration. This was carried out with the purpose to model the influence on the subject vehicle given by a certain number of vehicles driving slower in the adjacent right-side lane. These parameters included: the number vehicles, or the vehicles driving downstream of the vehicle in the adjacent slower lane; the maximum distance, representing the distance from the current vehicle within which the number vehicles are taken into account; the maximum speed difference, or the differences of speeds between two adjacent lanes. The calibration process also included the adjustments for the maximum and minimum values of the desired speed, namely the maximum speed that a certain type of vehicle can travel at any point in the network. For the freeway link, the traffic demand was defined by subsequent O/D matrices for a total time interval of 13 hours, from 7:00 am to 8:00 pm.

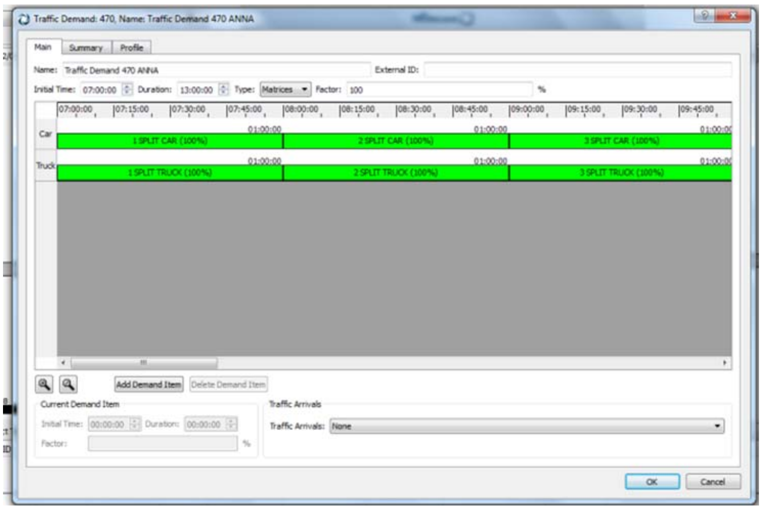

Fig. 3.2. Traffic demand of car and truck in Aimsun

| model parameter | default value | calibrated value |
|---|---|---|
| maximum speed [km/h] - right lane | 120 | 95 |
| maximum speed [km/h] - passing lane | 120 | 125 |
| reaction time [s] | 0.75 | 0.8 |
| maximum distance [m] | 100 | 100 |
| maximum speed difference [km/h] | 50 | 50 |
| minimum desired speed [km/h] for cars | 80 | 85 |
| maximum desired speed [km/h] for cars | 150 | 125 |

Table 3.2. The model calibration parameters

An ADT of about 30,000 vehicles per day was considered and hourly modulated for representing traffic conditions on A22 Freeway. Passenger cars only were considered; their attributes were chosen within the range that Aimsun gives. Detectors were located so that they could replicate the location of field detectors. The simulated values of speed and density were verified against the corresponding empirical values as shown in Figure 3.3 Specifically, the graph shows the plots of empirical and simulated data for the considered link (S. Michele section - Southbound) and the corresponding speed-density relationships. The *V=V(D)* function for simulated data was obtained converting equation 1 into linear form by using the logarithmic transformation:

$$\ln(V) = \ln(V_{FF}) - \frac{1}{2 \cdot \mathrm{D}_c^2} \cdot D^2 \text{ or else } V_1 = a + b \cdot D_1 \qquad (3.13)$$

where $V_1$ is $ln(V)$, $a$ is $ln(V_{FF})$, $b$ is $-1/(2D^2_c)$ and $D_1$ is $D^2$, with $V_{FF}$ and $D_c$ as previously defined. By using simulated data $V_{FF}$ and $D_c$ values were calculated and equation 3.13 was calibrated; with $V_{FF}$ equal to 109.46 km/h and $D_c$ resulted equal to 58.77 veh/km/2-lanes, corresponding to a capacity value of 3900 veh/h/2-lanes ($R^2$= 0.88). In Fig. 3.3 the speed-density relationship for empirical data is also shown for both lanes of the carriageway; it was built by using $V_{FF}$ and $D_c$ values reported in Table 3.1 for S. Michele Section – Southbound.

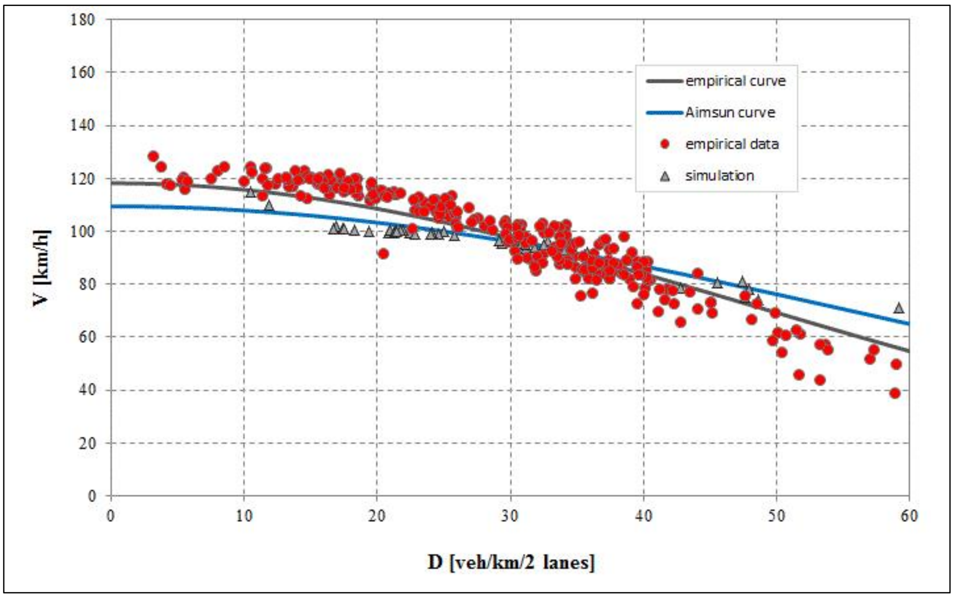


Fig. 3.3. Speed-density graphs with plots of field and simulated data.

For the examined case study, the GEH index was calculated as criterion for acceptance, or otherwise rejection, of the model (Barceló, 2011). Since the deviation of the simulated values with respect to the measurement was smaller than 5% in 96% of the cases, the model was accepted as being able to reproduce local conditions and traffic behavior with statistical confidence.

Once the global parameters were adjusted to produce a good fit between observed and simulated data, i.e. they began to have little further influence on the model outputs, the validation of the calibrated model was addressed also. In this first step of analysis, simulation outputs were compared with two empirical data sets that were not used in the calibration process. Fig. 3.4 shows the comparison among the simulation data and the empirical equation V=V(D) for two observation sections on A22 Brenner Freeway in Table 3.1. For performing the comparison, each observed speed was calculated from the speed-density equations, as specified by the values in Table 3.1 for Rovereto (Southbound) and Adige (Southbound) sections, by using the simulated values of density. Since the deviation of the simulated values with respect to the measurement was smaller than 5% in 96% of the cases for Adige Section (Southbound) and smaller than 5% in 94% of the cases for Rovereto Section (Southbound), the model validation could be accepted. It is noteworthy that field data did not exceed (or just in few cases) the critical density and not cover sufficiently oversaturated conditions; therefore, in this study is applicable under capacity conditions only.

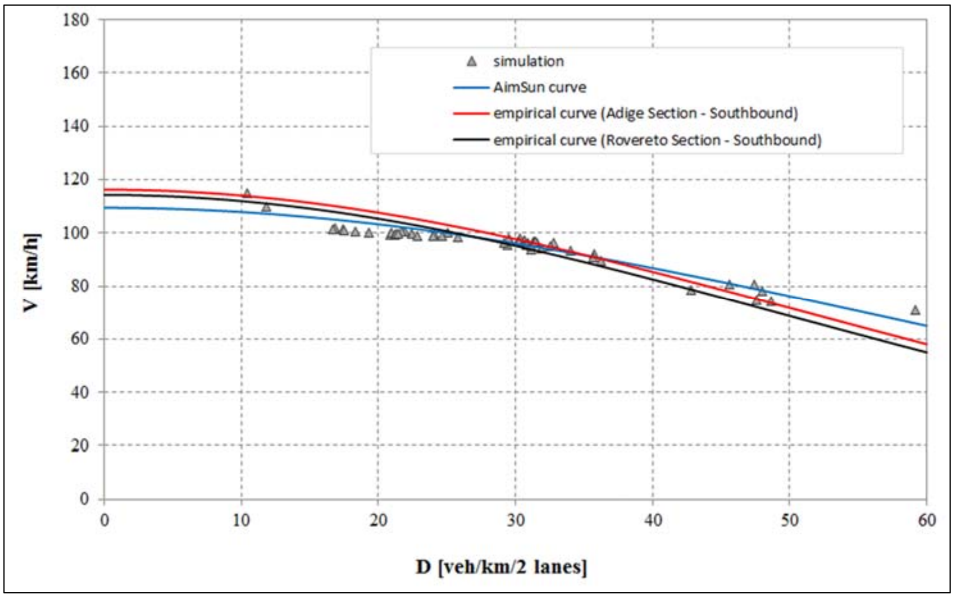


Fig. 3.4. Speed-density graphs with plots of simulated data.

## III.4 STUDY METHODOLOGY

PCEs will estimated as a function of variables that are found to have a critical effect on PCE values. In this explorative study, the influence of the following traffic and road design characteristics on PCEs will be investigated: grade and length of grade, percentage of heavy vehicles in the traffic stream, and traffic flow rate. According to Elefteriadou et al. (1997), the effect of a heavy vehicle on the quality of traffic flow, and then its PCE, is related to the performance characteristics of the heavy vehicles also. In this work, the heavy vehicles mix included single trucks and single trailer trucks having the following characteristics: the maximum length was assumed equal to 12 m; the maximum desired speed was equal to 80 km/h (with a minimum and a maximum value of 70 km/h and 90 km/h, respectively). For the heavy vehicles mix a maximum acceleration of 1 $m/s^2$ (with a range 0.6-1.8 $ms^2$) and a maximum deceleration of 5 $m/s^2$ (with a range 4-6 $m/s^2$) were assumed. For the other heavy vehicle attributes, default values as proposed by Aimsun (version 8.0.4) were assumed. The dynamics of interaction between passenger cars and heavy vehicles during overtaking and the driving behaviour in the neighborhood of heavy vehicles is handled internally by the Aimsun model (Barcelò, 2011). Simulation data were used to develop the relationships among the variables of traffic flow and to calculate the passenger car equivalents for heavy vehicles by comparing a fleet of cars only with a mixed fleet characterized every time by different percentages of heavy vehicles.

### III.4.1 METHOD OF PCE ESTIMATION

In this study PCE values were estimated based on the method developed by Huber (1982). The method consists of the steps as explained in the following:

- Q = Q(D) curve was generated by simulating a passenger-car-only traffic stream from free flow up to critical density. Since the passenger car is the base vehicle, this curve is called the base curve (see Fig. 3.5);

- using a vehicle mix, which includes passenger cars and heavy vehicles, another flow-density curve was generated (see Fig. 3.5);
- Q = Q(D) functions in presence of different percentages of heavy vehicles can be developed; O/D matrices must be assigned to reproduce a wide range of operational conditions on the roadway, from free-flow to critical density;
- estimation of passenger car equivalents for a given percentage of heavy vehicles was achieved by comparing at equal density values, the flow rate obtained for entering traffic flows with passenger cars only ($Q_B$) with the flow value ($Q_M$) corresponding to a traffic demand characterized by a percentage $p_T$ of heavy vehicles; the estimation can be developed considering:

$$E_T = \frac{1}{p_T} \cdot \left( \frac{Q_B}{Q_M} - 1 \right) + 1 \tag{3.14}$$

This equation starts from $Q_B = Q_M \cdot (1 - p_T) + Q_M \cdot p_T \cdot E_T$, where $Q_B$ is a heterogeneous flow including the share referable to passenger cars $Q_M \cdot (1 - p_T)$ and the share of heavy vehicles ($Q_M \cdot p_T$), multiplied by $E_T$ for obvious reasons of homogeneity.

- $Q = Q(D)$ functions $Q_B$ and $Q_M$ for different flow percentages (that is 100% passenger cars, 10%, 20% , 30%, heavy vehicles) for the freeway roadway can be now developed. In order to apply this criterion for calculating $E_T$, $\ln V$-$D^2$ regressions on simulated data are necessary.

Base and mix curves were developed for a combinations of freeway grade and length of grade, and percentages of heavy vehicles. It is to be expected that each set of conditions results in potentially different flow-density value for the base and mix scenario.

## III.5 MODELING RESULTS

As an example of the above proposed method of PCE estimation, the investigation of the effect of traffic flow rate and road design variables on PCE is shown here. Table 3.3 shows the resulting PCE values for the subject types of heavy vehicles and for the explored combinations of traffic and road design variables considered in the base and mix curves. PCE values are limited to $Q_M$ < 3000 veh/h/2 lanes in order to avoid saturated conditions for which the simulation model was not calibrated. In this explorative study estimations in Table 3.3 show that PCEs are sensitive, to some degree, to all variables here examined:

- the effect of heavy vehicles tend to increase with traffic flow rate for upgrades as well as downgrades;

- increasing the flow rate, the effect of heavy vehicles increases even at level grades;
- having the same value of grade length, there is an increasing effect of heavy vehicles at an increasing flow rate;
- having the same value of freeway grade, there is a higher effect of heavy vehicles at high flow rate values;
- increasing the percentage of heavy vehicles, the effect of heavy vehicles on traffic operations slightly decreases, especially when traffic flow rates are higher than 2,000 veh/h/2 lanes.

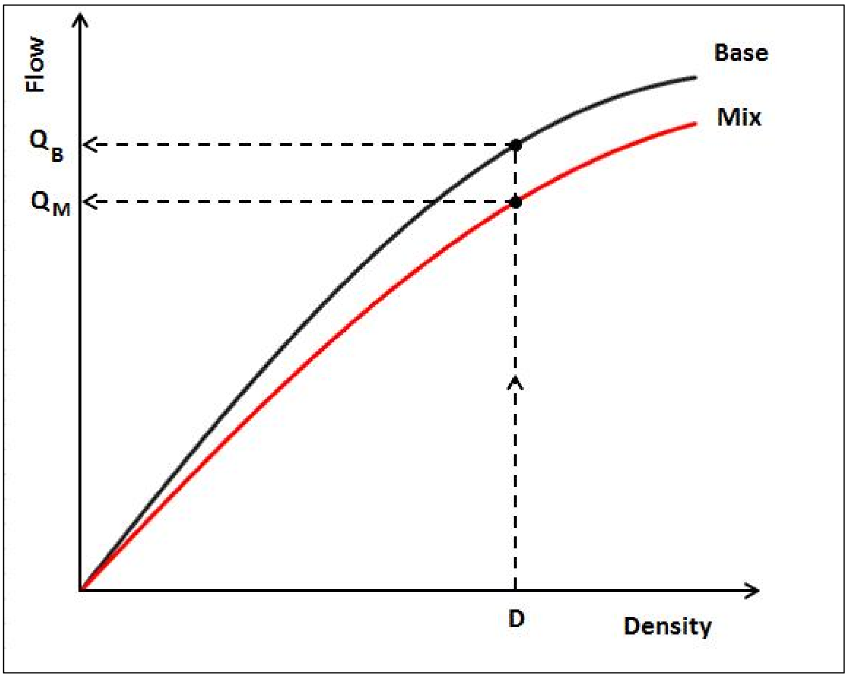


Fig. 3.5. Method of PCE calculation.

PCE values obtained in this research are similar to those shown in the HCM (2010) at level and slight upgrades (≤3%) especially at low values of flow rate (< 2000 veh/h/ lanes); increasing the flow rate, at high grade, HCM PCE values, in turn, are greater when the flow rates increase for steep and long upgrades as well as downgrades.

| Grade | length of grade [km] | Flow rate [veh/h/2 lanes] and percent heavy vehicles [%] | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | $Q_M \leq 1000$ | | | $1000 < Q_M \leq 2000$ | | | $2000 < Q_M \leq 3000$ | | |
| | | 10 | 20 | 30 | 10 | 20 | 30 | 10 | 20 | 30 |
| level | 1 | 1.1 | 1.4 | 1.4 | 1.2 | 1.5 | 1.5 | 1.8 | 1.7 | 1.6 |
| | 2 | 1.1 | 1.4 | 1.4 | 1.2 | 1.5 | 1.5 | 1.8 | 1.7 | 1.6 |
| up-grade 2% | 1 | 1.2 | 1.5 | 1.3 | 1.3 | 1.5 | 1.5 | 1.6 | 1.6 | 1.6 |
| | 3 | 1.2 | 1.5 | 1.5 | 1.4 | 1.6 | 1.6 | 1.8 | 1.7 | 1.7 |
| | 5 | 1.2 | 1.6 | 1.6 | 1.4 | 1.6 | 1.6 | 1.8 | 1.8 | 1.7 |
| up-grade 3% | 1 | 1.3 | 1.5 | 1.5 | 1.4 | 1.5 | 1.5 | 1.8 | 1.7 | 1.6 |
| | 3 | 1.3 | 1.5 | 1.5 | 1.4 | 1.6 | 1.6 | 1.9 | 1.7 | 1.6 |
| | 5 | 1.4 | 1.5 | 1.6 | 1.6 | 1.6 | 1.6 | 1.9 | 1.8 | 1.7 |
| up-grade 5% | 1 | 1.3 | 1.5 | 1.5 | 1.4 | 1.5 | 1.5 | 2 | 1.7 | 1.6 |
| | 3 | 1.4 | 1.5 | 1.7 | 1.5 | 1.6 | 1.6 | 2 | 1.8 | 1.8 |
| | 5 | 1.5 | 1.6 | 1.7 | 1.6 | 1.6 | 1.7 | 2 | 1.8 | 1.8 |
| downgrade 3% | 2 | 1.1 | 1.4 | 1.5 | 1.3 | 1.5 | 1.5 | 1.8 | 1.6 | 1.6 |
| | 3 | 1 | 1.3 | 1.4 | 1.2 | 1.5 | 1.6 | 1.8 | 1.8 | 1.7 |
| downgrade 5% | 2 | 1.1 | 1.4 | 1.5 | 1.3 | 1.5 | 1.6 | 1.9 | 1.8 | 1.7 |

Table 3.3. PCE estimations for different grade level and flow rates

These difference are due to the different definition of PCE applied in this research, compared to the definition applied in obtaining the HCM PCEs. According to Linzer et al. (1979) indeed, the PCEs in the HCM were based on equivalent effect on traffic speed, while the PCEs in this research were obtained using the definition of PCE as equivalent effect on traffic density. Moreover, heavy vehicles considered in this study (having a length less than 12 m) are only a part of those considered in the simulation model used to estimate the PCEs provided in the HCM .

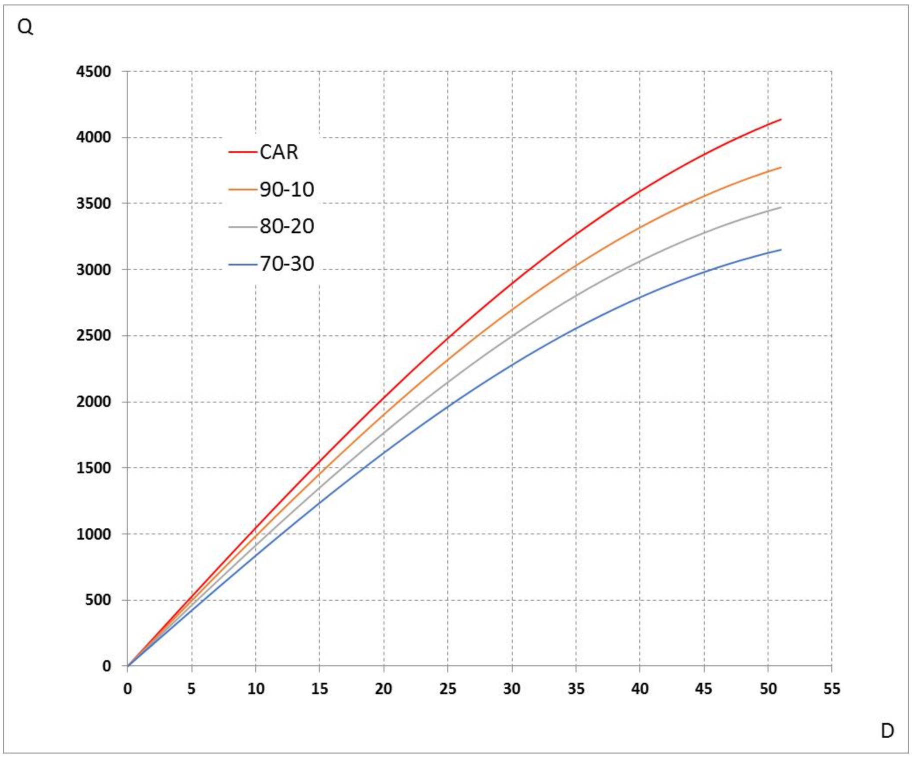


Fig. 3.6. Flow- density curves for different percentage of truck

## III.6 CONCLUSIONS

The effect of highway and traffic variables on the equivalency between heavy vehicles and passenger cars was investigated in this research. Technical literature still presents few studies related to the calculation of passenger car equivalents for heavy vehicles in Italian context. The reasons for this are due to time, resources and efforts required for a PCE estimation study based on data collected on field. As a consequence, microsimulation can be a useful tool for the functional analysis of freeway and highways, and for the estimation of the impact of heavy vehicles on the quality of traffic flow. Starting from an overview of data collected on A22 Brenner Freeway, Italy, the issues associated with calibration and validation of the simulation model for the selected case study were described. The study methodology that used the traffic density as equivalency criteria for the estimation of passenger car equivalents for heavy vehicles was then presented. Starting from the Huber criterion, passenger car equivalents for heavy vehicles on basic freeway sections were estimated using the densities of the mix flow generated by Aimsun. Using Aimsun software it was possible to evaluate the variation in the traffic quality on freeway, varying the percentage of heavy vehicles in the traffic demand. Thus traffic conditions difficult to capture in the field were isolated and replicated to have a huge amount of empirical data. Simulations have permitted values of the fundamental variables of traffic flow (namely speed, flow, density) for different percentages of heavy vehicles to be derived. Data simulated by Aimsun were used to develop the relationships among the variables of traffic flow and to calculate the passenger car equivalents for heavy vehicles by comparing a fleet of cars only with a mixed fleet, characterized every time by different percentages of heavy vehicles.

Despite the exploratory nature of this study, some implications can be drawn from the application of the proposed procedure. PCE values of a heavy vehicle changes with change in traffic volume and composition. The PCE values here estimated resulted sensitive, to some degree, to all variables examined: increasing the flow rate, the effect of heavy vehicles increased for upgrades and downgrades, as well as at level grades; moreover, increasing the flow rate, an increasing effect of heavy vehicles on segments having the same value of length occurred. Analogous considerations could be made for segments characterized by the same grade value, for which there was an increasing effect of heavy vehicles at an increasing flow rate. At last, decreasing the percentage of heavy vehicles, the effect of heavy vehicles on traffic operations slightly increased, especially for traffic flow rates higher than 2000 veh/h/2 lanes. The differences between the values of PCEs estimated in this study and the HCM values for PCEs were briefly described; reasons for the difference between these two set of values were also discussed. However, at this stage of the research, the methodological path followed for estimating the PCEs of heavy vehicles in terms of their effects on the operations of a basic freeway section has been described. Two objectives were pursued: i) to investigate the influence of a variety of traffic, road design, and vehicle characteristics on PCEs; ii) to propose a set of PCE values to be used in analyzing the operation of basic freeway sections.

More research remains to better understand and confirm these findings. Results, indeed, could be improved upon using an automated procedure in the calibration process in order to include the effect of further parameters on the model outputs. Moreover, PCEs should be calculated for other types of heavy vehicles such as multi-trailer trucks and buses, as well varying the traffic scenarios and/or considering other geometric variables (for example exploring situations in which a segment of freeway consists of composite grades). Collection of typical vehicle distribution in real field would be also needed. Only afterwards, a validation study of the PCE values estimated for A22 Brenner Freeway could carried out using data collected in the field. It should be noted that such a field data collection effort was already conducted (Mauro, 2003, 2005, 2007); however data updating and integration could be hindered by difficulties both in the selection of vehicle types for the data collection, because it can be difficult to obtain typical vehicle performance characteristics, and in the selection of a time period for collecting typical traffic volumes on basic freeway sections.

# IV. AN AUTOMATED PROCEDURE BASED ON GA FOR CALIBRATING TRAFFIC MICROSIMULATION MODELS

Numerous problems in science and engineering require the optimization of model performance by minimizing the error between the model outputs and observations of the real system (Pujol and Poli (2004)). As it is known the optimization problems consist of maximizing or minimizing an objective function, which expresses how far an observable variable is from its simulated value, constrained by the set of feasible values of the model parameters on which the simulated variable depends (Hourdakis et al. (2003); Ma et al. (2007)). Parameter optimization represents, thus, a problem in which the objective is to set the system parameters so as to maximize its performance. Microsimulation has been increasingly used in engineering applications, but various issues concerning the extent to which its outputs reproduce field data still need to be addressed (Barceló et al. (2010)). In traffic modelling, microscopic simulation requires many different parameters to describe traffic flow characteristics, driving behavior, traffic control systems, and so on. Since some calibration parameters, for example those corresponding to the car following and lane changing models, are often difficult to collect on the field, it is common practice to use the default parameters provided by the microscopic simulation models. However, the simulation models under default calibration parameters may not accurately represent field conditions and usually produce unreliable results (Vasconcelos et al. (2014); Barceló et al. (2010); Park and Schneeberger (2003)). In turn, the different kind of errors which could affect the outputs of the models, limits the required accuracy of the model results (Vasconcelos et al. (2009)). A proper calibration of the traffic model parameters has to be performed so as to obtain a close match between the simulated and the actual traffic measurements. In this perspective the calibration process could be a complex and time-consuming task because of the large number of unknown parameters (Toledo et al. (2004)). The formulation of the calibration process of a traffic model as an optimization problem is perhaps the most recommended practice (Barceló et al. (2010)). However, increasing the number of variables and parameters, also the number of possible parameter values becomes too large to handle without automation (Bukharov and Bogolyubov (2015); Ma and Abdulhai (2002)). In order to solve the optimization problem, various automatic calibration methods and procedures have been used by researchers in the process of calibration of microsimulation traffic models. For the calibration of microscopic traffic simulation models some studies used sensitivity analysis and trial-and error method which could be very resource-intensive and/or time-consuming (Park and Schneeberger (2003); Moridpour et al. (2012)); for calibration purposes some other studies used multistart algorithms (Ciuffo et al. (2008)), neural networks (Otkovic et al. (2013)) and genetic algorithm for input parameters of the simulation model (Kim et al. (2005); Park and Qi (2005); Menneni et al. (2008); Onieva et al. (2012); Camilleri and Neri (2014)). However, the search for an effective solution to the calibration problem cannot be exhausted by the choice of the most efficient optimization algorithm. The use of available information concerning the phenomenon could allow calibration performance to be enhanced, for example, by reducing the dimensions of the domain of feasible solutions (Vasconcelos et al. (2009); Ciuffo et al. (2008)). According to Hale et al. (2015), this reduction in domain could allow use of different optimization methods.

For the purpose of calibrating a microscopic traffic simulation model, a reliable calibration process must include: 1) the definition of a criterion to evaluate the performance of a model in terms of an objective function; 2) the selection of the parameters that will be calibrated and an appropriate algorithm to minimize or maximize the objective function; 3) the test of calibration results against new data sets. Starting from these considerations, the study presents a calibration methodology that was implemented and tested on the A22 Brenner Freeway, Italy, based on a real traffic data set. A macroscopic approach was followed in order to compare the field measurements with the corresponding simulated outputs obtained by using the microscopic traffic simulation package AIMSUN for a freeway test segment under congested and uncongested traffic conditions.

This work shows the first results obtained by applying a genetic algorithm in the microsimulation traffic model calibration process. The calibration was formulated as an optimization problem in which the objective function was defined to minimize the differences of the simulated measurements from those observed in the speed-density diagram. The Genetic Alghorithm tool in MATLAB® was applied for calibrating the simulation models. In order to implement this process, the optimization technique was attached to Aimsun via a subroutine that allowed the data transfer between the two programs. The MATLAB® software acted as an interface with Aimsun via external scripting written in Python.

Taking in consideration the best combination of the Aimsun parameters resulted from the genetic algorithm, the simulation with optimized parameters generated a satisfactory fit to the field data in comparison with the simulation using the default parameters. The results also indicated that the procedure gave a good fit both in the calibration and validation sections.

## IV.1 DATA GATHERING AND CALIBRATION ISSUES

This section sets out not only how data were gathered on different segments of the A22 Brenner Freeway, Italy, but also the study efforts initially made to investigate the methodological issues associated with the calibration of the microsimulation model parameters for the A22 Brenner Freeway, Italy. These subjects of study will be preceded by an overview of the calibration methodologies used for traffic microsimulation models. Preliminary results from the comparison between the empirical measurements of speed density values, and the simulated pairs of speed-density as generated by Aimsun (using the default values for the parameters of the model) will be also presented.

### IV.1.1 DATA GATHERING PROCESS

The data needed for this study were obtained from a series of experimental surveys carried out at different observation sections on the A22 Brenner Freeway and multiple days in 2003, 2005, and 2007 (Mauro (2007)). The A22 Brenner Freeway refers to a major European trunk route, which connects Innsbruck in Austria to Modena in northern Italy. High traffic volumes up to 40,000 vehicles per day (of which up to one-third are heavy vehicles) move on the freeway, with high seasonal tourist flows during holiday times; however, all vehicle categories on the A22 Freeway are growing similarly to the national trend.

Details concerning the issues regarding the experimental data collection and the treatment of traffic data surveyed at specific observation sections along the A22 Freeway are also available in Mauro et al. (2013). The summary of the characteristics at the observation stations which were selected away from the merging or diverging operations near to the on/off ramps is reported in Table 4.1; the same table shows the ratios of the peak hour traffic volume (both in the 30th and 100th peak-hour) to the annual average daily traffic (AADT) for each location.

The traffic data were measured at specific stations (Adige, Rovereto and S. Michele) on the A22 Freeway and were processed for the purpose of deriving the fundamental diagram of traffic flow, namely the flow-density-speed relation; thus the relationships between flow and density, Q = Q(D), speed and density, S = S(D), speed and flow, S = S(Q), were developed for the carriageway, the inside lane and the passing lane.

The measurements of traffic flows, Q, were expressed in passenger car units/hour, by homogenizing the traffic flows, measured at 15-minute intervals, with the site specific values of Passenger Car Equivalent (PCE) factors which were calculated from field traffic data. The criterion based on the average headways (Roess et al. (2004)), namely calculating the ratio of the average headways between pairs of vehicles (passenger cars, heavy vehicles, passenger cars-heavy vehicles, heavy vehicles-passenger cars) to the average headways between pairs of passenger cars only was used.

| Station | Geometric conditions around station | | | | | $Q_{\alpha}$/TGM (Southbound) | | $Q_{\alpha}$/TGM (Northbound) | |
|---|---|---|---|---|---|---|---|---|---|
| | on-ramp | off-ramp | alignment | | | $Q_{30}$/TGM | $Q_{100}$/TGM | $Q_{30}$/TGM | $Q_{100}$/TGM |
| | | | horizontal | vertical | | | | | |
| | | | | Southbound | Northbound | | | | |
| Adige km 187+300 | km 187+400 | km 187 | tangent | slope= -0.28 % | slope= 0.28 % | 15.10% | 13.40% | 14.30% | 12.60% |
| Rovereto km 161+100 | km 158+500 | km 158 | R= 1200 m | slope= 0.43% | slope= -0.43% | 15.50% | 13.80% | 15.20% | 13.50% |
| S. Michele km 126+100 | km 121+400 | km 121 | tangent | slope= -0.09% | slope= 0.09% | 13.50% | 12.10% | 13.80% | 12.00% |

Tab. 4.1. Geometric conditions around stations and peak hour traffic volume as a percentage of AADT by station.

Since there is the relation Q = D*S, the estimation of one of three relations, Q = Q(D), S = S(D), S = S(Q), involves the specification of the other two. For this purpose, different models were examined (Greenshields et al. (1935); Greenberg (1959); Edie (1963)); the single-regime model proposed by May (1990) seemed to fit the data much better than the other models, especially the values of the maximum densities in congested traffic conditions. According to the May model, the relation between speed and density, S = S(D) is expressed by the equation (4.1) as a function of the free flow speed (SFF ) and the critical density (Dc), or the density with which the capacity C is associated:

$$S = S_{FF} \cdot \exp\left[-0.5 \cdot \left(\frac{D}{D_c}\right)^2\right] \quad (4.1)$$

Thus, considering the fundamental relation between flow Q, density D and speed S, Q = D*S, the relations between flow and density, Q = Q(D), and speed and flow, S = S(Q), are expressed by the following equations:

$$Q = S \cdot \sqrt{\frac{\ln\left(\frac{S_{FF}}{S}\right)^2}{0.5 \cdot D_c^2}} \quad (4.2)$$

$$Q = S_{FF} \cdot D \cdot \exp\left[-0.5 \cdot \left(\frac{D}{D_c}\right)^2\right] \quad (4.3)$$

which allow the speed-flow function, S = S(Q), and the flow- density function, Q = Q(D) to be developed for each of the selected stations. According to traffic engineering literature (Roess et al., 2004), first the relation between speed and density was estimated. This expresses, the interaction of vehicles in the traffic stream, where drivers experience the density, variations of which imply larger or smaller distances between vehicles, and thus they adapt their driving behaviour.

Traffic flow models were calibrated for the inside lane, the passing lane and the carriageway at the sections under examination. Based on the scatter plot (ln(S); $D^2$), a least squares estimation was performed; $S_{FF}$ and Dc were calculated for all observation sections. By using Equations (4.1), (4.2) and (4.3), the speed-flow-density relationships were specified for each observation section.

Then the homologous determinations of $S_{FF}$ and $D_c$ at the observation sectionswere averaged; using the obtained values of $S_{FF}$ and Dc, the speed-flow-density relationships for each lane and the roadway for A22 Freeway were developed. See for further details Mauro et al. (2014).

Table 4.2 shows, for example, $S_{FF}$ and $D_c$ values which were estimated for each Southbound station from ln(S)- $D^2$ regressions; estimations of capacity C and critical speed $S_c$, corresponding to C, as well as the values of coefficient of determination $R^2$ for each regression line (ln(S); $D^2$), were also reported; the mean values of the traffic parameters (Southbound and Northbound) are also shown.

Due to restrictions on the movement of heavy vehicles during the days of surveys, it is noteworthy that for S. Michele section only a fleet of cars was observed. The restriction was about the movement of some category of heavy vehicles which transit was forbidden with an ordinance decreed by the A22 managing institution. In particular, the regulation forbade the entry of heavy vehicles (up to 7500kg) during the days of survey.

For the other sections under observation, traffic flows were homogenized before the calibration of the May's model to consider the effects of heavy vehicles on traffic flow. For this purpose the passenger car equivalents calculated by Mauro (2007) were used.

| Station (Southbound) | lane/lanes | $S_{FF}$ | Dc | C | $S_C$ | $R^2$ |
|---|---|---|---|---|---|---|
| Adige | right | 109.4 | 24.22 | 1607 | 66 | 0.93 |
| | passing | 128.6 | 26.2 | 2043 | 78 | 0.93 |
| | 2-lanes | 116.3 | 50.92 | 3592 | 71 | 0.95 |
| Rovereto | right | 105 | 23.45 | 1493 | 64 | 0.89 |
| | passing | 127 | 26.1 | 2012 | 77 | 0.92 |
| | 2-lanes | 114.3 | 49.61 | 3440 | 69 | 0.92 |
| S. Michele | right | 105 | 24.36 | 1551 | 64 | 0.88 |
| | passing | 131.5 | 24.67 | 1967 | 80 | 0.7 |
| | 2-lanes | 118.2 | 48.35 | 3467 | 72 | 0.91 |
| Average (Southbound and Northbound) | right | 106.95 | 23.65 | 1534 | 64..86 | - |
| | passing | 130.28 | 25.09 | 1983 | 79.02 | - |
| | 2-lanes | 117.45 | 48.56 | 3459 | 71.23 | - |

Table 4.2. Parameters of speed-flow-density relations for each traffic station.

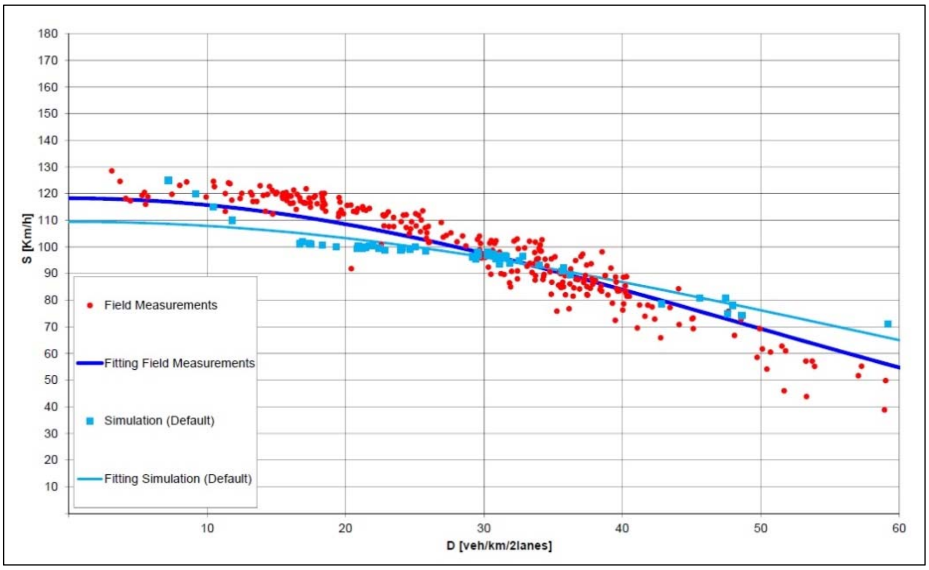


Fig. 4.1. Speed-density graphs with plots of field and simulated data.

### IV.1.2 CALIBRATION ISSUES FOR THE A22 FREEWAY

As mentioned above, the aim of the study was to explore methodological issues involved in applying a genetic algorithm in the microsimulation traffic model calibration process. A calibration was a method thet ensured that Aimsun gave outputs close to the empirical measurements of the pairs speed-density, flow-density, flow-speed was investigated. First for executing Aimsun the model network for the A22 Freeway was created and the geometric and functional characteristics of the basic freeway segments, on–off ramps, as well as traffic detectors at specific locations were represented. Note that in the model network of the A22 Freeway detectors were located so that they could replicate the location of detectors on field. Then a basic freeway segment, centered on the Southbound S. Michele station, having the length of about 2 kilometers and the cross section of A22 Freeway (two traffic lanes, each 3.75 m wide, in each direction), was considered. Since the basic freeway segment was selected far enough from the influence area of ramps, uninterrupted flow conditions were guaranteed. Before having recourse to an automated procedure to test better the validity of the microscopic traffic simulation model, local traffic conditions on A22 Freeway were reproduced performing trial simulation runs by using the default values only for the model parameters. Based on the empirical data detected on the Southbound station of S. Michele, the time series of traffic flow, speed and density were replicated in Aimsun in order to test the ability of the model to reproduce the real data series. Passenger cars only were considered; their attributes were chosen within the range that Aimsun gives. An AADT of 35,000 passenger cars per day was simulated and hourly modulated for representing traffic conditions on A22 Freeway. For this purpose, a total OD matrix of 35,000 passenger cars was then distributed in subsequent O/D matrices for a total time interval of 13 hours, from 7:00 am to 8:00 pm, assuming the same percentages distribution of traffic detected in reality. In this first step, as above mentioned we considered the default parameters of Aimsun version 8.0.5. The simulated data set was fitted as the empirical data by using the May model; thus the comparison between the two sets of data was performed by using two continuous curves. The simulated values of speed and density were verified against the corresponding empirical values as shown in Figure 4.1; it shows indeed, the speed-density graph diagram with the two curves interpolating the empirical data and the simulation outputs (gained by using default parameters) together with the plots of field and simulated data.

## IV.2 FORMULATION AND SOLUTION OF THE CALIBRATION PROBLEM

In this section the problem of the formulation and solution of the calibration problem is considered. In particular a formal interpretation of the problem is given, subsequently a solution by applying genetic algorithms is proposed.

### IV.2.1 FORMAL INTERPRETATION

Let $\{u_k\}_{k=1}^{N}$ and $\{y_k\}_{k=1}^{N}$ be two input-output sequences of observed data acquired during suitable traffic measurements and they represent the "experimental surveys". Now we want to reproduce the same output sequence corresponding to the same input sequence by means of simulation. Obviously, in order to obtain the simulated output, indicated with $\{y'_k\}_{k=1}^{N}$ , we need to calibrate the model, and this means to find values for the model parameters such that the simulated output $\{y'_k\}_{k=1}^{N}$ tracks as well as possible the observed output $\{y_k\}_{k=1}^{N}$ given the same input $\{u_k\}_{k=1}^{N}$ .

Therefore, the problem can be formulated as follows. Let us define the following objective function:

$$\mathrm{j}(\beta)=\frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{w_i} \left[\sum_{K=1}^{N} g\left(y_{i,k}-y'_{i,k}\,(u_k,\beta)\right)\right] \tag{4.4}$$

where $k$ is the discrete time instant, $N$ is the number of measures, each one at each time instant, $q$ is the number of outputs taken into consideration for the identification procedure, $w_i$ is the weight associated with the error on the *i*- th variable (the generic i-th variable will be specified for the problem under study in the next subsection), $g(\cdot)$ is either the square or the absolute-value function, $y_{i,k}$ is the experimental value of the i-th variable at the instant k and $y'_{i,k}\,(u_k,\beta)$ is the corresponding simulated value that is a function of the input $u$ and of the parameter vector $\beta$. The solution of the calibrating problem will be the parameter vector $\beta^*$ that minimize the objective function (see equation (4.4)), i.e.:

$$\beta^* = \arg min_\beta \, j(\beta) \tag{4.5}$$

Equation (4.5) can be solved iteratively; however there are in fact two problems: the first one is the stopping criteria, and the second is the choice of the initial condition. The first problem can be easily solved by selecting a maximum number of iterations or, the algorithm can be stopped when:

$$\left|\frac{j(\beta)_k - j(\beta)_{k-1}}{j(\beta)_{k-1}}\right| < \varepsilon \tag{4.6}$$

Where $\varepsilon$ is the error stop quantity and $j(\beta)_k$ and $j(\beta)_{k-1}$ are the values of $j(\beta)$ computed at the iterations *k* and *k-1*, respectively. This stopping criteria means that the algorithm will be stopped when the objective function variation, between two consecutive instants, is less than a freely chosen quantity $\varepsilon$.

The problem of the initial condition is not trivial; actually most algorithms search only for local minima, and in case of multiple minima (non-convex problem), the algorithm generally converges only if the initial guess is already somewhat close to the final solution. For this reason, the choice of the initial condition is crucial. However, this problem is avoided if genetic algorithms are used, since they are evolutionary optimization algorithms robust with respect to the initial condition (Davis et al. (1991)).

### IV.2.2 PARTICULARIZATION FOR THE CASE UNDER STUDY

In our case the "experimental surveys" consist of measurements of the speed S and of the density D for one day. The estimated output is generated by means of Aimsun, i.e. the software Aimsun is running with a fixed model corresponding to the model under study, and tuned with a suitable set of parameters. Obviously if the selected parameters are incorrect, then the estimated speed-density diagram does not coincide with the experimental survey. For this reason let us select (4.4) as follows:

$$J(\beta)=\frac{1}{N}\sum_{k=1}^{N}\left[\frac{1}{2}\left(D_k - D'_k(\beta)\right)^2 + \frac{1}{2}\left(S_k - S'_k(\beta)\right)^2\right] \tag{4.7}$$

where N = 96, since we have one day of survey data, one for each 15 min. We choose as parameters for the optimization the following:

$$\beta = [R_T \, S_{max} \; d_{min}] \tag{4.8}$$

Where $R_T$ is the reaction time, $S_{max}$ is the maximum desired speed, and $d_{min}$ is the minimum distance vehicle.

Note that the reaction time is the time in seconds that it takes a driver to react to speed changes of the preceding vehicle, the maximum desired speed represents the maximum speed that a certain type of vehicle can travel at any point in the road network, and the minimum distance between vehicle is the distance, in metres, that a vehicle keeps between itself and the preceding vehicle when stopped.

Now using equations (4.7) and (4.8), the problem (4.5) can be solved using the genetic algorithm in MATLAB. In particular starting from a generic initial condition, the genetic algorithm generates a set of parameters $\beta$, and then the software Aimsun is running with the parameters $\beta$ (the Aimsun is attached to MATLAB® via a python subroutine that allowed the data transfer between the two programs). The Aimsun gives a set of estimated outputs (one for each β) and the algorithm computes the objective functions (4.7) associated with each $\beta$. Finally the algorithm selects the best parameter $\beta$ and generates a new set of parameters β that represent the new generation. This cycle goes on until the stopping criteria occurs.

In our case the stopping criteria is chosen with a specified fixed maximum number of iterations (20 generations).

In our case, the initial population contains 20 individuals and the stopping criteria is chosen fixing a maximum number of iterations (20 generations). With these choices, the computational time is almost 4 hours using an Intel(R) Core (TM) 2 Quad CPU Q9300 2.50GHz and

8Gb of RAM. Note that we stopped the algorithm after 20 iterations because, after 20 iterations, the value of the cost function (4.7) reaches a steady-state and the algorithm can be stopped. The steady-state condition can be checked using condition (4.6), which is satisfied, in our case, with ε= 0:1. In other words after 20 iterations the objective function variation, between the 20th and the 21st instant, is less than ε = 0:1. Obviously if ε is set to a smaller value, then the algorithm will stop after 20 iterations.

In order to avoid the algorithm generating parameters without a physical meaning (i.e. negative reaction time, negative distance among vehicles, etc...), the search domain has been reduced defining an upper bound $\beta''$ and a lower bound $\beta'$ for $\beta$ , i.e. $\beta' \leq \beta \leq \beta''$.
The best $\beta^*$ obtained from the solution of this optimization problem will be the best value of reaction time, maximum desired speed, and minimum distance vehicles such that the simulated speed-density diagram tracks as well as possible the experimental one. This represents an efficient automated calibration procedure for simulation with Aimsun. The results are presented in the next Section. A block diagram of the processing steps to execute the algorithm are shown Figure 4.2. The details of the genetic algorithms are not given here since it is not the objective of this work, instead we are interested on their applications in the calibration procedure for traffic simulations with Aimsun. The reader is referred to the online MathWorks's® website or to the large number of online manuals for basic knowledge of genetic algorithms.

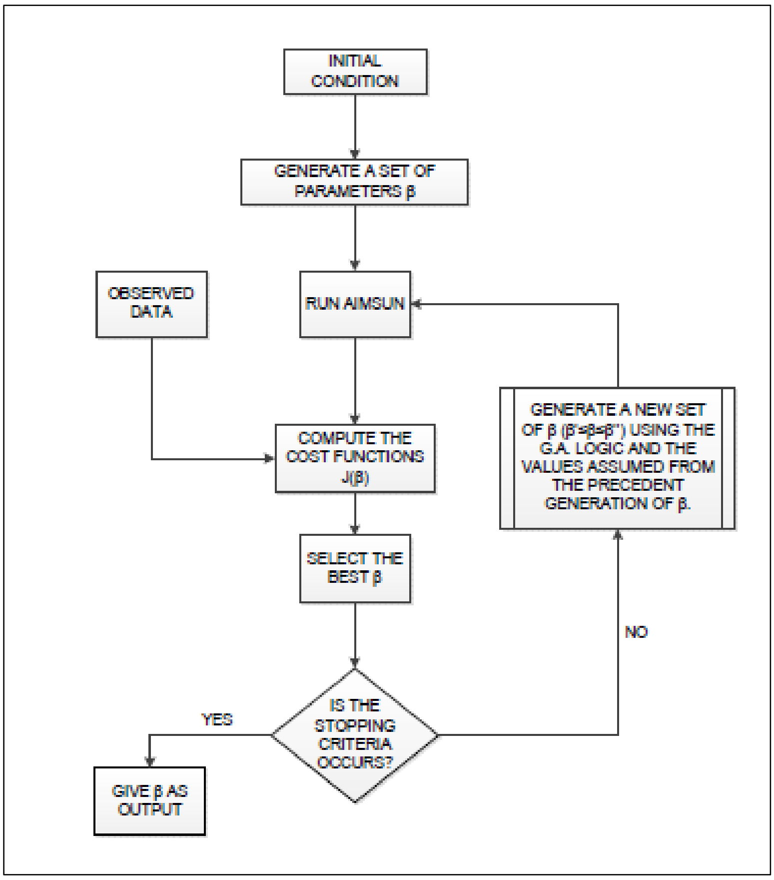


Fig. 4.2 Block diagram of the algorithm.

## IV.3 SIMULATION RESULTS

The algorithm detailed above was applied to solve the optimization problem as described in Section 3. After 20 generations (approximately 4 hours of computing time), the algorithm reached the convergence condition and returned the optimal solution. The best combination of the values of the simulation parameters included the value of 0.72 s (instead of the default value of 0.8 s) for the reaction time, which is the time in seconds taken for a driver to react to speed changes in the preceding vehicle, the value of 0.84 m (instead of the default value of 1 m), for the minimum distance between two vehicles, or the distance, in metres, that a vehicle keeps between itself and the preceding vehicle when stopped, and the value of 104.27 km/h (instead of the default value of 110 km/h) for the maximum desired speed, or the maximum speed that a certain type of vehicle can travel at any point in the road network.

To test the consistency of results from GA optimization was tested by repeating the GA process two more times with 10 generations and 20 populations. Naturally increasing the number of generations or populations would help to reach goodness of fit value, but it requires more computation time.

Considering the best combination of the modeling parameters resulting from the genetic algorithm application, the following Figure 4.3 shows the speed–density graph with the two curves interpolating the empirical data and the simulation outputs (gained by using the best output parameters) together with the two series of observed and simulated data are plotted also. Compared to the graph shown in Figure 4.1showing the speed-density graph with the two curves interpolating the empirical data and the simulation outputs (produced by using default parameters only), together with the plots of field and simulated data, the simulation generated using the optimized parameters are a satisfactory fit to the field data.

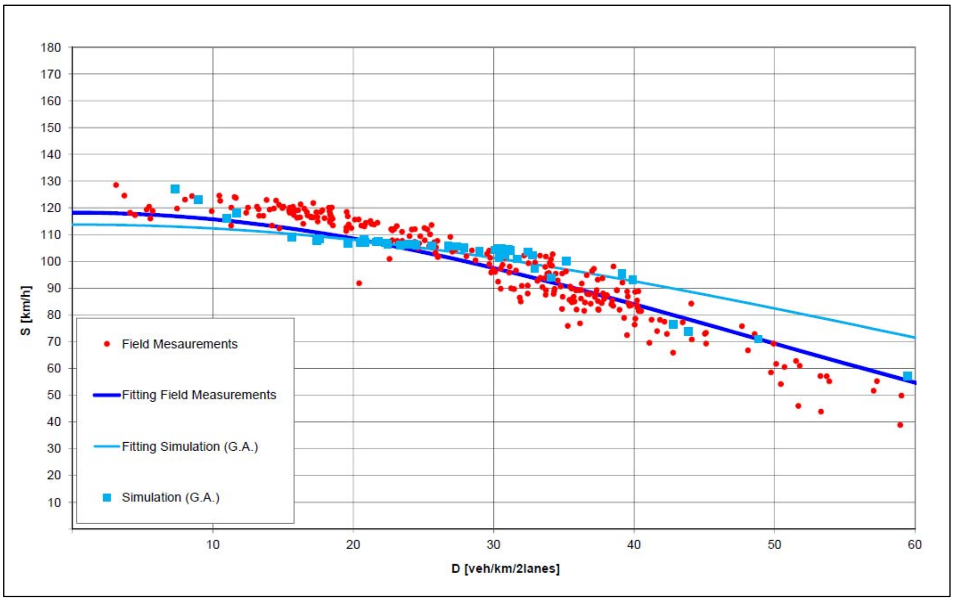


Fig. 4.3. Speed-density graphs with plots of observed and simulated data from genetic algorithm application.

Infact, a comparison of the uncalibrated Aimsun models (default parameters), and the calibrated Aimsun model (GA-based parameters) shows the importance of calibration for microscopic simulation models.
Considering how the genetic algorithm works, namely that the genetic algorithm function minimizes the goodness of fit-function, the most favourable value value for a population is the smallest fitness value for any individual in the population. By minimizing the fitness function, we were able to express how far an observable variable was from its simulated value, constrained by the set of feasible values of the model parameters on which the simulated variable depends. Figure 4.4 shows the comparison of the density profiles both for the field measurements from the A22 Freeway and for simulation with the default and optimization parameters. A better match to the field data clearly is obtained using the optimization parameters compared to the default parameters. Similar considerations can be made for count and profiles as shown in Figure 4.5.

Figure 4.6 shows the values of the cost function $J(\beta)$ in Equation (4.7) during the optimization period, and the corresponding value of the same $J(\beta)$ computed using the default parameters. From this figure it is evident the beneficial effect obtained with the proposed algorithm, since a better matching to the field data is clear in comparison with the simulation generated by using the default parameters. This fact is confirmed by the computation of the cost function in both cases, which is equal to $J(\beta) =$

69 for optimized parameters and it is equal to J(β) = 82:5 for default parameters.

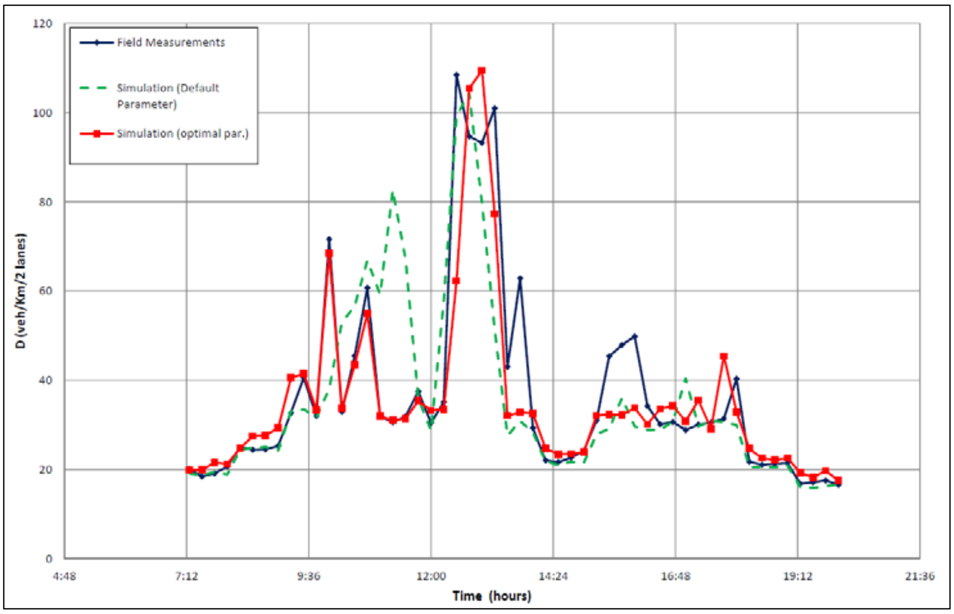


Fig.4.4. Density profiles for field measurements and simulation outputs.

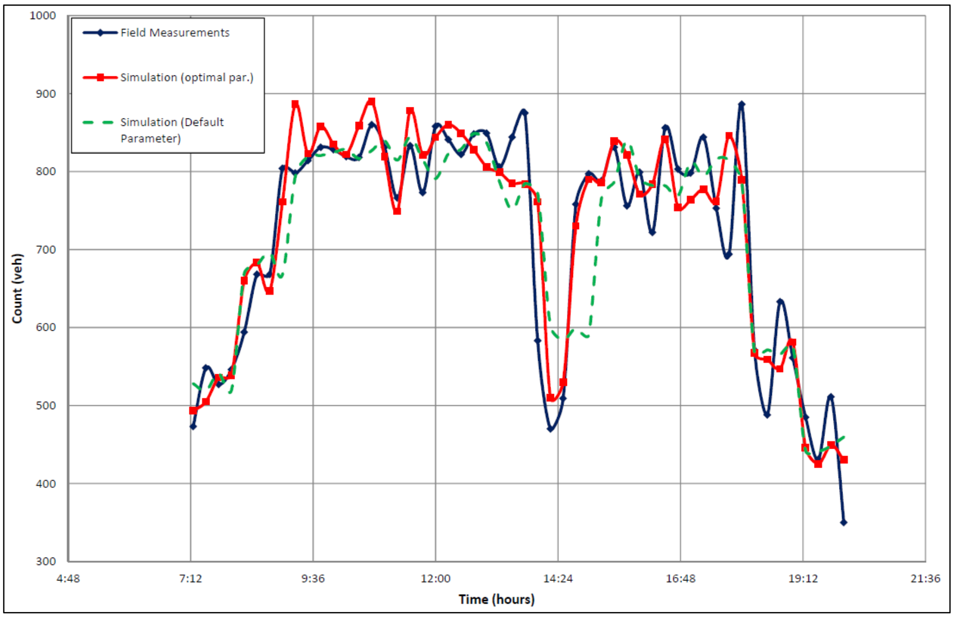


Fig.4.5. Count profiles for field measurements and simulation outputs.

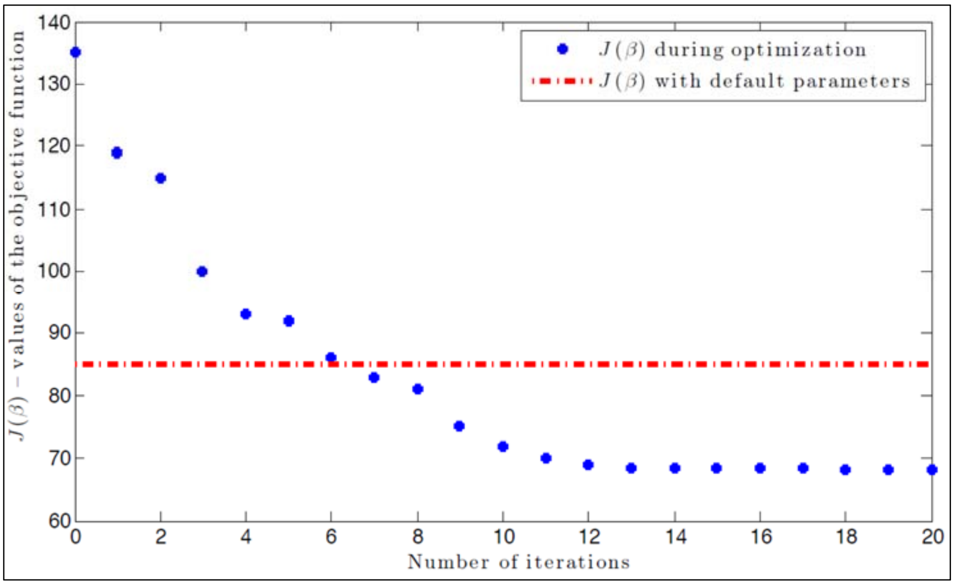


Fig.4.6 Values of the cost function J(β) in Equation (7) during the optimization period.

In order to validate the calibrated model, the process of checking to what extent the (calibrated) model replicates reality was also performed. Once the parameters were optimized to produce the best fit between observed and simulated data, i.e. when they had little further influence on the modeling results, the validation of the calibrated model was addressed. The validation was performed by comparing the simulation outputs with an empirical data set which was not used in the calibration process. Figure 4.7 shows the empirical and simulated speed-density graphs. Specifically the same figure shows the comparison of the simulation data (together with the curve which interpolate them), and the empirical equation S = S(D) in which the mean values of the traffic parameters (Southbound and Northbound), for the observation stations on A22 Brenner Freeway, were inserted (see Table 4.2).

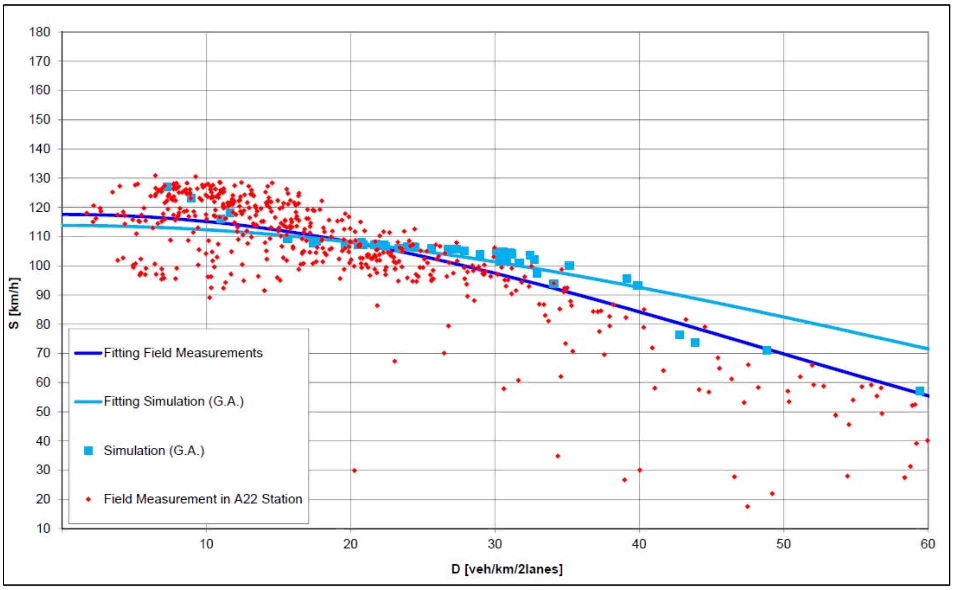


Fig. 4.7. Validation process: empirical S-D curve versus simulation outputs.

Two further comments can be made. Figures 4.4 and 4.5 show good results for some time interval, but in some cases the behavior seems to deteriorate during periods of low traffic counts. This problem could be avoided using different optimal parameters for different time intervals, but this requires a more complex model and a larger number of parameters that leads to more computational effort. On the other hand, the calibrated values in the validation seem to have poor agreement at higher densities. The reason of this result is referable to the choice of a on-single regime model such as the May model proposed in Equation (4.1). In order to avoid this problem, given that the empirical data resulted in many more low-to-medium densities than for higher densities where the error between real and simulated data seems high, a two- or more regime model can be considered instead of the on-single regime model. Indeed, a two or more-regime model is likely to provide much improvement for higher densities. Both these comments represent an important recommendation emerging from this work and an area for further research.

For each time interval, the simulated density and values of speed were compared with the results from the empirical speed-density equation were compared and the GEH index was calculated as criterion for acceptance, or otherwise rejection, of the model (Barceló et al. (2010, p. 46)). Since the deviation of the simulated values with respect to the measurement was smaller than 3 in 100% of the cases, the model validation could be accepted. In particular a GEH of 2.85 has been obtained using the default parameters and a GEH of 2.18 has been obtained using the optimized parameters.

## IV.4 CONCLUSION

In transportation engineering, as in many other branches of computer science and mathematics, the benefits of automating the iterative process of manually adjusting the values of the parameters as proposed by a traffic microsimulation software can be pursued by solving the calibration process as an optimization problem. The optimization techniques, indeed, searching for an optimum set of model parameters through efficient search methods, find a solution that is close to the optimal solution and allow the simulation of complex phenomena that cannot easily be described analytically. The simulation of the traffic conditions on the highway and through intersections will give realistic microsimulation results when the objective function is embedded into the optimization problem to be solved and is able to effectively minimize the differences of the simulated measurements from those observed in the field. Thus, the formulation of the calibration process of a traffic model as an optimization problem is recommended as worthwhile offering much potential if adopted in practice .

Based on the above considerations, this research presents the first results of research on the application of a genetic algorithm to improve the calibration of a traffic microsimulation model based on speed-density relationships for freeways. The calibration method was implemented and tested by using a large set of traffic data collected from the A22 Brenner Freeway, Italy. Two sets of data measured at different stations of the A22

Freeway were identified, one to perform the model calibration and the others for the model validation.

Aimsun microsimulation software and a freeway segment were used as the basis of the study. The field measurements of the traffic variables here identified (i.e. flow, speed and density) were compared with the corresponding modeling results obtained by using the software Aimsun for the selected test freeway segment under congested and uncongested traffic conditions.

Before having recourse to an automated procedure to test better the validity of the traffic microsimulation model, local traffic conditions on A22 Freeway were reproduced performing trial simulation runs by using the default values for the model parameters. The empirical and the simulated data sets were fitted by using the May model; thus the comparison between the two sets of data was performed by using two continuous speed-density curves.

The calibration was then formulated as an optimization problem to be solved based on a genetic algorithm in which the objective function was defined so as to minimize the differences between the simulated and real data sets in the speed-density graphs. In order to solve the optimization problem and then calibrate the simulation model, the Genetic Alghorithm (GA) tool in Matlab was applied. Among the parameters within the simulation which could affect the simulation outputs and therefore considered potentially important for calibration purposes, were the reaction time, the minimum distance between vehicle and the maximum desired speed. These parameters had the biggest influence on the difference between the observed and the simulated traffic measurements. Having in mind the objective to automate the calibration process, the optimization technique was attached to Aimsun via a subroutine so that the data transfer between the two programs could automatically occur. An external script written in Python allowed the Matlab software to interact with the Aimsun software.

Taking into consideration the best combination of the modeling parameters resulting from the GA application, we were able to observe that the simulation with optimized parameters generated a satisfactory fit to the field data, i.e. there was a very good approximation of the field measurements. Indeed, the simulated values of speed and density gained by using both the best output parameters (resulting from the GA application) and the default parameters only (as proposed by Aimsun) were verified against the corresponding empirical values by developing the speed-density graphs with the curves interpolating the empirical data and the simulation outputs for both simulation scenarios.

Once the parameters were optimized to produce the best fit between observed data and simulation, the model calibration could be accepted, the validation of the calibrated model was made. This procedure involved a comparison of the observed and simulated data for the second set of data measured on the A22 Freeway. Thus it was possible to check to what extent the model replicated reality and to observe that the calibration process may be considered in a broader context and not only limited to one particular test freeway segment of the A22 Brenner Freeway.

Results showed that the genetic algorithm is applicable in the calibration and validation process of the traffic microsimulation model for the freeway under examination. It should be noted that the comparison between the field measurements and the simulation results obtained with the default and optimized parameters, only gives an insight into the performance of the calibration procedure, without solving the optimization issues on the nature of the obtained optimum (i.e. is it a local minimum or the absolute minimum?) and/or how well the absolute minimum is approximated by the local one, etc. However, beneficial tests resulting from the application of an optimization technique, which searches for an optimum set of parameters through an efficient search method, can compensate the further computational efforts deriving from the application of an optimization technique which automates the iterative process of manually adjusting simulation parameters not only for freeways but also for several other types of road infrastructures such as, at grade intersections and interchanges.

# CONCLUSIONS

In this work of PhD Thesis a methodology to find the fundamentals diagrams for the A22 Brenner freeway by microsimulations was presented. In traffic flow theory the fundamental diagram is an essential concept. The fundamental diagram relates two of the three variables average speed (v), flow (q) and density (k) to each other. If two of these variables are known, the third can be derived using the relation $q = kv$. Therefore, if only one variable is known, and the fundamental diagram is known, the traffic state can be determined. Furthermore, fundamental diagrams is also used to estimate some critical traffic parameters such as capacity/critical flow, critical density, etc. provided that the Fundamental Diagram truly reflects the intrinsic traffic characteristics.

The work of this PhD thesis started by introducing the fundamental diagram using Edie's definitions and the use of speed- density diagrams. After that, a statistical approach based on observed and simulated speed-density relationships was applied in the calibration process in order to measure the closeness between empirical data and simulation outputs. The comparison established between the lnS-$D^2$ linear regressions for all simulated (speed/density) values and the corresponding linear regressions for the empirical data allowed an assessment of the quality of the calibration for the traffic microsimulation model.

Afterward, it was developed a method that include an automated technique based on GA for automatize the process of calibration of the parameters in order to reproduce the fundamentals diagrams of the A22 Brenner freeway. In particular, the calibration was been formulated as an optimization problem in which the objective function was defined to minimize the differences of the simulated measurements from those observed in the speed-density diagram.

Furthermore, the most important models for the analytical calculation of PCEs (Passenger Car Equivalents) was presented and the performance of the Aimsun software was tested. After that, the results of microsimulations in Aimsun was evaluated in order to obtain the relevant parameters for the estimation of the PCEs and their comparison with those proposed by HCM.

From a wider point of view, the importance and the advantages of this procedure is also the capability of the model to predict different scenarios that may occur in reality in the freeway section by varying different initial conditions.

By using of microsimulation models, integrated with data collected on the field, the road managing authority can evaluate the effectiveness of an intervention by providing the positive or negative impacts that it will have on the operating conditions of the road infrastructure.

Another important result is that the calibrated and validated model is enough flexible to capture the intrinsic functional relationship for a large range of field data measured in a freeway section.

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