Integrating time of use in large scale traffic simulations

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Conference paper STRC 2003
Session "Time"

STRC | **3rd Swiss Transport Research Conference**
Monte Verità / Ascona, March 19-21, 2003

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Abstract

Given the limited set of features that analytical models can include and the level of details required by practical applications, many transportation models have privileged by now the simulation approach as a tractable way to describe the dynamics of traffic. Innovative models are mostly dynamic and concerned with the temporal patterns of travel decisions. We focus in this paper on the departure time choice of car drivers and on the within-day and day-to-day adjustment of the travel demand to the driving conditions and conversely. Taking into account the time of usage leads to the production of a richer set of evaluation indicators. We illustrate this statement on several experiments to advocate the modelling of the departure time choice and the segmentation of the population. We show that these are two key issues to evaluate, at the global level, the differentiate responses to the introduction of transportation policies such as traffic restraint and road pricing. Some preliminary results are shown for the simulation of the Zurich area.

Keywords

Dynamic traffic models – Departure time – Day-to-day learning – Measures of effectiveness

3rd Swiss Transport Research Conference – STRC 2003 – Monte Verità

1. Introduction

The general framework of this paper is that of dynamic traffic models. These models are now widely accepted in the transportation community as the "next big thing". However, their broad usage in transportation agencies still poses problems at several levels, among which the availability of input data, the requirements in computer power and the lack of adequate tools to analyse their results (see the review of Algers *et al.*, 1997). Part of the problem lies within the way that the temporal dimension is integrated into the models. Before we examine this issue, recall that, historically, first generation models, such as the four-step planning scheme, completely ignored the dynamics of transportation systems and assumed a sequence of static pictures of the real world: the generation of trips, the choice of a travel mode and then of an itinerary were seen as unrelated sequential choices. The progresses of research in travel behaviour have encouraged, since about two decades, the emergence of second generation models that share the common concern to provide a temporal framework to describe the dynamics of the travel phenomena along with the different timescales involved. The main behavioural assumption behind this trend is that users decisions are the outcome of several interacting levels: for instance household lifestyle decisions affect home location and car ownership, which in turn affect the activity patterns and daily schedules, which eventually define the travel choices in term of mode, route and departure time (see the agent-based approach of Raney *et al.*). Note that this line of research is also fuelled by political reasons since current transportation policies in western countries are mostly oriented toward travel demand management (TDM) rather than improvement of the existing infrastructure. Intelligent Transportation Systems (ITS) such as road guidance play also an increasing role in the way people select travel options. Taking these systems into account obviously requires from traffic models to provide a temporal framework to measure the reaction of users to expected and unexpected traffic conditions.

The time horizon modelled in this work is that of the morning peak up to a few days, as we focus on within-day and day-to-day adjustments. Within that time frame, the selection of a time of usage of the transportation system depends on many factors: the availability of public transportation, the congestion incurred on the road, the individual daily schedules, the opening and closing hours of facilities (schools, shops), etc. We restrict ourselves to the context of car drivers who only have to perform one single trip in the morning period at a desired moment. As in most microscopic models, drivers are simulated individually with personal characteristics. The variables that affect their choices are the traffic conditions incurred, the satisfaction of their schedule wishes and, optionally, the tolls they have to pay to use some facilities. Obviously, the explanation of the schedules is left to upstream models such as activity pattern models and trip chaining models. These latter often require the acquisition and processing of a lot of socio-economic data (see Bowman, 1998). As stated in the preamble, we favour dynamic traffic models that do not require too many additional data as compared to first generation models. Trip tables are often available and drivers schedules can be estimated independently. Nevertheless, this approach remains easy to integrate in a broader hierarchy of travel decision models.

In the virtual world of the simulation, once drivers have selected their departure time and their itinerary, it is the role of the Dynamic Traffic Assignment (DTA) to compute the subsequent traffic conditions given the properties of the transportation network (topology and capacities). Several methodologies exist to carry over this task. They are often categorized according to their level of details: macroscopic models assume that vehicles are homogenous and that traffic variables (i.e. speed, flow, density) are continuous (DTA is often called the dynamic network loading problem in this context). Microscopic models instantiate individual vehicles with their own characteristics and describe their complex motions in the network (lane changing, overtake, acceleration, etc.). The approach adopted here models congestion at an intermediate "mesoscopic" level: it uses speed-density functions and discrete events instead of time slices for the time representation. We refer the reader to de Palma and Marchal (2002) for an exhaustive description of the simulation environment METROPOLIS and of its assignment module (see Figure 1 for the overall framework of model). Basically, the mesoscopic level of detail yields fast executing times by assuming that road sections behave as simple linear queues with fixed capacities. This allows to simulate large-scale systems (i.e. above several thousands links and 100,000 vehicles) two order of magnitude faster than micro simulations but at the cost of a loss in congestion details.

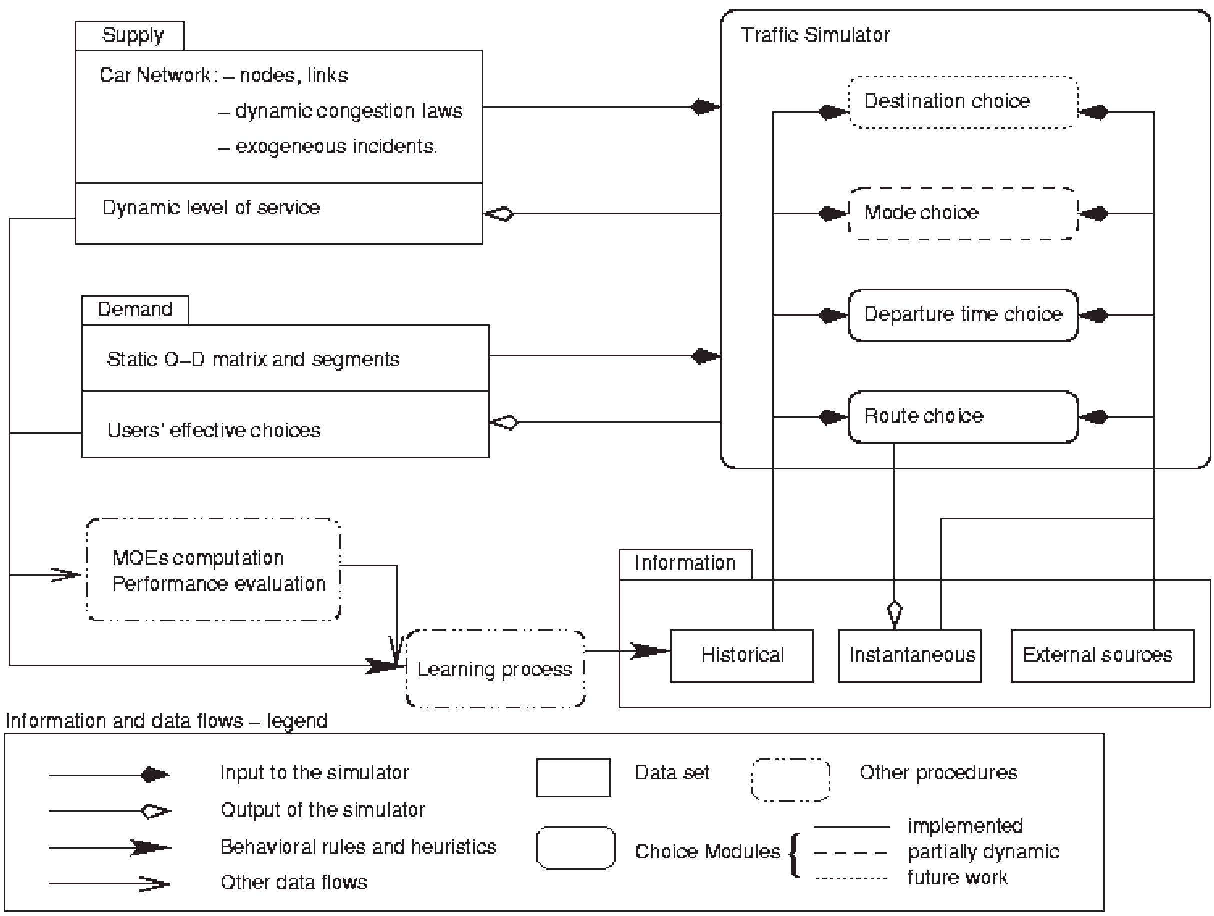
The simulation of large data sets has at least two motivations. Firstly, most agencies have already available city-wide coded networks that have been used for transportation planning with static models. These data, together with the corresponding origin-destination matrices, are expensive data that usually require several man-years to gather and to code. The transition to a system of exactly the same size is obviously a benefit. Secondly, network data are often encoded manually and the estimation of origin-destination matrix typically requires a lot of manipulation from the operator. These tasks are likely to be performed automatically in the years to come: road networks can be extracted more or less automatically from aerial or satellite images and coded into geographical information systems. In practice, the level of details of these databases exceeds by far the need of the transportation planner and the simplification or reduction of these data is costly and ambiguous. Likewise, the data collection needed for origin-destination matrices can be extracted from various digital sources (e.g. GPS equipped vehicles, cell phones tracking, traffic counters, etc.). As the electronic automation of transportation systems proceed, we can conjecture that the cost of collecting data will steadily decrease while the cost to perform manual aggregation, reduction or interpretation will remain the same or even increase with the complexity of the databases.

Day-to-day dynamics refers in this article to the adjustment of the balance between traffic conditions and users decisions. After each simulation of the morning period, users update their choices based on their driving experience. Given these choices, a new DTA can be performed. The whole system can loop until some stationary regime is observed, under constant conditions. The update of users choices is performed using an information data structure that is constantly improved (see the main loop of Figure 1). The more drivers use the network, the better their "knowledge" of the time-dependent variations of the traffic conditions. This learning process, also detailed in de Palma and Marchal (2002), attempts to model how users react to unexpected conditions but it is not calibrated or backed up with real day-to-day observations. Its main purpose is to feature the feedback of traffic conditions on the patterns of the time of usage. The information data block (see Figure 1) is also constantly accessed as the drivers are allowed to revise their route choice in the presence of unexpected conditions. To summarize, the dynamic aspects appear at several levels in this framework:

- departure time choice (i.e. pre-trip decision),
- traffic dynamics (i.e. en-route diversion and time-dependent traffic),
- information modelling (i.e. day-to-day adjustments)

The discussion of the use of a departure time choice model instead of dynamic origin-destination matrix is extended in Section 2. The remainder of this paper is organized as follows: Section 3 is devoted to the definition of new evaluation indicators adapted to the dynamic framework defined so far; Section 4 provides some preliminary results of the simulation of the Zurich area; Hypothetical scenarios are presented to illustrate the concepts developed in the previous sections; Section 5 concludes.

Figure 1 Simulation framework of METROPOLIS



2. Synthetic demand module (SDDM)

In most DTA models, the variability of demand over time is captured by dynamic origin-destination matrices (DOM) that are input into the model (see the left part of Figure 2). The incoming rate of vehicles at each entry point is considered to be exogenous. The acquisition and estimation of these DOMs rely on traffic sensor data. Various sophisticated techniques, essentially originated from optimal control theory, have been developed to solve the DOM estimation problem (see Ashok (1996), Ashok and Ben_akiva (1993)). However, it should be noted that, while these methods have proven to be efficient on small networks (typically highway corridors with ramp metering), it is still unclear if DOMs can be estimated for large-scale dense urban networks. Because the time-dependency of demand is not included, DTA models have to be fed with a historical database of DOMs to cover different types of days or traffic conditions. When such systems are embedded in real-time control schemes, a preliminary DOM estimation is performed by an expert system that combines this historical database with current traffic counts. Other demand data that play a part in the DTA model (e.g. driving behaviour, access to information provision or vehicle parameters) are usually assigned to the drivers by using disaggregate models such as prototype sampling or by assuming multiple classes of users (like in DYNAMIT, see Ben-Akiva *et al.* (1998)).

The use of DOMs offers several advantages: the traffic counts can be acquired for a large variety of conditions in an automatic way. The records over long periods can produce reliable historical databases. Moreover, real-time data acquisition allows an accurate instantaneous demand estimation, which makes DOMs very well suited for applications with a short-term horizon such as local traffic control or monitoring. However the DOM/DTA scheme suffers from disadvantages that limit its usage for medium to long term planning and for the evaluation of ITS introduction or TDM policies:

- DOMs are costly to collect for large-scale dense urban networks because of the prohibitive number of loop detectors that would be required. However, this may improve with future technologies such as car equipped with GPS.
- If there is a lack of sensors data, the estimation of DOMs may be unreliable because there are just too many degrees of freedom (the underlying mathematical problem is over determined, see the method of Bierlaire (2002) to improve the quality of trip tables).
- The assignment of specific characteristics to the drivers (e.g. value of time) is not completely consistent. Indeed, DOMs identify vehicles, not users: any measure that

affects the departure time choice differently for two classes of users (e.g. blue and white collars) cannot be properly captured.

- DOMs are easy to upgrade with real flow data streams but are difficult to link with upstream models like activity models.
- Any modification of the infrastructure (e.g. traffic restraints or capacity expansion) is likely to affect the route choice but also the departure time choice of users, thus invalidating previously estimated DOMs
- Similarly, the introduction of ITS is also likely to modify the behaviour of users in term of departure time choice, making calibrated DOMs inappropriate to evaluate or assess those policies ex ante.

For all these reasons, the DOM/DTA scheme appears to be adequate for short term applications and for online control of real systems. However, this scheme falls short to provide enough structure in the demand to model the medium to long run required by planning applications or ITS introduction.

Several types of explanatory models can be added to the picture to tell how users select the hour to start their trips (or sequence of trips), whether they are referred to as “daily schedule” models, “period switching” models or “departure time choice” models (DTC). Since the time of usage is given by those models, the remaining data is time-independent and can described in its simplest form by a static O-D matrix (SOM). We denote by “synthetic dynamic demand module” (SDDM) such a demand specification that consists of two separate blocks: a time-independent trip table and a specification of departure time behaviour (see the right part of Figure 2). It is synthetic in the sense that it does not require time-disaggregate data. We propose to populate the SDDM with “demand segments”, each segment being composed of a static O-D trip matrix (SOM) and a set of behavioural rules that define how typical user types select their departure time choice. The overall demand specification can be segmented in an arbitrary number of segments. For the study of a given transportation system, these segments can reflect (a) the main trip purposes: home-to-work, business, leisure, etc. and (b) the main classes of users: white collars, blue collars, drivers with/without access to information, drivers with/without parking availability, etc. The set of behavioural rules that determines when users decide to initiate a trip should satisfy two constraints:

- The DTC model should be consistent with the demand segmentation. In our view, the segmentation criteria should depend on the socio-economic characteristics, on the purpose of the trip (e.g. distinction between commute and non-commute trips, morning and evening commute, etc.) but not on the actual departure time choices.
- The DTC model and its parameter values should remain invariant for long term prediction. It should be fairly independent of the features of the supply, except in term of performances (e.g. travel times). Ideally, it should only depend on variables

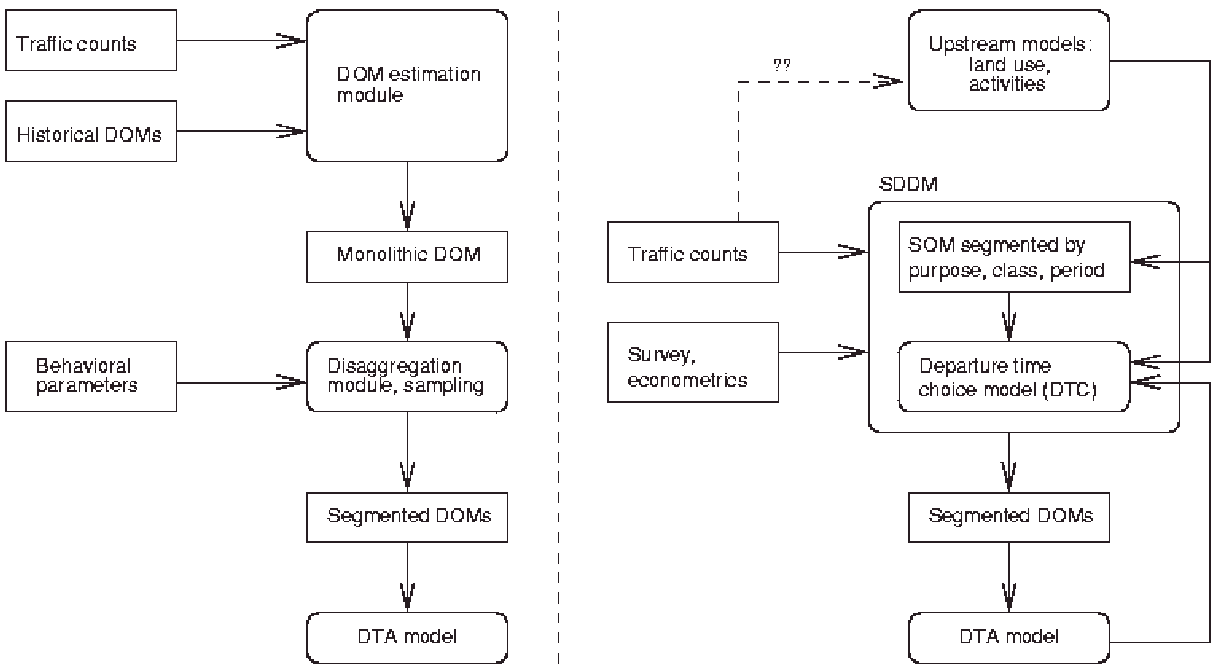
of performances (e.g. travel times). Ideally, it should only depend on variables that are exogenous to the transportation field (e.g. socio-economic variables or behavioural parameters like the cost value of time).

Finally, for innovative policies such as ITS introduction and TDM measures, the DTC model should have the following features:

- Compliance with an information provision framework: the extension of the DTC model to integrate any pre-trip information system should be straightforward,
- Availability of standard and relatively inexpensive econometric techniques to estimate the DTC parameters from RP/SP surveys or from sparse traffic counts,
- Straightforward extension to activity, trip chains and scheduling models.

The SDDM scheme has more predictive power and is adequate for planning. However, traffic counts are used only to estimate the trip table and the time-dependent information is not exploited. Ideally, an hybrid scheme would conciliate both schemes although it is not clear how traffic counts could be back-propagated to calibrate the activity models for instance. The specific DTC adopted in METROPOLIS is an extension of Vickrey's model (see appendix B).

Figure 2 Two different schemes to model time-dependent demand. DOM=dynamic O-D matrix; SOM=static O-D matrix; DTA=dynamic traffic assignment



3. Evaluation measures

This section discusses some issues about the management of output data of second generation models and the new evaluation measures they can provide. A classification is proposed below, that may help to define some data exchange standard between different dynamic models. A major difference between static and dynamic models lies in the output variables. Firstly, almost all static models share the same definition of output variables or measures of effectiveness ("MOEs"), which is not the case for dynamic models. Secondly, most microsimulators models provide animated visual outputs of traffic dynamics but lack meaningful indicators that can be used to measure the system-wide performance of a given scenario. A set of MOEs for mesoscopic dynamic models with link-based congestion models is proposed below. We distinguish *atomic* MOEs that consist of the core output data (e.g auto volumes, travel times) of the models from *derived* MOEs that are combination of the atomic MOEs (e.g. CO emissions).

The atomic output of static models consists in the static traffic flow on each link of the coded network. These flows correspond to the car volumes for the time period considered. Since the demand is often described as a continuous variable, the result is a vector of N_L real numbers, where N_L is the number of links in the network (we consider a network with N_Z zones and N_I intersections). From this atomic results, several derived MOEs can be computed: the average travel times and speeds are computed using the volume-delay relationships; turning proportions at each intersections are deduced from the same data; point-to-point shortest routes are computed by static shortest path algorithms (e.g. Djikstra's algorithm) using average travel times. All these MOEs are assigned to individual spatial entities of the system: links, zones or intersections. The following list presents a list of MOEs available for each of these types of element in the static case. Note that the number of trips is only considered as an output in the case of static models if there is elastic demand (i.e. mode choice).

Table 1 Static MOEs assigned to simulation entities

Simulation entity	MOE	Source	Dimension
Link	Traffic flow, density	Atomic	N_L
	Travel time, speed, congestion	Volume-delay functions	N_L
	Concentration of pollutants	External emission models	N_L
Intersection	Turning proportions, throughput	From flows	N_I
Zone	Emission and attraction	From flows	N_Z
	Accessibility	Static shortest path algorithm	N_Z
O-D pair	Shortest path, travel time	Static shortest path algorithm	N_Z N_Z

In the case of dynamic models, the atomic outputs are the time-dependent traffic flow patterns. For each link, the output of the model is a pair of time-vectors that represent the inflow and outflow of the road section. These variables are directly available in analytical dynamic models but they have to be aggregated over some time interval (e.g. every 5 minutes) for simulation models by counting entering and outgoing vehicles like real counter loops. The time-dependent travel time for each road section is not, in general, a simple function of the inflow. It is a well-known effect from real traffic observation that there is no one-to-one relationship between speed and flow because of hysteretic effects in traffic. Even with mesoscopic congestion models, there is no fast way to compute the link travel time link from flows. (The computation of the travel time output vector from the flow vectors for a given link is equivalent to run again the simulation for that link.) Moreover, in the presence of spill-back effects, the waiting time component cannot be exactly reproduced with the knowledge of the time aggregated inflow and outflow. Therefore, the atomic dynamic output must include three time-dependent vectors: inflow, outflow and incurred travel time (or speed). These vectors have the dimension of the number of aggregation steps N_T. For instance, if we assume record intervals of 10 minutes each and a simulation period of 5 hours (e.g. morning peak), this yields three time-dependent vectors with N_T =30. The total of 90 components is to be compared to the single traffic flow value in static models. This simple fact explains why dynamic models generate at the minimum two order of magnitude more results than static models. This has important consequences for the design of analysis tools and databases. The following table provides the list of MOEs updated for the dynamic case. MOEs specific to the demand have been added, based on the atomic demand results that are the departure and arrival times for each individual vehicle (the total number of vehicles being N_U).

Table 2 Dynamic MOEs assigned to simulation entities

Simulation entity	MOE	Source	Dimension
Link	Inflow, outflow, travel time	Atomic	$N_T\ N_L$
	Density, speed, congestion	From atomic MOEs	$N_T\ N_L$
	Concentration of pollutants	External emission models	$N_T\ N_L$
Intersection	Turning proportions, throughput	From inflows	$N_T\ N_I$
Zone	Departure and arrival rates	From inflows	$N_T\ N_Z$
	Accessibility	Dynamic shortest path algorithm	$N_T\ N_Z$ $N_T\ N_U$
O-D pair	Shortest path, travel time	Dynamic shortest path algorithm	$N_T\ N_Z\ N_Z$
User	Departure and arrival times	Atomic	N_U
	Travel cost, schedule delays	From atomic MOEs	N_U

Note the following changes from the static case:

- Accessibility is now time-dependent and depends also on the user schedule. Obviously, some aggregation is needed. The logsum of the logit model corresponding to the departure time choice can be used as a time aggregated value (see Appendix B).
- Deterministic dynamic shortest paths between O-D pairs are time-dependent and do not necessarily coincide with the actual paths taken by simulated vehicles since some models do not assume that drivers will take the shortest route at any time. However, the difference between the two measurements (i.e. path taken vs. deterministic path) could be a useful indicator of the simulation realism and ease the comparison between models.

For the technological aspects, an SQL database supporting these MOEs has been designed in METROPOLIS. A set of Java classes (i.e. a database wrapper) has been also implemented to easily retrieve these results for any scenario. The graphical user interface (GUI) (used to visualize the results presented here) is just a database client that queries a MySQL server where the input and output data resides. Import and export filters using XML technology could be easily implemented from that starting point. This track of development is currently under consideration to automate the data exchange with upstream activity models. Ideally, some XML format should emerge to allow transparent exchange of time-dependent network data. However, most GIS packages do not yet support temporal data so the emergence of a standard is still lagging behind.

4. Simulation experiments

This section presents as a proof of concepts a few experiments performed on the test site of the Zurich area (see appendix A for the details of the data set). The technical requirements for a typical simulation of a morning period are 250Mbytes to 500Mbytes of RAM and 11 minutes of CPU on a PC with a 2.5 GHz Intel Pentium 4 processor. This yields a faster-than-real-time ratio of about 25. (see de Palma and Marchal (2002) on performance issues).

We consider four hypothetical scenarios:

- a free-flow scenario provided to get a picture of the situation if drivers where not hindered by congestion,
- a base case scenario (with congestion),
- a traffic restraint case where capacities have been reduced by a factor of 2 in the area of Zurich city during the period from 07:30 to 08:30,
- a road pricing test where the access to that same area is priced 3$. This setting is reminiscent of the central London pricing scheme that was recently introduced but we tested a modular version (e.g. access priced between 07:30 to 08:30).

Global indicators for the whole transportation system are provided in Appendix C for these scenarios. The MOE "consumer surplus" is measured as the weighted sum of all accessibilities in the driver population, that is the accessibility averaged over users. The MOE "equity" is the opposite of the standard deviation of the accessibility distribution. Note that the schedule delay cost is about 2$ while the variable cost (i.e. travel cost minus the fixed free flow cost) is about 4$, a result compatible with the model of Vickrey. The MOEs are given after different periods of time for the traffic restraint and the pricing scenarios. Note the difference, for instance, of travel time and congestion, after one day or after 50 days. Obviously, drivers have adjusted both their routes and their departure after 50 days, while on the first day their departure rate was the same as before. Using fixed dynamic O-D matrices would generate the same result as day #1. Consequently, the use of a departure time choice model seems relevant to assess medium to long term impacts of access control policies. Note also the fairly limited impact on the mileage: drivers may have diverted their route choice but not in favour of much longer alternatives. In the case of pricing, it is noticeable that driving conditions have slightly improved.

Figure 3 presents the time evolution of the network occupancy for the different users segments. A first interesting result is that the overall time horizon is completely endogenous: schedule constraints have been set between 07:30 and 12:00 and drivers adjust their departure time accordingly. No arbitrary period has been specified. As intuitively expected, Blue Collars (BC) travel earlier (about 18 minutes) in the morning since earlier arrival is less costly for them than for White Collars (WC). This figure also picture the "soft" interaction between commuting and non-commuting drivers: the overlapping period when they both occupy the network is endogenous. The distribution of Non-Commuters (NC) is slightly skewed to the left since they incur an impediment caused by the late congestion provoked by commuting activities.

Figure 3 Network occupancy in the base case scenario

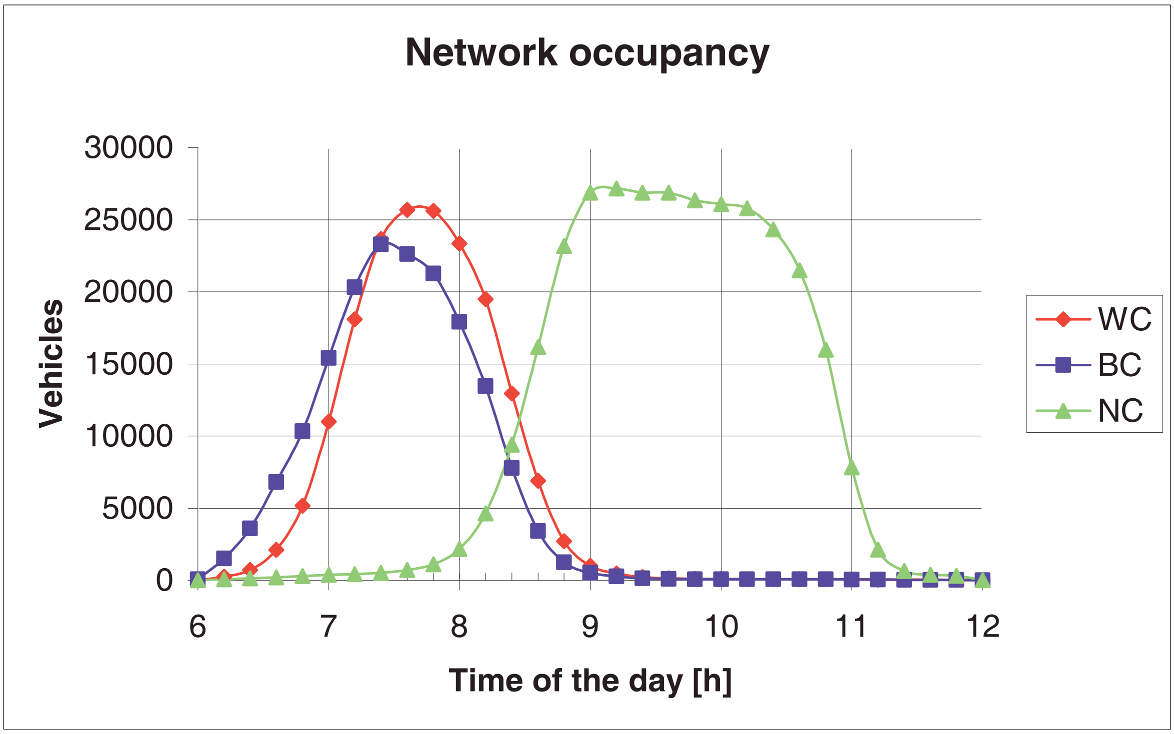


Figure 4 Isochrones from a zone close to Zurich downtown. Evolutions for two periods (left: from 6AM to 7AM; right: from 7AM to 8AM).

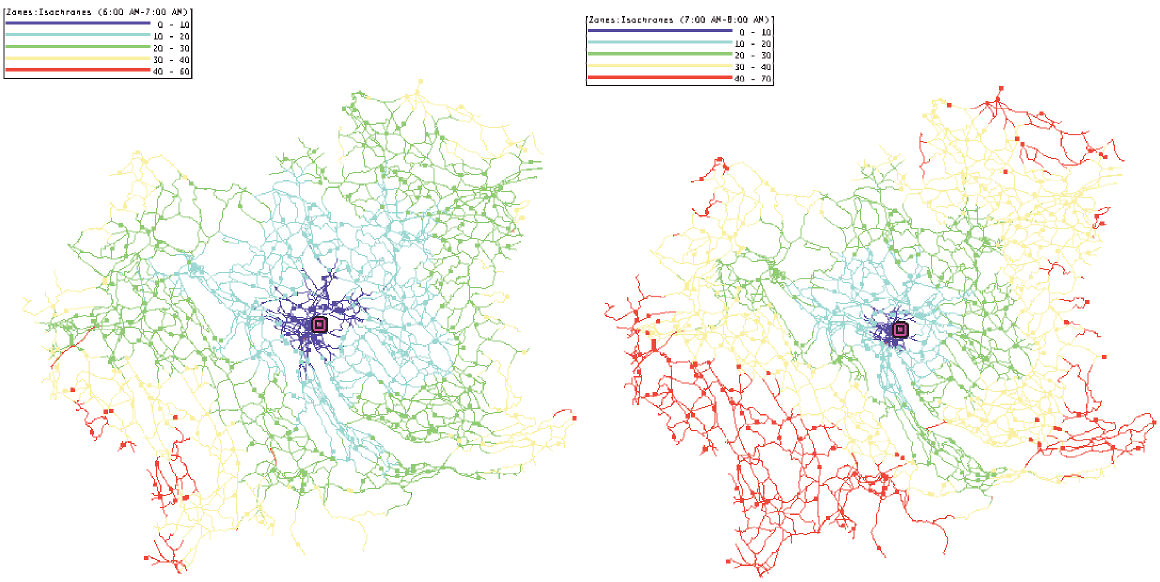
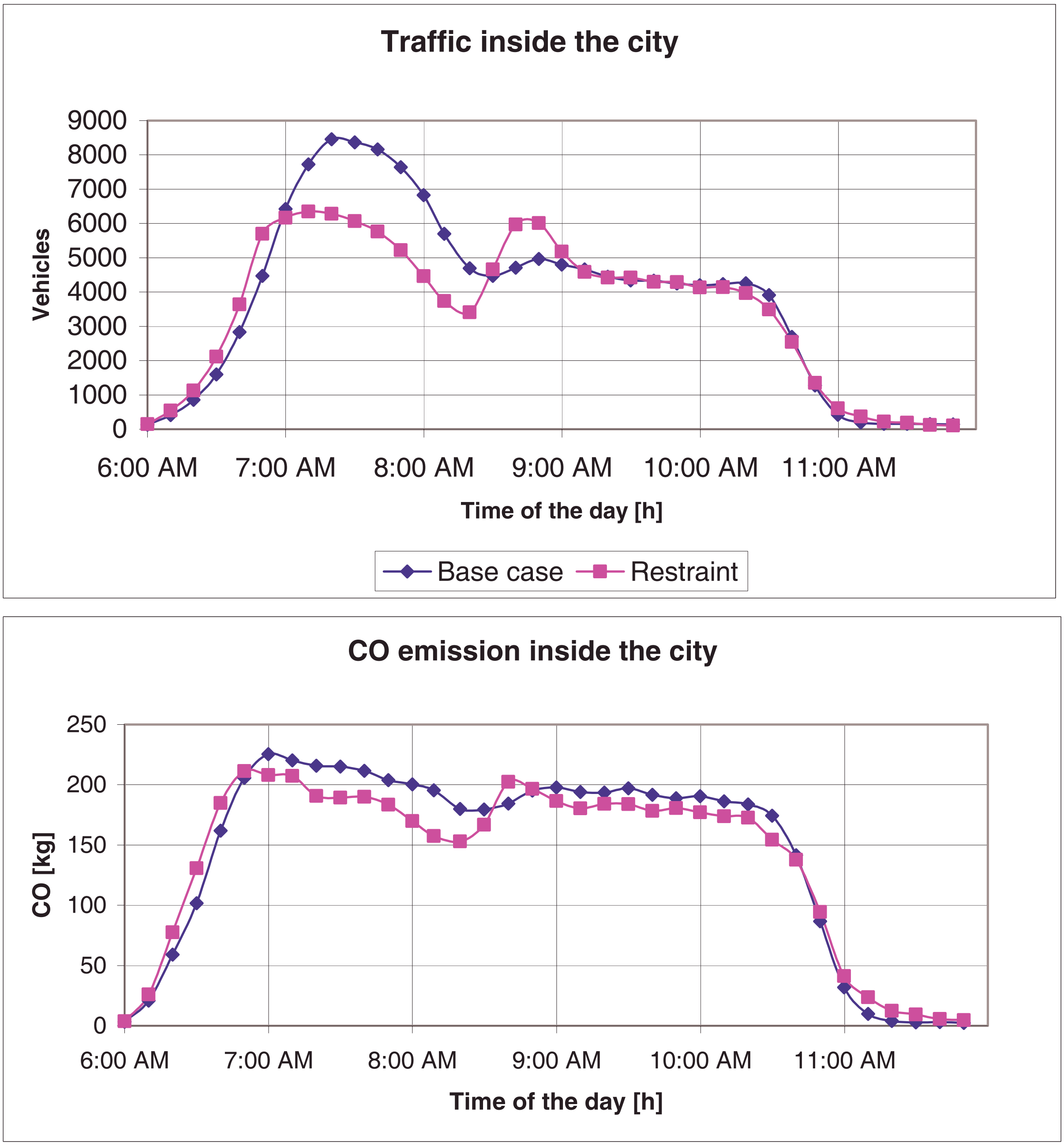


Figure 4 illustrates the congestion evolution during the time of the day for the base case scenario: isochrones graphs taken from a zone close to downtown Zurich shrink due to the congestion that builds up between 07:30 and 08:30. Note that accessibility maps would not reveal the same behaviour exactly since travel cost integrates not only travel time but also schedule delay costs.

Figure 5 shows the change of traffic occupation inside the restrained area of the city and the corresponding change in CO emission. The small "load surge" of non-commuting trips at the end of the period (08:30) indicates that the restraint period may be too small to be fully efficient.

Figure 5 Traffic inside the city and CO emission. Base case and traffic restraint scenario.



5. Conclusion

This paper presents the barebones of the time-dependent specification of the demand implemented in METROPOLIS. Basically, it stresses out the advantages of modelling the choice of departure time to overcome some problems of dynamic models, namely 1) limiting the amount of input data, 2) performing fast computations and 3) providing analysis tools. Performance issues have been studied in other publications. The focus here is on the input and output issues that are often more important to the practitioner. The so-called Synthetic Dynamic Demand Module has very low data requirements and can cope with large-scale databases. At the other end of the process, we provided a tentative list of standard MOEs that every dynamic traffic model could produce. This could in turn improve the comparison between models and allow test suites, benchmarks, etc. The benefit of the selected approach is demonstrated on a sample of results that can be obtained easily with such an architecture. Our next goals are to calibrate this database of the Zurich area. Future research efforts will be devoted to link the traffic model with upstream models such as an activity model (medium term forecast) (see the agent-based approach of Raney *et al.*) or a land use model (long term forecast).

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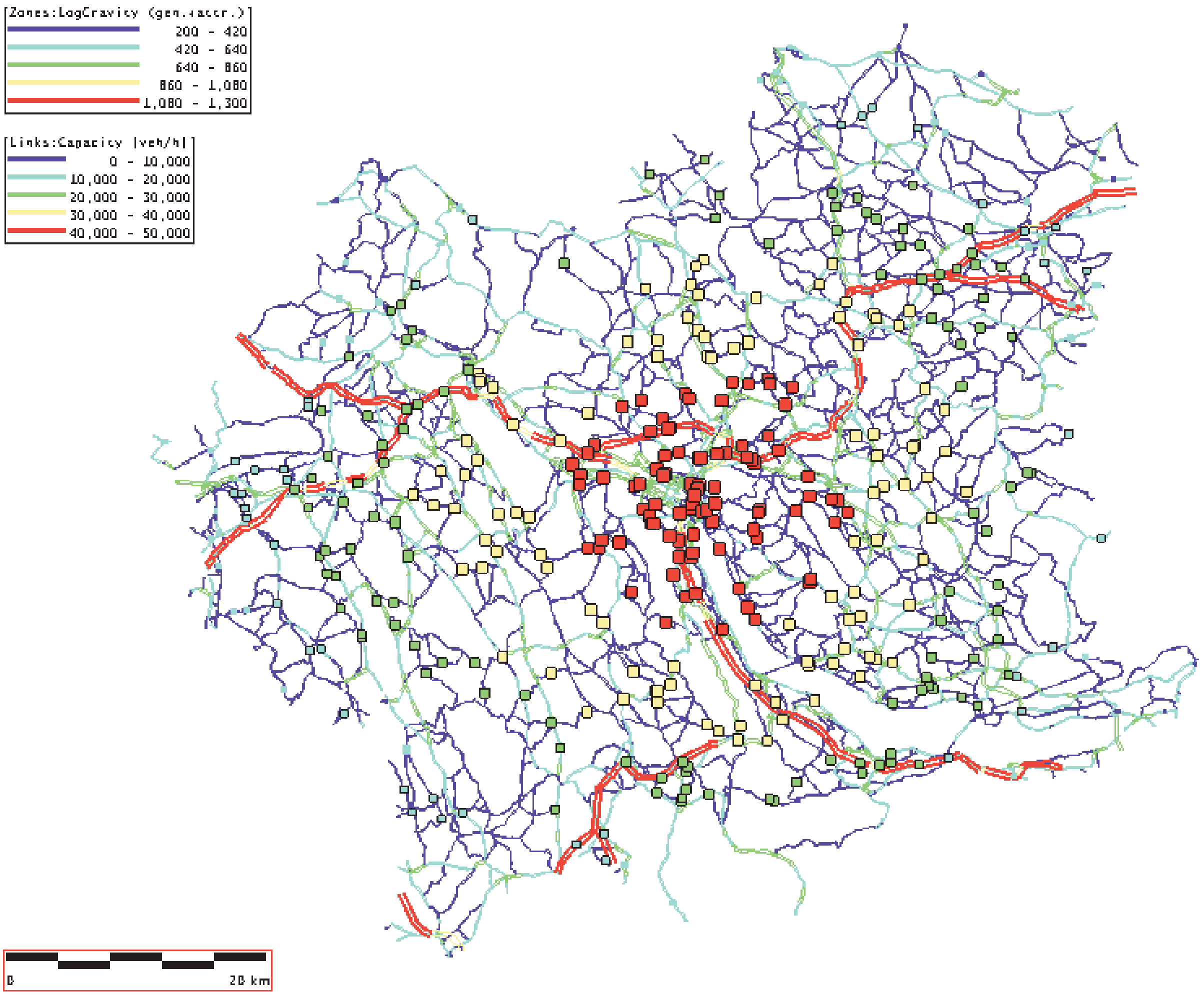
Appendix A: Data set

A1: Network

The network data set was provided by the IVT team of Professor Axhausen at ETH. It consists of a detailed NavTech road database for the region around Zürich. The studied area is about 4200 square kilometres (roughly a square of 65x65 kilometres). The car network pictured below has 75,203 links and 37,588 nodes.

Figure 6 Zurich area network with 12-hour capacities. The square are the zones with size and colour proportional to the sum of emissions and attractions.



A2: Demand

In this preliminary study, we had no data for the trip matrix so it was build artificially. We created 400 traffic zones (that is approximately one zone for every 3.2km x 3.2km square) for the sources and sinks of traffic (origin and destination zones). They are uniformly assigned to random intersections so that more zones are present where the network is denser as represented on Figure 6. For the simulation of the morning peak, we used a logistic-like matrix: the number of trips *N* between two zones distant from a distance *d* is given by

$$N = A\frac{\exp(-K(d-d_0))}{1+\exp(-K(d-d_0))},$$

where *A, K* and d_0 have been adjusted so that the total number of vehicles is 269,000 vehicles and the distribution of trips has a mean of 28km and a standard deviation of 13km.

The demand has been categorized as follows:

- Commuters that travel during the peak period from home to work.
- Non-commuters that perform other purpose trip during the off-peak morning period.

Moreover, we distinguish commuters with a high value of time (i.e. “White Collars”) from commuters with a low value of time.(i.e. “Blue Collars). The following table provides the values of the dynamic parameters associated to each of them. Note that these are hypothetical values that have not yet been calibrated.

Table 3 Demand segmentation and values of parameters of the Vickrey model

	# of vehicles	α (VOT)	β	γ	μ	t*	Δ
	[-]	[$/hr]	[$/hr]	[$/hr]	[$]	(distribution)	[min.]
Blue Collars	67,500	10	5	20	1.6	[07:30 - 08:30]	10
White Collars	67,500	20	19	21	3.0	[07:30 - 08:30]	10
Non- Commuters	135,000	14	12	20	2.3	[08:00 - 12:00]	10

Appendix B: The Vickrey model

This section recalls the original model due to Vickrey (1969). Assume *N* drivers commute from a given origin (*O*) to a given destination (*D*) connected by a single road *O-D*. Commuters face a unique choice: departure time. Let *tt(td)* be the travel time of a commuter departing from the origin *O* at time *td*. The arrival time of this commuter is therefore *ta=td+tt(td).* The desired arrival time for all commuters is assumed to be the same and equal to t^*. Therefore, the early delay is $t^*-[td+tt(td)]$ and the late delay is $td+tt(td)-t^*$. Commuters select their departure time in order to minimize a combination of travel time costs and schedule delay costs. Schedule delay costs occur because commuters who arrive too early or too late at the destination are penalized. Without any travel time cost all commuters would depart at the same time, generating a large amount of congestion. Conversely, without any schedule delay cost the departure distribution would be infinitely spread over time. Commuters therefore face the following trade-off: either they arrive on time and incur a maximum level of congestion, or they arrive very early (or very late) and incur no congestion. Clearly, intermediary cases are possible. The user cost (or travel cost) function is assumed to be the sum of penalties due to travel time and (early or late) schedule delay costs:

$$C(td) = \alpha\, tt(td) + \beta \max\left\{ \left[td + tt(td) - t^*\right], 0\right\} + \gamma \max\left\{ \left[t^* - td - tt(td)\right], 0\right\}, \qquad (1)$$

where α is the unit price of time, β is the unit price for early arrival and γ is the unit price for late arrival. Typically we have: $\beta<\alpha<\gamma$ (see Bates (1996)). The travel time *tt(td)* is assumed to be the sum of a fixed travel time tt_0, and a variable travel time $tt_v(td)$. The total and variable travel times are given by:

$$tt(td) = tt_0 + tt_v(td) = tt_0 + \frac{Q(td + tt_0)}{s}, \qquad (2)$$

where s is the capacity of the bottleneck (i.e. its maximum discharge rate). *Q(.)* is the number of cars waiting in the queue, hence $Q(td+tt_0)$ is the number of cars that will be waiting in the queue when the driver reaches the shoulder of the bottleneck. At the equilibrium, no driver can modify her departure time in order to strictly decrease her travel cost. This definition is the natural extension of the static Wardrop user equilibrium concept -Wardrop's first principle. Solving the equilibrium yields:

$$C^E = \alpha t_0 + \frac{\beta\gamma}{\beta+\gamma}\frac{N}{s} = \alpha t_0 + \frac{1}{2}\frac{\beta\gamma}{\beta+\gamma}\frac{N}{s} + \frac{1}{2}\frac{\beta\gamma}{\beta+\gamma}\frac{N}{s}, \qquad (3)$$

where the first term is the free flow cost and the second term is voluntarily split into the queuing time cost and the schedule delay cost (each of these terms is equal). Note that queuing costs equals to schedule delay costs: this shows that the cost for early and late arrivals, for any parameter values is expected to be of the same order of magnitude as the variable or queuing time cost. METROPOLIS uses a stochastic extension of the model given by the following continuous logit model:

$$\Pr(t < td \le t + dt)\Delta t = \frac{\exp(-C(td)/\mu)}{\int_{-\infty}^{+\infty}\exp(-C(u)/\mu)du}\Delta t, \quad (5)$$

where $Pr(.)\Delta t$ gives the probability to select a departure time in interval $t, t+\Delta t$. Moreover, we allow a time period without schedule delay penalty (Δ) around t^*. We denote by SDP the set of dynamic parameters $\{\alpha, \beta, \gamma, t^*, \Delta, \mu\}$. This model offers several advantages for the SDDM scheme:

- The SDP reflects intuitive properties from the users behaviour.
- It seems unlikely that the SDP will change with infrastructure changes, with TDM measures or with the introduction of ATIS because:
  - the penalties incurred in the car (α) can change only on the long term given the improvement in comfort and safety,
  - the penalties at the arrival (β, γ) are completely exogenous to the transportation system,
  - the schedule constraints (t^*, Δ) can change if local policies provide incentives to do so, but in this case, it defines a TDM measure in itself,
- The SDP depends on socio-economic values that can be linked with upstream models (e.g. parameterisation with respect to job, revenue, age, etc.), The segmentation into classes of trip purposes or behaviours is straightforward and it should be embeddable in an activity model.
- It provides an estimate of the schedule delay costs.
- The time-aggregated logsum can be interpreted as the time-independent accessibility:
  $A = \mu \ln \int_{-\infty}^{+\infty}\exp(-C(u)/\mu)du$

Appendix C: Global system-wide indicators

MOEs	Units	Free flow	Base case	Traffic restraint			Pricing	
				1 day	15days	50 days	5 days	40 days
Travel time	[min.]	22.4	30.7	37.1	32.8	31.6	31.6	30.4
Travel cost	[$]	6.9	9.6	12.9	10.3	9.9	10.3	9.8
Schedule delay cost	[$]	1.5	2.1	3.8	2.3	2.2	2.3	2.2
Free flow cost	[$]	5.4	6.0	5.9	6.1	6.0	6.1	6.0
Collected revenues	[$]	0	0	0	0	0	68856	71599
Consumer surplus	[$]	-9.0	-11.1	-10.6	-11.1	-11.0	-10.9	-10.9
Equity	[$]	-3.5	-5.0	-4.8	-5.2	-5.1	-5.1	-5.0
Late delay	[min.]	7.1	11.6	23.4	13.0	12.4	13.3	12.1
Early delay	[min.]	13.2	15.5	15.7	16.1	15.9	16.0	15.9
Early ratio	[%]	42.6	49.3	37.8	43.8	45.0	42.7	44.0
On-time ratio	[%]	34.0	28.3	25.7	28.5	29.0	29.1	29.8
Late ratio	[%]	23.4	22.4	36.5	27.6	26.0	28.1	26.2
Period	[h]	4.5	4.6	4.5	4.5	4.6	4.5	4.5
Congestion	[%]	0.0	16.8	31.9	20.7	18.7	18.3	15.2
Mileage	[10^6 km]	7.6	7.8	7.7	7.9	7.9	7.9	7.9
Num. of arcs	[-]	186.7	210.6	210.2	221.2	216.7	220.0	216.4
Speed	[km/h]	75.0	59.9	53.4	58.0	59.2	59.0	61.2