

Chapter 10

SIMULATION-BASED EVALUATION OF ADVANCED PUBLIC TRANSPORTATION INFORMATION SYSTEMS (APTIS)

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Abstract: Despite the great success and the broad diffusion of Advanced Public Transportation Information System (APTIS), there is a lack of studies, in the literature, investigating “systematically” how and to what extent such systems can affect network performances and travelers’ path choices. In this paper, we use a realistic case study of the city of Naples (South-Italy), to investigate the impacts of information offered in a Public Transportation (PT) network under different network conditions, i.e. irregular vs. regular services, congested vs. un-congested lines. The focus is on APTIS deploying shared en-route descriptive information. The results presented are based on the simulation of the three main components of the PT system, namely the network, the information provider (i.e. the Operation Control Center) and the travelers. The simulation of these components and their interaction is achieved using different modeling approach as: the schedule-based approach for the network representation and traffic assignment, a statistical model based on the Kalman filter for the prediction of the link travel times within the simulation period, and behavioral discrete choice models, following the Random Utility Theory, for simulating travelers’ behavior.

1. INTRODUCTION

Advanced Public Transportation Information Systems (APTIS) is the generic term under which all those technologies aiming at providing Public Transportation (PT) travelers with information on the performance of a transit network, are included. Different kinds of information can be provided for different phase of the trip. For example information could be the line, or the sequence of lines, to reach a given destination available through an internet web-site; the arrival time of a bus (referred to as a “run”) available

through Variable Message Signs (VMS) at the bus-stop, as well as the name of the next stop for the travelers on board.

In general, information can be available either before trip departure (*pre-trip*) or during the trip (*en-route*). Pre-trip information systems are a means of alleviating the uncertainty about transit schedules and routes that is often cited as a reason for not using transit. Providing accurate and timely information to all travelers before their trips, enables them to make more informed decisions about routes and departure times.

En-route information systems offer a wide variety of information to public transit riders who are already traveling. This information can be communicated via *in-terminal* or *wayside* media such as electronic signs, interactive information kiosks, and closed-circuit television monitors, or via *in-vehicle* information devices (e.g. display and/or real-time or automated enunciators) supplying a combination of audible and visual messages such as: next stop, major intersections, and transfer points. While different agencies use different approaches, the overall goal is to provide information that will provide real-time bus arrival and departure times, so as to reduce waiting anxiety, and increase customer satisfaction.

In general, information provided can be either *descriptive* or *prescriptive*. In the former case travelers are provided with a description of network conditions, e.g. waiting time at the stop for a given transit line. This aims mainly to improve travelers' knowledge and awareness of the actual state of the network, contrary to *prescriptive* information that includes advice on travel choices (departure time, route choice, ...) which travelers can follow or not. In transit networks, pre-trip information can be either descriptive or prescriptive, while en-route information is typically descriptive.

Finally information can be classified as either *Individual* or *Shared*, the former being information specific to the individual traveler (e.g. the travel time to destination), the latter being information which can be used effectively by different traveler groups (e.g. the arrival time of buses at a stop).

APTIS have been broadly expanding during the last decade. VMS's at the bus-stops deploying information such as the arrival time of approaching buses, are widely used, not just in the core of the big metropolis but also in medium-size cities. Moreover, many transit agencies offer trip itinerary planning via touch-tone telephone, as well as via the Internet, kiosks, cable television, hand/held data receivers and/or other communication devices.

The benefits that such systems offer in terms of customer satisfaction, increasing Public Transport patronage travelers choices and so on are well-documented by different studies reporting the results of the introduction of APTIS in specific case-studies. These are mainly based on before-and-after

analysis (see for instance Nuzzolo and Coppola, 2002). However, in the literature there is a lack of study investigating “systematically” how and to what extent information can affect travelers choice, under different network conditions, e.g. irregular vs. regular service, congested vs. un-congested transit lines.

The aim of this paper is to provide a systematic analysis of the impacts of the *en-route descriptive shared* information to the travelers of a transit network under different levels of demand (un-congested vs. congested transit lines), network characteristics (regular vs. irregular services) and kind of information provided (waiting time and/or bus occupancy). This analysis could be used for an *ex-ante* evaluation of the benefits deriving from the introduction of an APTIS in the Public Transportation network.

The paper is organized as follows. In section 2, for sake of clarity, we review a modeling architecture previously developed (Coppola and Rosati, 2002) aimed at forecasting bus arrival time and occupancy at the stop. In section 3 the modeling framework for the simulation of the overall PT system, namely the transit network, the Operation Control Center (OCC), that is the information provider, and the travelers, is presented. Finally in section 4 the results of the application of the modeling architecture developed to the case study of Naples (South-Italy) are discussed and some general conclusions drawn.

2. MODELING ARCHITECTURE

The modeling architecture developed to forecast real-time the bus arrival times at the stops and the bus occupancy is conceived (Coppola and Rosati, 2002) to work in a software environment interfaced, on the one hand, with a surveillance system gathering raw data from the “real world” and, on the other hand, with a communication system broadcasting the transformed data (i.e. the information) to PT operators and travelers.

The surveillance systems consists of monitoring technologies such as Global Positioning System (GPS), Automated Vehicles Monitoring (AVM), Infra-Red Motion Analysis (IRMA). Such technologies are able to detect the location of the buses on the network at any point in time and the number of passengers boarding alighting from a bus at stops, and transmit these to the Operation Control Center (OCC).

Based on the data collected the model systems proposed can predict the arrival time and the level of occupancy of the incoming buses at the stops.

Finally this information can be transmitted to the operators and the travelers by means of the communication system consisting of long-range radio communication, cables, etc.

A schematic representation of the model system developed to predict the above information is depicted in Figure 1. Here the main components of the model as well as the interactions with the external environment (the surveillance system and the communication technology) are clearly outlined.

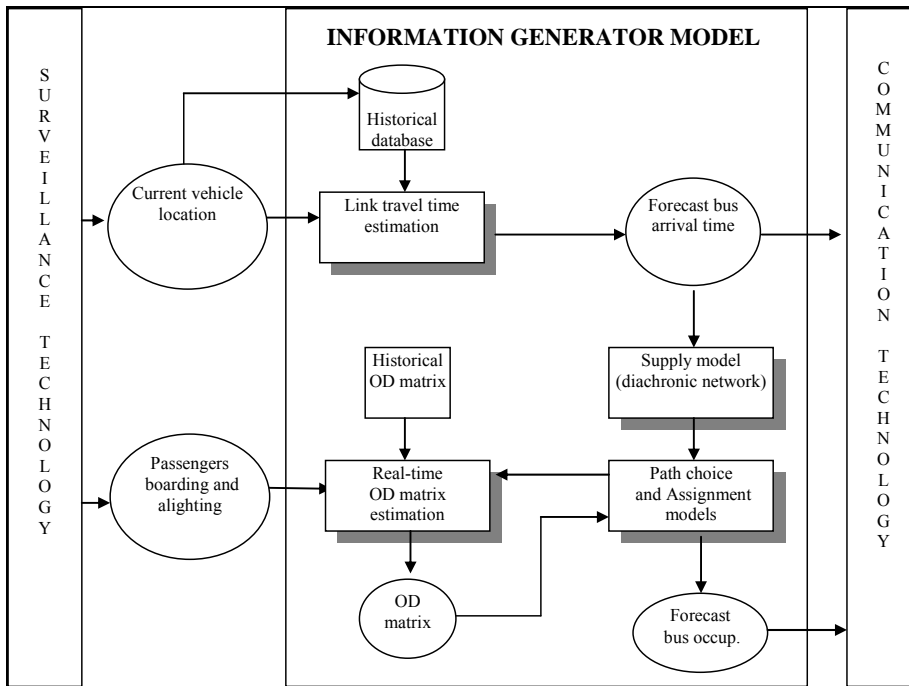


Figure 1. Schematic representation of the model system for generating the information (Information Generator Model).

It can be seen that the main components of the model system are the link travel time estimator and schedule-based dynamic transit assignment model.

It should be noted that, in order to predict the bus occupancy an alternative simpler approach could have been adopted. Such a method would forecast the future boardings and alightings based on adjusting the historical data by means of the current data. This approach would simplify the modeling architecture since it would avoid the estimation of real-time OD matrices and the estimation of path flow on the diachronic network. However, in doing so the model could provide accurate prediction only in normal conditions on the system; it could not be applied to provide accurate

estimates in case of irregularity or during occasional events such as service disruptions.

2.1 The link travel time prediction model

The link travel times estimator updates in real-time the historical travel times of the links and allows predicting of the arrival times of the incoming buses at the stops. At any time instant τ , based on the current location of a set of buses on the network (that is the data gathered from the surveillance system), the model forecasts the travel time of each link of the network for any future time instant $\tau' > \tau$, using an algorithm based on the Kalman filter (Rosati 2004):

$$\text{KALMAN FILTER} \rightarrow \mathbf{t}^{for}(\tau') \forall \tau' > \tau; \tau \in \Theta$$

$\mathbf{t}^{for}(\tau)$ being the “forecast” link travel time vector at time τ .

Once forecast the link travel time, $t_{ij}^{for}(\tau')$, the waiting time at a given stop s for a given run r at the generic (future) time instant τ' , is given by:

$$\begin{aligned} wt_{r,s}^{for}(\tau) = & at_{r,s}^{sched} - \tau + \sum_{\tau' < \tau} \sum_{ij} \delta_{ij,r}(\tau') \cdot [t_{ij}^{act}(\tau') - t_{ij}^{sched}(\tau')] + \\ & + \sum_{\tau' > \tau} \sum_{ij} \delta_{ij,r}(\tau') \cdot [t_{ij}^{for}(\tau') - t_{ij}^{sched}(\tau')] \end{aligned}$$

where:

- $wt_{r,s}^{for}(\tau)$ is the waiting time at stop s for the generic run r forecast at time τ ;
- $at_{r,s}^{sched}$ is the scheduled arrival time of run r at stop s ;
- $\delta_{ij,r}(\tau)$ is the generic element of the dynamic incidence matrix “link, run” at time τ , equal to 1 if run r at time τ has exited the link ij , 0 otherwise;
- $t_{ij}^{act}(\tau)$, $t_{ij}^{for}(\tau)$, $t_{ij}^{sched}(\tau)$ are respectively the actual, the forecast and the scheduled travel time on the link ij at time τ .

Note that the above formula holds only for the runs r which are not yet arrived at the stop s , that is $at_{r,s}^{sched} - \tau > 0$.

2.2 The bus occupancy prediction model

In the proposed modeling architecture the bus occupancy is predicted by means of a schedule based dynamic transit assignment model. This consists of:

- a supply model representing the time-dependent transit network, whose temporal co-ordinates are updated in real-time, based on the bus location information;
- a sequential path choice model based on Random Utility Theory, simulating PT travelers behavior;
- a within-day dynamic assignment procedure following a schedule-based approach, to forecast the loads on each run of the transit system at any time τ of the reference period, $f_r^{for}(\tau)$.

In addition, as with any dynamic transit assignment model, the model proposed here requires, on the demand side, the time distribution of the PT travelers over the simulation period, i.e. the time-varying Origin-Destination (OD) matrices. To this end an estimation procedure based on real-time observation of numbers of passengers boarding and alighting from buses at stops has been included in the modeling architecture (Nuzzolo and Crisalli, 2001).

At any time instant, given the OD demand flows, the bus occupancy results from the dynamic loading of the diachronic network demand flows according to specified path choice probabilities.

In principle, in a time-space (i.e. diachronic) network the choice of a path is a joint choice of the initial stop, s , and of run (or sequence of runs), r , from the travelers origin o to their destination d . Therefore, the path choice probability for travelers i (e.g. those departing at time τ_{Di} from the origin) is the joint probability of choosing run r and stop s and can be expressed as:

$$p^i[r, s] = p^i[s] \cdot p^i[r | s]$$

where:

- $p^i[s]$ represents the probability of choosing stop s for travelers i ;
- $p^i[r | s]$ represents the probability of choosing run r conditional on the choice of stop s for travelers i .

For the sake of simplicity, the stop choice probabilities are assumed to be known and, within the simulation, independent of the network performance

(buses occupancy, service regularity, etc.). In other words, we are assuming that for any origin there exists one specific stop to which the OD demand flows are assigned at any departing time τ_{Di} . Based on this assumption, the path choice probability can be estimated using a run choice model.

The run choice model considered here is “sequential” (Nuzzolo et al., 2001), meaning that, at time instant τ_r when the generic run r arrives at the stop, the generic traveler chooses to board that run or wait for another one and, in the latter case, he/she repeats the choice when the subsequent run arrives at the stop and so on. This is a discrete choice model (Ben Akiva and Lerman, 1985) requiring a) the definition of the travelers’ choice-set and b) the specification of the utility functions which the travelers associate with each alternative, in terms of attributes as well as of the probability distribution of random residuals.

In the case of a PT network with information offered at stops, it is possible to assume that travelers can define dynamically the run choice set in relation to the current supply configuration. Let $K^{s,i}[\tau_r, \underline{b}(\tau_r)]$ be the choice set for travelers i at stop s at time τ_r , given the service configuration $\underline{b}(\tau_r)$. This set is specified by runs connecting stop s directly or indirectly to the destination and satisfying the following rules:

- they are the first run of each line leaving after user arrival at stop s , which are not dominated;
- they satisfy some criteria such as maximum number of transfers, maximum transfer time, maximum travel time, etc.

At time instant τ_r , the instant when a run r arrives at the stop, the travelers can choose whether to board that run or to wait for another one belonging either to another line (e.g. a faster one) or the same line (e.g. if r is over-saturated). This depends on the utility of the run r perceived by the travelers i , U_r^i and on those, $U_{r'}^i$, of the runs belonging to the choice set, $r' \in K^{s,i}[\tau_r, \underline{b}(\tau_r)]$.

According to Random Utility Theory (Cascetta, 2001), the perceived utility can be assumed to be the sum of the systematic utility V_r^i and a random term ε_r^i :

$$U_r^i = V_r^i + \varepsilon_r^i$$

where the systematic utility is given by the linear combination of the following attributes:

- TW_r , the waiting time on the minimum paths including run r from stop s ;
- CFW_r , a proxy for the on-board comfort, e.g. a function of bus occupancies on the minimum paths including run r from stop s ;

- TB_r , the on-board time to the final destination on the minimum paths including run r from stop s ;
- TE_r , the egress time from the arrival stop to the destination centroid on the minimum paths including run r from stop s ;
- TC_r , the transfer time on the minimum paths including run r from stop s ;
- NT_r , the number of transfers on the minimum paths including run r from stop s ;
- TP^i , the time already spent at the stop, equal to the difference between the arrival time of run r and the arrival time of traveler i at the stop.

Note that the waiting time at the stop s is null for run r , while it is assumed to be equal to the difference between the estimated arrival time provided by the APTIS and time instant τ_r , for other runs r' . Moreover, the on-board comfort is a function of the bus occupancy which, given the bus capacity, can be estimated based on the actual flow, $f_r^{act}(\tau_r)$, for run r and according to the forecast flow, $f_r^{for}(\tau_r)$ for runs r' .

The waiting time and the on-board comfort, in the proposed modeling framework are the only attributes which travelers are provided with by the APTIS. In principle travelers compare the information received with their own experience and, then, chose accordingly. It could be the case that some travelers believe in the APTIS forecasts, other do not, and stills others average their experience with the information provided. In other words, the attributes included in the systematic utility function for which information is provided are a result of a process of information acquisition and knowledge updating. In the context of road networks, this has been simulated by means of exponential smoothing filter (Cascetta and Coppola., 2001), that is:

$$X_r^i = \lambda^i \cdot X_r^{for}(\tau) + (1 - \lambda^i) \cdot X_r^{exp}(\tau)$$

where:

- X_r^i is the value of the generic attribute X assigned to run r (e.g. WT_r) by traveler i , i.e. the one included in the utility function
- X_r^{for} is the value of the generic attribute X_r related to run r provided by the APTIS;
- X_r^{exp} is the value of the generic attribute X based on traveler i 's experience;
- λ^i is a parameter proportional to the trust of the travelers i in the information received from the APTIS.

Given the systematic utilities of the runs belonging to the choice set $K^{s,i}[\tau_r, \underline{b}(\tau_r)]$, the probability that travelers i board run r is given by:

$$p^i[r | s] = Prob[U_r^i \geq U_{r'}^i] = Prob[\varepsilon_{r'}^i - \varepsilon_r^i \leq V_r^i - V_{r'}^i]$$

$$\forall r \neq r', r' \in K^{s,i}[\tau_r, \underline{b}(\tau_r)]$$

Assuming that the random terms of all the runs belonging to the choice set are identically and independently Gumbel-distributed (Cascetta, 2001), the probability that the travelers choose the generic run r is given by the Logit model specification:

$$p^i[r | s] = \frac{\exp(V_r^i)}{\sum_{r' \in K^{s,i}} \exp(V_{r'}^i)}$$

Note that the above equations express only the probability of boarding run r , with respect to runs r' which still have to arrive at stop s . For travelers not choosing run r , the choice is reconsidered when the next run arrives and so on (*sequential run choice behavior*).

Given the probability of choosing run r at stop s , it is possible to compute the number of travelers boarding run r at time τ_r :

$$f_r^{act}(\tau_r) = \sum_i d_{\tau_r}^i \cdot p^i[r | s]$$

$d_{\tau_r}^i$ being the number of travellers i who have arrived at stop s and not yet boarded any previous runs (see figure 2):

$$d_{\tau_r}^i = \sum_{i: \tau_{D_i} < \tau_r} d^i \cdot \prod_{r': \tau_{D_i} < \tau_{r'} < \tau_r} (1 - p^i[r' | s])$$

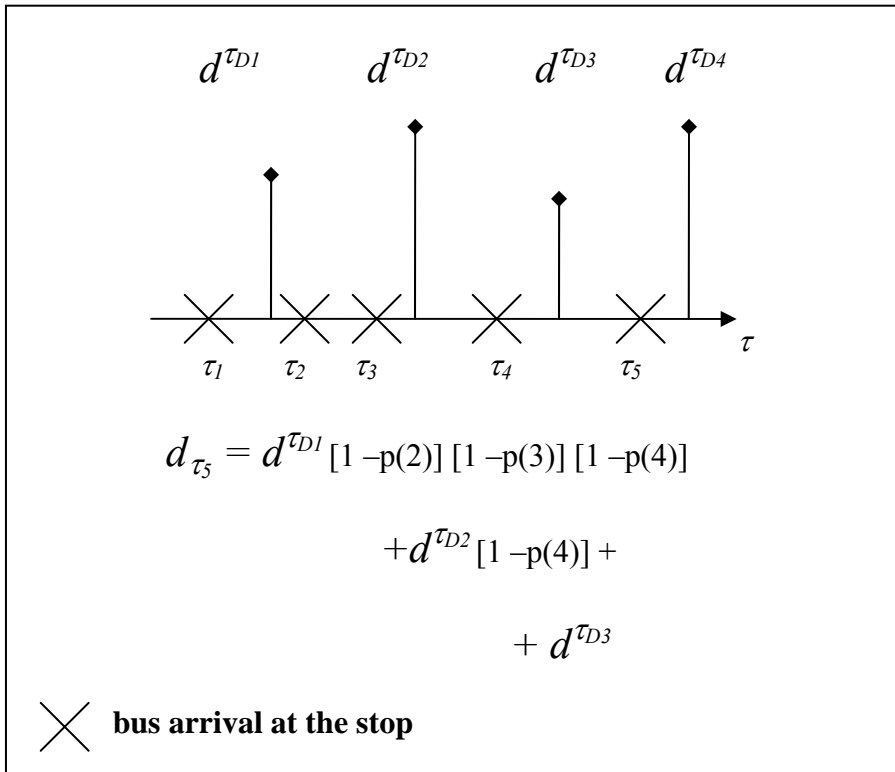


Figure 2. Example of calculation of number of travelers at stop s , at time τ_5 ($r=5$)

Note that in the above formulae the index referring to stop s has been omitted since for the assumption made, that the centroid nodes coincide with the stops, it is redundant:

$$i = (o, d, \tau_{Di}) \supset s = o \rightarrow \begin{cases} d_{s, \tau_r}^i = d_{\tau_r}^i \\ d_s^i = d^i \end{cases}$$

3. SIMULATION LABORATORY

The modeling architecture presented in the previous section can be used to forecast real-time arrival time of the buses at the stops and their occupancy. Such estimates can in turn be used either by the transit operators to implement transit control strategies (e.g. adjusting the service in response to random events) or can be communicated to the PT travelers as information to upgrade their knowledge of the network conditions.

In order to evaluate *a priori* the impacts of information provided to travelers on the overall network performance a laboratory based on the

simulation of the three main components of a PT system is proposed here. A schematic representation of such a simulation laboratory is depicted in Fig. 3.

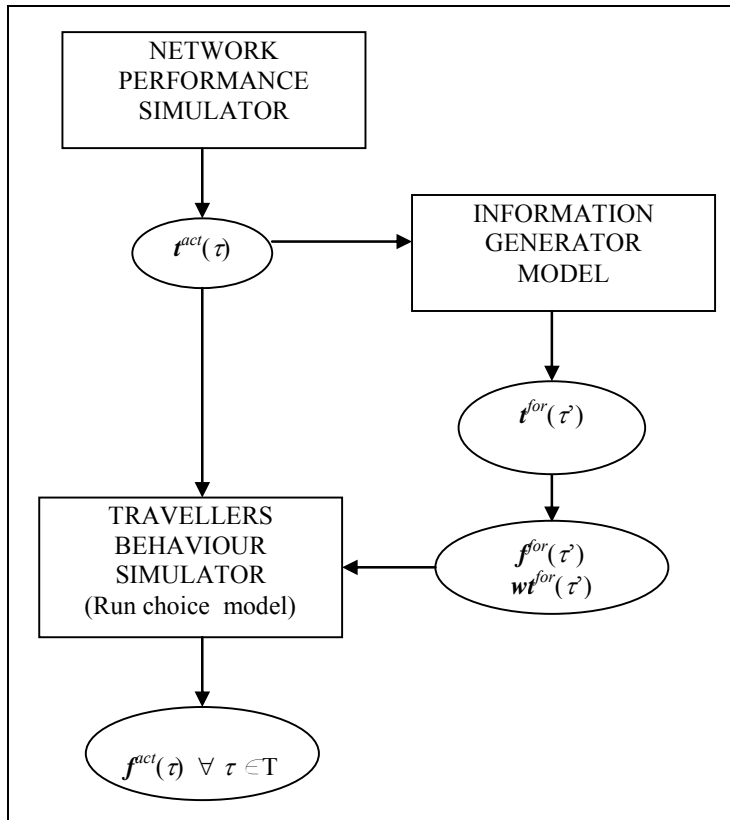


Figure 3. Schematic representation of the simulation laboratory

As can be seen it consists of:

- the transit supply module, simulating the “real-world” network performance (Network Performance Simulator);
- the Operational Control Center (OCC) module, simulating the process from data acquisition to prediction of the information to be deployed in the network;
- the travelers’ module, simulating how, based on their experience, travelers react when they receive information at the stop on buses arrival time and on bus occupancy.

3.1 The network performance simulator

The Network Performance Simulator aims at reproducing, at any time instant, the travel time on each link of the network.

Let $\mathbf{t}^{act}(\tau)$ be the “actual” link travel time vector at time τ . For each link the actual travel time is here assumed to be a normal random variable whose mean μ_l and variance σ_l are known; $\mathbf{t}^{act}(\tau)$ is generated, time instant by time instant, sampling from a multivariate-Normal random variable:

$$\mathbf{T}^{act}(\boldsymbol{\mu}, \boldsymbol{\sigma}) \rightarrow \mathbf{t}^{act}(\tau) \forall \tau \in \Theta$$

$\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ being the vectors of the mean and variance respectively of the link travel times on the network and Θ the simulation time period. The differentiated variance of the links of the network allows simulating the service irregularity (e.g. bus delay w.r.t. the schedule) for a predetermined selected number of links by means of increasing the value of the actual travel time variance of those links.

3.2 The Operation Control Center simulator

At a given time τ , the Operation Control Center (OCC) forecasts the arrival time and the occupancy of the incoming buses at the stop for any future time instant $\tau > \tau'$, and communicates these to the travelers. In the simulation laboratory, the prediction of such information is carried on using the modeling architecture framework presented in the previous section.

Note that the modeling architecture requires the estimates of the passengers boarding and alighting at the stop in order to update the OD matrices over the simulation period. In principle the passengers boarding and alighting are random variables. However, for sake of simplicity, these are assumed to be deterministic. In doing so the time varying OD matrix can be considered known *a priori* for all the time instant τ in the simulation period Θ . The extension of the model to consider random passenger boarding and alighting at stops is simple in principle and will be considered for further research.

3.3 The travelers' path choice simulator

Given the forecast arrival time of buses at the stop, $wt_{r,s}^{for}(\tau')$, and given the forecast run flows, $f_r^{for}(\tau')$, for any future time instant $\tau' > \tau$, the travelers' behavior simulator aims at estimating the actual flows on runs r , $f_r^{act}(\tau)$, given the time-varying OD demand flows and path choice probabilities.

In order to estimate the parameters of the path (run) choice model described in the previous section, a travel survey has been conducted. This consists of 205 interviews taken at the stops of the PT network of the city of Naples. Here an Advanced Public Transportation System, based on a surveillance system covering about 106 transit lines and based on more than one hundred VMS's providing travelers real-time estimated of the waiting time for incoming buses at stops, has been operating successfully for the last 7 years.

By means of the disaggregated data gathered, a run choice model has been specified and calibrated. In doing so, a binomial Logit specification has been adopted, that is the travelers are assumed to consider only two alternatives: the run arriving at the stop and the next arriving run. In fact, according to survey only 1% of the survey respondents reconsider the choice of the run more than once, that is 99% of the travelers in the sample who do not board on the first incoming bus, board the next bus to arrive.

The specification of the utility functions of the alternatives (the run arriving at the stop and the next one (belonging to the choice set) is as follows:

$$U_r = \beta_{TB} TB_r + \beta_{TE} TE_r + \beta_{CFW} CFW_r + \varepsilon_r$$

$$U_{r'} = \beta_{TW} TW_{r'} + \beta_{TB} TB_{r'} + \beta_{TE} TE_{r'} + \beta_{CFW} CFW_{r'} + \varepsilon_{r'}$$

where

- r is the run arriving at the stop;
- r' is the next incoming run belonging to the traveler choice set
- TW is the waiting time on the minimum paths from stop s to the destination;
- CFW is a proxy of the on-board comfort, assumed here to be a dummy variable equal to 1 if the occupancy of the run (i.e. the

ratio between the travelers flow on the run and the bus capacity) is greater than 50%, 0 otherwise;

- TB is the on-board time to the final destination on the minimum paths to the destination from stop s ;
- TE is the egress time from the arrival stop to the destination centroid.

Two classes of travelers' have been considered based on the travel purpose: "commuting" and "other" travel purposes (including shopping, personal and leisure). The estimates of the β -parameters are reported in Table 1.

Table 1. Attributes and parameters of the run choice models estimated for the case study.

Attribute	Unit	Commuting	Other purposes
<i>waiting time</i>	Minutes	-0.29 (-3.6)	-0.24 (-3.4)
<i>On-board time</i>	Minutes	-0.19 (-2.1)	-0.12 (-2.2)
<i>Egress time</i>	Minutes	- 0.70 (-2.5)	-0.38 (-2.2)
<i>boarding comfort</i>	[0/1]	-2.1 (1.9)	-1.8 (2.9)
<i>Likelihood with Zero Coefficients</i>		-47.1	-49.2
<i>Likelihood with Constants only</i>		-35.9	-35.2
<i>Initial Likelihood</i>		-47.1	-49.2
<i>Final value of Likelihood</i>		-19.4	-27.0
<i>"Rho-Squared" w.r.t. Zero</i>		0.59	0.45
<i>"Rho-Squared" w.r.t. Constants</i>		0.46	0.23

It can be seen that all the estimated parameters have the expected (negative) signs and are significantly different from zero at a level of confidence of 95%, the t-ratio's (reported in brackets) being greater than 1.9 in absolute value. The value of "Rho-squared" statistics are both significantly greater than zero, confirming a high goodness-of-fit of the model.

Looking at the single values of the parameters, it can be noted that the estimates for "commuting" purpose are all systematically greater than the

ones for “other” purposes, meaning that there is a higher perception of the level of service attributes (i.e. waiting time, on-board time, egress time) for frequent trips (e.g. commuting) than for occasional ones (i.e. other purposes). Moreover, the parameter of the waiting time is 1.5 times that related to the on-board time for “commuting” and 2 times for “other”. The egress time is 2 times the waiting time for commuting and 1.5 times for other purposes. Finally it can be noted that, the coefficient of the on-board comfort is significantly greater than the other parameters.

4. CASE STUDY

In order to evaluate to what extent information can affect network performance, in this section we present the results of an application of the proposed laboratory to a realistic case study.

The transit network of Fuorigrotta (Figure 4), a residential area within the city of Naples has been simulated. The study area has been subdivided into 11 zones; for each zone the centroid node is connected to a predetermined given stop. The transit network includes 9 lines and 188 runs (Table 2). The diachronic representation consists of about 38000 nodes and 75000 links (Table 3).

Table 2. Characteristics of the transit network

Line	Number of runs [7.00-9.00]	Centroids Connected
<i>C2</i>	8	(40,64)
<i>C6</i>	6	(40,64)
<i>C9</i>	8	(28, 34, 62)
<i>C10</i>	8	(28, 34, 62, 86)
<i>C12</i>	20	(56, 81)
<i>C15</i>	20	(40, 62)
<i>C18</i>	6	(36, 60)
<i>C19</i>	12	(36, 61)
<i>CU</i>	5	(40, 62)

Table 3. Characteristics of the diachronic network

	Services Network	Access/Egress links Centroids
<i>links</i>	73373	1920
<i>nodes</i>	36841	1320

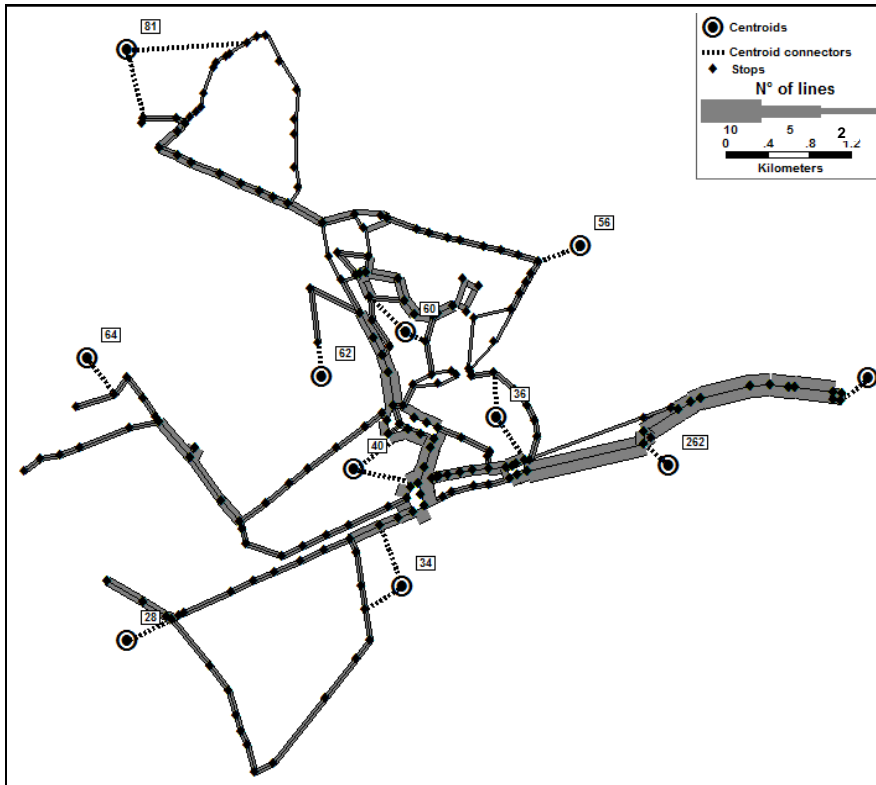


Figure 4. The transit lines and the spatial graph of the transit network of Fuorigrotta (Naples)

Within the simulation period of 2 hours (from 7.00 to 9.00 am), we have assumed a uniform OD demand pattern (i.e. constant arrival rates at stops) consisting of frequent travelers with knowledge of the network and complete trust in the APTIS ($\lambda=1$).

The following four different levels of demand were considered:

- no congestion;
- low level of congestion (i.e. average bus occupancy at about 25%);
- medium level of congestion (i.e. average bus occupancy at about 50%);
- high level of congestion (i.e. average bus occupancy at about 80%).

For each level of demand, six simulation tests have been run combining the following factors (Table 4): regular vs. irregular service, information available on waiting times (yes or no) and information on bus occupancy (yes or no). The results of the simulation are analyzed in terms of average

waiting time at stops, average total travel time, and average systematic utility.

Table 4. Simulations carried on for the four considered levels of demand

Index	Service irregularity	Information on waiting time	Information on buses occupancy
1		no	no
2	no	yes	no
3		yes	yes
4		no	no
5	yes	yes	no
6		yes	yes

Note that the case of information only on the bus occupancy and not on waiting time has not been considered since it is not realistic.

4.1 Low congestion

Table 5 shows that the network performance declines when the services are irregular, particularly the waiting time whose average value, estimated over all the travelers, almost doubled from a range of (4.7 - 5.2) (see scenarios 1,2 and 3) to a range of (8.7 - 8.9) minutes (see scenarios 4,5 and 6).

Table 5. Low congestion scenarios

Scenario	Avg. Waiting time [min]	% variation w.r.t. base scenario	Avg. Total Travel time [min]	% variation w.r.t. base scenario	Avg. Systematic Utility [Util]	% variation w.r.t. base scenario
1 (<i>base</i>)	4.7		38.3		-9.5	
2	5.2	+11%	37.1	-3.1%	-9.2	+2.9%
3	5.2	+11%	37.1	-3.1%	-9.2	+2.9%
4 (<i>base</i>)	8.7		42.9		-10.9	
5	8.7	+0.6%	42.8	-0.4%	-10.7	+1.9%
6	8.9	+2.1%	42.9	0.0%	-9.5	+6.9%

In case of regular services, when information on bus waiting time is provided (scenario 2), we observe an increase of the average waiting time of 11%, a decrease of the average total travel time of -3.1%, and an increase of

travelers utility of +2.9%. This is because when travelers receive information on actual waiting time of the runs, they many prefer to wait longer for faster lines seeking to minimize their total travel time (or equivalently maximize their utility), following “intelligent adaptive” run choice behavior, instead of an “indifferent adaptive” one (i.e. boarding the first run of the choice set arriving at the stop).

The additional information on bus occupancy (scenario 3) has a null impact in case of regular services. This results because the simulation assumes that the demand is made up of frequent travelers with deterministic arrival rate. As a results, the travelers have knowledge of the network conditions which coincides with the one provided by the APTIS. In other words, in the case of regular services (and deterministic demand) the information on bus occupancy does not provide travelers with additional knowledge of the network and, therefore, does not affect their path choice.

On the other hand, in case of irregular services, the benefits of information on waiting time (scenario 5) decline in terms of average waiting and total travel time as well as average systematic utility.

Moreover, the impact of information on bus occupancy (scenario 6) is negligible in terms of average total travel time. The slight increase of waiting time (+2.1%) is due to the fact that typically in an irregular system there is an alternating sequence of crowded and empty runs (the limiting case is the well-know phenomenon of “bus bunching”). If this is the case when information on the next run occupancy is available the travelers can wait longer for the next less crowded run. Contrary to waiting and total travel time, the information on bus occupancy greatly improves the travelers’ utility (scenario 6), which increases from 1.9% to 6.9%. This is due to the fact that, despite the travel times remaining the same, the benefits of the information offer in case of irregular services is due to the fact that travelers are able to choose less congested and thus more comfortable runs.

4.2 High congestion

In the case of highly congested transit services, Table 6 shows a clear increase of both waiting and on-board times in all the scenarios as well as a decrease of systematic utility. The former effect is due to the fact that when the transit lines are congested, there is a high probability that the runs are overcrowded. In such cases, travelers could prefer to wait for a subsequent less crowded run: when such run belongs to the same line then the generic traveler experiences only a longer waiting time; when the subsequent run belongs to another line, he/she may experience not only a longer waiting time but also a longer on-board time, if this run takes longer to reach the to destination. The second effect (i.e. the decrease of systematic utility)

depends on the level of comfort that the travelers experience, which in case of congestion is lower.

Table 6. High congestion scenarios

Scenario	Avg. Waiting time [min]	% variation w.r.t. base scenario	Avg. Total Travel time [min]	% variation w.r.t. base scenario	Avg. Systematic Utility [Util]	% variation w.r.t. base scenario
1 (<i>base</i>)	4.7		38.4		-12.8	
2	5.3	+12.5%	37.7	-1.9%	-12.4	+3.0%
3	5.3	+12.5%	37.7	-1.9%	-12.4	+3.0%
4 (<i>base</i>)	8.9		43.47		-13.9	
5	8.9	+0.8%	43.04	-1.0%	-13.7	+1.7%
6	9.1	+1.1%	43.21	-0.6%	-12.8	+8.9%

The results of the simulation in the six simulated scenarios, are similar to the case of low congestion. The difference is in the magnitude of the percentage difference with and without information. It can be seen, for instance, that in case of irregular services (scenarios 6) the information induces a negligible effect on average waiting time and travel time but a high increase of systematic utility; +6.9% in the case of low congestion (Table 5) and +8.9% in the case of high congestion (Table 6).

5. CONCLUSION

In this paper, a simulation laboratory aimed at simulating the overall Public Transportation system with APTIS has been presented. This requires the simulation of three main components: the Public Transportation (PT) network, the information provider (i.e. the Operation Control Center) and the travelers. The interaction between these components is simulated using different modeling approach:

- the schedule-based approach for the network representation and traffic assignment,
- a statistical model based on the Kalman filter for the prediction of the network performance within the simulation period, and
- behavioral discrete choice models, based on Random Utility Theory, for simulating travelers behavior under different network conditions and information availability.

The results of the simulation of the case study of the transit network of Fuorigrotta, a residential area in city of Naples (Italy), was presented to analyze to what extent the deployment of Shared-en route-descriptive information can affect frequent travelers choice and thus impact the network performance. These have shown that:

- 1) the impact of the information provision on waiting time is an increase of the travelers' average waiting time and a decrease of the average total travel time because travelers follow "intelligent adaptive" run choice behavior, and do not board the first arrival run available ("indifferent adaptive" behavior);
- 2) the impact of information on bus occupancy is null in the case of regular services and negligible in the case of irregular service in terms of average waiting and on-board time;
- 3) the impact of information on bus occupancy is very significant in terms of travelers' utility: an increase of 6-9% is observed in the simulation: the higher increase corresponding to the higher level of congestion on the network.

Finally, it is worth noting that most of the assumption made in the application presented, such considering frequent travelers and complete trust in the APTIS ($\lambda=1$), can be easily removed and will be analyzed in future research.

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