Individual path choice modeling in a pre-trip planner for transit networks with ATIS

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Abstract

The paper presents the results obtained by some tests carried out for setting up a single-user pre-trip path choice model for multi-service transit networks. The model is a component of a new Advanced Traveler Advisory Tool, able to suggest to each user the best paths according to his/her personal preferences through the estimation of personal model parameters. These parameters are defined using a two-step procedure (initialization and up-dating process). The tests gave us some indications on the types of model to be used, and on the performances that can be reached in each step.

Keywords: Advanced traveler information systems, transit trip planner, personalized pre-trip information, transit path choice models, user preference learning process

1. INTRODUCTION

Within the Advanced Traveler Information System (ATIS), the Advanced Traveler Advisory Tools (ATAT) are able to assist users in multiservice and multimodal networks, to suggest to each user the best path set according to his/her personal preferences. Some of these tools, in order to find the best personal paths within the Random Utility Theory framework, assign an estimate of the utility perceived by user to each path alternative. This personal perceived utility is function of several attributes (e.g. total travel time, walking time) and their effects on utility are given by model parameters that depend on user personal preferences. Thus, the parameters of an individual path choice model have to be estimated. The choice model has to be tailored to each user and to learn user's interests and preferences from usage data.

The literature presents different systems that allow to assist the user in a decision-making process by giving personalized recommendations (Fink and Kobsa, 2002; Ricci and Mahmood, 2007; Tumas and Ricci, 2009). Arentze (2013) proposes, in a multimodal network, a system that provides personal travel path advices updating the user's utility model parameters from their revealed path choices through a Bayesian method.

In recent years, researchers have sought to develop ATAT that support user travel and both theoretical and practical solutions were proposed, but further studies should be still carried out. A tool of this type has been developed at Transport Centre of the University of Rome Tor Vergata (Nuzzolo et al., 2013). It includes a pre-trip planner for transit networks, and suggests to each user a set of alternative paths. These paths are evaluated as the best for a given user according utility parameters, and are hence proposed in their utility order. Pre-trip choice behavior on transit networks underlies user path choices before departure. It includes the comparison of possible alternative strategies and the choice of one of them on the basis of characteristics, or attributes that are expected and/or provided by ATAT.

Pre-trip information plays a key-role in reducing uncertainty about routes and timetable that, for example, is the main reason for rejecting transit as travel mode. ATAT provides accurate and real-time information about routes and

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departure times to all users before their trips via web or mobile devices (smartphones), enabling them to take more aware decisions on paths.

To obtain the individual pre-trip path choice model and the utility parameters that take into account the single user preferences, a two-step procedure is proposed. The first step serves to initialize the path utility function parameters of a new user, on the base of Stated Preference (SP) Interviews. In this step, each respondent is several times provided with some alternative paths; among them, he has to choose the perceived best one. The second step, which up-dates the initial parameter estimation, uses revealed choices by Traveler Tool during its use. In order to move from step 1 to step 2, one has to develop a user preference learning component that allows the system to dynamically detect personal preferences, revealed by the choices made while using the system.

The paper presents the first results obtained by a test case, carried out in order to set up the initialization step and the user preference up-dating process. The paper is structured as follows. Section 2 describes the modeling framework, while section 3 presents the results of parameter estimation using surveys carried out in a metropolitan area. Finally, some conclusions and further developments of this study are presented in section 4.

2. THE MODELING FRAMEWORK

2.1. Pre-trip path choice behavior

Travel alternatives are represented through paths on a multi-service transit network. A path *k* represents the space-time sequence of transport infrastructures and services used by user travelling from an origin *o* at a given origin departure time τ_{Di} to a destination *d*, with the relative arrival time at destination τ_d. A path *k* on a transit network also includes access stop *s* with relative arrival time at stop τ_{Dis}, line and run with run departure time τ_r from access stop (or sequence of lines and runs including the relative stop interchanges) and egress stop s'. Given an origin-destination pair *od* and a departure time τ_{Di}, different travel alternatives (paths) are usually available.

According to Random Utility Theory (Domencich and McFadden, 1975; Ben-Akiva and Lerman, 1985), the user is considered a rational decision-maker who maximizes utility relative to her/his choices. Basing on this theory, we assume that:

- the generic decision-maker considers mutually exclusive alternative choice set I^i suggested by the tool;
- the decision-maker assigns to each alternative *k* a perceived utility (U_k^i) and selects the alternative maximizing this utility;
- the utility (U_k^i) assigned to each choice alternative depends on a number of measurable characteristics (attributes) of the alternative itself (and of the decision-maker), $U_k^i = U^i\left(\boldsymbol{X}_k^i\right)$, where $\boldsymbol{X}_k^i$ is the vector of attributes relative to alternative *k* and to decision-maker *i*;
- the utility assigned by the decision-maker to alternative *k* is not known with certainty by an external observer (analyst) due to a number of factors and must therefore be represented by a random variable.

In general, we can express the random utility of an alternative as a sum of observable (or systematic, V_k^i) and unobservable components of the total utilities (ε_k^i) as follows:

$$U_k^i = V_k^i + \varepsilon_k^i \qquad \forall k \in I^i$$

The systematic utility is expressed as a function $V_k^i\left(X_{hk}^i\right)$ of attributes X_{hk}^i relative to the alternatives and the decision-maker. Although the function $V_k^i\left(\boldsymbol{X}_k^i\right)$ may be of any type, for analytical and statistical convenience it is usually assumed that the systematic utility V_k^i is a linear function in the parameters β_h of the attributes X_{hk}^i or of their functional transformations $f_h\left(X_{hk}^i\right)$:

$$V_k^i\left(\boldsymbol{X}_k^i\right) = \sum_h \beta_h X_{hk}^i = \boldsymbol{\beta}^T \boldsymbol{X}_k^i$$

or

$$V_k^i\left(\boldsymbol{X}_k^i\right) = \sum_h \beta_h f_h\left(X_{hk}^i\right) = \boldsymbol{\beta}^T \boldsymbol{f}\left(\boldsymbol{X}_k^i\right)$$

The estimation of individual coefficients β_h can be performed using the information collected from a sample of observations. Given a sample of *N* observations of a single user, the problem is to find the estimates of coefficients β_h that allow to suggest the best perceived paths and/or to order them.

Except for laboratory choice experiments in psychology (Thurstone, 1927), it is rare to see discrete choice models estimated for single people. After Chapman (1984), there was little work on ways to measure and model individual choices in survey applications until recently (Frischknecht et al., 2011). In fact, demand models are traditionally used to simulate the average number of trips of given characteristics undertaken by homogeneous user groups and it is not easy to obtain large choice samples of single decision-maker (it is easier to have choice samples from many decision-makers). Therefore, user groups (homogeneous with respect to their attributes, parameters and the functional form of the models) are used and aggregate behavioral models have been developed instead of disaggregate or individual behavioral models. Different types of aggregate models have been proposed but their performances could seem limited for suggesting personal travel advices, because of the dispersion among users, or variations in taste or preferences among users. Therefore, in the following some aspects of the individual model developing are discussed.

2.2. The individual pre-trip path utility function

In the case of pre-trip choices, the path choice model has mainly to simulate the choice of run (or sequence of runs) which allows users to travel from the origin to the destination. When personal information are provided to single user, the path choice parameters have to be calibrated on the basis of single user preferences. It implies that the model functional form could be the same, as the same could be the values of considered attributes for path choice, but different sets of parameters (different for each registered user) have to be considered and calibrated according to his/her personal travel preferences.

The information system considers space-time paths in which users leave at a given time τ_{Di} (that due to congestion can differ from τ_{TTi}), to access at a given stop *s* and to board a given run *r* (or sequence of runs) to reach the destination. The systemic utility, associated with path *k* belonging to a set of possible alternative paths, is defined according to traveler (user) characteristics, transport system performance (e.g. travel times and costs on different modes) and traveler behavioral assumptions.

The systemic utility ($V^{\tau}_{od,\tau_{TT_i}}[k]$) related to user *i*, path *k* at time τ for travelling from *o* to *d* at desired target time τ_{TTi} can be expressed as linear combination of groups of attributes relative to path *k*, for example:

- access and egress time (*AE*);
- waiting time (including transfer time) spent for boarding on the first run of the transport mode *m* (TW_m);
- on-board time spent on the transport mode *m* (OB_m);
- average on-board oversaturation factor of run of transport mode *m* on *od* pair (CFW_m);
- preference attributes for the transport mode *m*, e.g. expressed as function of share of path spent on mode *m* (ASA_m);
- number of transfer on each transport mode *m* (NT_m);
- Early or Late arrival time (*EL*).

Therefore, the utility $V^{\tau}_{od,\tau_{TT_i}}[k]$ is specified as follows:

$$V^{\tau}_{od,\tau_{TT_i}}[k] = \lambda \cdot AE_k + \sum_m \beta_m \cdot TW_{\tau,m,k} + \sum_m \gamma_m \cdot OB_{\tau,m,k} + \sum_m \chi_m \cdot CFW_{\tau,m,k} + \sum_m \alpha_m \cdot ASA_{\tau,m,k} + \sum_m \delta_m \cdot NT_{\tau,m,k} + \pi \cdot EL_k \quad (1)$$

where λ, β, γ, χ, α, δ and π are the individual model parameters.

2.3. The parameter estimation

The estimation of discrete choice model parameters with repeated observations for each respondent gives rise to an obvious correlation of disturbances, or heterogeneity (e.g. the parameters can also vary for the same user according to the travel scope, context), which refers to variations in unobserved contributing factors across behavioral units. If behavioral differences are largely due to unobserved factors, and if unobserved factors are correlated with the measured explanatory variables, then estimates of model coefficients will be biased if heterogeneity and correlation are not properly treated. The problem may be more pronounced in repeated measurement data since unobserved factors may be invariant across the repeated measurements. Currently, there has been growing interest in the representation of unexplained heterogeneity in choice data, using random coefficients models such as Mixed Multinomial Logit (Hess and Rose, 2009). Besides, in order to consider that the paths could not be completely independent, because some overlapping can exist, different specifications could be used (e.g. nested logit models, error components logit model). Such a data panel contains multiple observations of the same user and making an assumption of independence between choices for the same user may not be appropriate. Therefore, in the following models of increasing complexity were estimated, starting with the simplest multinomial logit (MNL), followed by a flexible random parameters mixed logit (ML) specification in order to test the possible heterogeneity of estimated parameters. The development of model forms able to capture correlations (e.g. nested or error components logit model) among choice alternatives did not provided satisfactory results, then further analyses are in progress. Therefore, in the following only the results obtained by MNL and ML estimation are discussed.

As said, at the initialization step, even if other authors use a different approach (for example, in Molin and Arentze 2013, the updating starts from initial average parameters obtained through multi-user Stated Preference surveys), in our approach when a new user fills in the registration form, some data are requested in order to initialize her/his path utility function. The data refers to information about origin and destination of a typical and well-known transit trip, and desired arrival time. Then, the system builds some alternatives according to the system past-recorded data. Sequentially, some alternative path scenarios are provided to user, which has to choose the preferred option among those suggested. In the proposed choice contexts, the options vary in relation to a set of values, for example: total travel time, waiting and on-board time according to transport mode, number of transfers and early/late arrival time and so on. The results of this SP survey are then used to estimate the initial values of parameters of *eq. (1)*.

After the initialization phase, at the second step, the parameters are up-dated according to the choice revealed when traveler uses the system. The parameter up-dating procedure can use two different approaches based on: Bayesian (Arentze, 2013) or Maximum Likelihood (MaxL) (Nuzzolo et al., 2013) method.

Within the Bayesian approach, the model parameters are usually represented by a prior normal distribution and their mean values represent the current best estimate of the user's values of the parameters. Each time a choice (of the user) is observed, the system updates the model parameters by updating the posterior distribution of each parameter, i.e. by updating means and standard deviations, through the theorem of Bayes. Besides, although Bayesian updating is a suitable technique to learn the hidden parameters incrementally, existing Bayesian methods of learning continuous parameters are not feasible due to the long computation times involved in sampling steps. Then, Arentze (2013) proposed a new method that reduces computation time by assuming a sequential processing of parameters and a systematic sampling of the parameter space.

In the Maximum Likelihood method, after a given number of choices (of user) is observed, the system, using the Maximum Likelihood estimation method (Ben-Akiva and Lerman, 1985; Lancsar and Louviere, 2008), provides a new estimate of model parameters, as is reported in the next part of the paper.

3. EMPIRICAL ANALYSIS

Some tests were performed in order to investigate some issues of the utility function calibration:

- best random utility model; different models forms where tested in order to estimate utility parameters moving from the simplest multinomial logit model to mixed logit model that allows to point out the heterogeneity in parameter estimates for the same user; the correlations among paths were also investigate through nested logit specification where different nests were tested according to the characteristics of paths (e.g. ratio of overlapping); as said before, nested logit models did not provide satisfactory results, then further analyses are in progress; therefore, in the following only MNL and ML models are reported;
- optimization of parameter initialization and up-dating procedure; in order to reduce the time spent by user during registration phase, the focus was on the definition of minimum number of Stated Preference (SP) observations, number of options to propose for each SP scenarios, and number of parameters to consider in utility estimate before giving a reasonable suggestions;
- influence of suggestions on user's travel behavior; we tested if user could modify his/her choices if personalized suggestions are provided.

In the following, a test case used for answering to the above queries is detailed. Before the dataset used for investigating user's behavior is presented, then the analyses carried out on individual path choice model development are detailed.

3.1. The dataset

One of the tests was performed considering a working-day journey from Frascati (a town near Rome) to the center of Rome (i.e. Piazza Sempione) with the desired arrival time at 9.30 am. The locations are distant about 25 km by road (Figure 1). Four different paths were available to travel on this *od* pair (Figure 2). They differ in terms of travel time, waiting and transfer times, modes to be used (train, metro or bus) and the early/late arrival time respect to desired one.

A set was obtained of 150 scenarios with path alternatives randomly extracted from the previous experimented status of the transportation system. The Table 1 reports the average characteristics of each path. We can see that the travel time is averagely close to 2 hours.

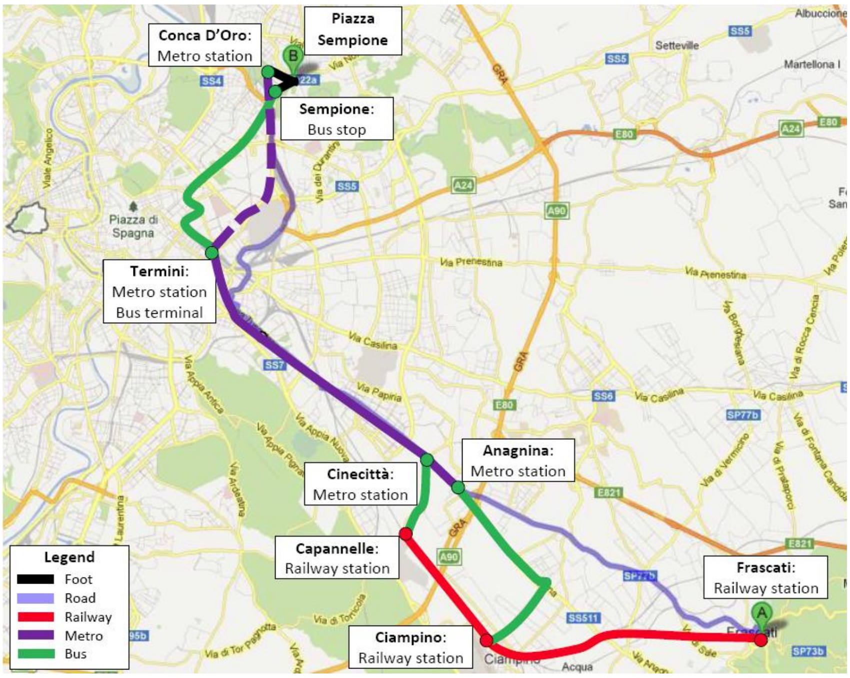

Figure 1: Origin, destination and path alternatives of the test case.

Path 1)	Frascati -	Train -	Bus -	Metro -	Bus*	Piazza Sempione
Path 2)	Frascati -	Train -	Bus -	Metro -	Metro**	Piazza Sempione
Path 3)	Frascati -	Train -	Bus -	Metro -	Bus*	Piazza Sempione
Path 4)	Frascati -	Train -	Bus -	Metro -	Metro**	Piazza Sempione
* different bus line; ** different metro line						

Figure 2: Path alternatives.

Table 1. Path alternative characteristics

Path	Path attributes				
	Attribute	*min*	*Max*	*Average*	*Standard deviation*
1	Waiting time (minutes)	7	19	13	4.0
	On board (train; minutes)	37	46	41	2.7
	On board (bus; minutes)	41	50	45	2.9
	Access and Egress Time (minutes)	8	8	8	0.0
	Late arrival time (minutes)	0	0	0	4.3
	Early arrival time (minutes)	0	12	5	0.0
	Number of transfer	3	3	3	0.0
	Total Travel time (minutes)	***100***	***112***	***107***	***4.3***
2	Waiting time (minutes)	8	18	14	3.1
	On board (train; minutes)	48	56	52	2.5
	On board (bus; minutes)	23	28	25	2.1
	Access and Egress Time (minutes)	16	16	16	0.0
	Late arrival time (minutes)	0	30	0	4.0
	Early arrival time (minutes)	0	12	5	0.0
	Number of transfer	3	3	3	0.0
	Total Travel time (minutes)	***100***	***112***	***107***	***4.0***
3	Waiting time (minutes)	5	27	18	7.8
	On board (train; minutes)	44	50	47	2.0
	On board (bus; minutes)	43	53	47	3.3
	Access and Egress Time (minutes)	6	6	6	0.0
	Late arrival time (minutes)	0	19	7	7.8
	Early arrival time (minutes)	0	1	1	0.0
	Number of transfer	3	3	3	0.0
	Total Travel time (minutes)	***111***	***131***	***118***	***7.8***
4	Waiting time (minutes)	10	33	22	8.0
	On board (train; minutes)	55	60	58	1.9
	On board (bus; minutes)	24	32	27	3.1
	Access and Egress Time (minutes)	14	14	14	0.0
	Late arrival time (minutes)	0	25	9	9.2
	Early arrival time (minutes)	0	4	1	0.0
	Number of transfer	3	3	3	0.0
	Total Travel time (minutes)	***108***	***137***	***120***	***9.2***

3.2. The individual path choice model

In order to investigate the best functional form of the individual path choice model, several models were estimated carrying out a SP survey with 150 sets of four alternatives on a test user (a university student) that was asked to choose the preferred one. Table 2 reports the number of times in which each alternative was chosen. We can see that path 3 was never chosen, although it does not present averagely the worst travel attributes. The minimum on-board total travel and early/late arrival time are the main criteria affecting user's choices (Table 3). We note that user preferred to arrive early to destination, and, when possible, does not use the bus. Besides, attributes analysis of Table 3 shows that user preferred in 79% of choices the minimum on-board time path.

Table 2. Path alternatives chosen in 4-alternative scenarios

Path	Path attributes		
	Chosen	*Present in a scenario*	*Success share [%]*
1	6	150	4.0%
2	119	150	79.3%
3	0	150	0.0%
4	25	150	16.7%

We estimate multinomial, nested and mixed logit models (with normal distribution of parameters). According to Hensher and Greene (2003), the random parameters were selected assuming all parameters, included in logit models, are random and then examining their estimated standard deviations, with a zero-based *t*-test for individual parameters and the likelihood-ratio test for establishing the overall contribution of the additional information. Then, only the early/late arrival time was selected as random parameter, while the other parameter estimates remain quite constant between the two specifications.

The multinomial and mixed logit model, although all the attributes displayed in the *eq. (1)* were tested, only those reported in Table 4 were statistically significant: the total waiting time (*TW*), the on-board time disaggregated for transport mode (*OB*) and the early/late arrival time (*EL*). The estimated parameters corresponding to different components of travel time (e.g. waiting, on board and delay time) have increasing absolute values for less appreciated components. For example, the time spent on bus is lower than on metro and is about twice lower than the early/late arrival time. The lowest value of travel time refers to time spent on regional train. The *%-of-right* was calculated and we can see that 4-alternative model predict at least the 84% of the chosen paths. If the first and the second options suggested by the tool (i.e. the first two paths with the highest estimated utility) are considered, the *%-of-right* grows up to 99%.

Table 3. Attributes of path chosen in 2 and 4-alternative scenario

Attribute	**Path attributes**			
	Chosen in 2-alternative scenario	*%*	*Chosen in 4-alternative scenario*	*%*
Minimum waiting times	99	66%	50	33%
Minimum waiting times on train	128	85%	122	81%
Minimum waiting times on metro	54	36%	6	4%
Minimum waiting times on bus	123	82%	99	66%
Minimum on-board time on train	114	76%	70	47%
Minimum on-board time on metro	26	17%	0	0%
Minimum on-board time on bus	121	81%	83	55%
Minimum on-board time	132	88%	119	79%
Minimum access and egress time	21	14%	0	0%
Minimum travel time	116	77%	72	48%
Minimum early or late arrival time	94	63%	47	31%
Minimum number of transfer on bus	133	89%	144	96%
Minimum number of transfer on metro	70	47%	6	4%
Early arrival time in Early *vs* Delay	82 on 95	86%		
Maximum early arrival time in paths with only early arrival time	30 on 43	70%		
Minimum late arrival time in paths with only late arrival time	10 on 12	83%		
Early			141	94%

As the performances of the MNL and ML are quite similar, in the following only the MNL model was used, for reasons of operational simplicity in the applications. As the use of scenarios with only 2 path alternatives could reduce the time of initialization phase, in order to analyze the performances of the model in this way obtained, the investigation was carried out also with an SP survey including 150 2-alternative path scenarios. The Table 5 reports the number of times that each path was chosen in each 2-alternative scenario, while Table 3 gives the choice shares according to some criteria (e.g. minimum travel time, minimum number of transfer, minimum delay). We can see that the path 2 has the highest success share according to be usually the path with the minimum total travel time and the minimum value of standard deviation. We have to point out that path 3 was chooses 9 times, although it does not present the highest values of path attributes. From the analysis of Table 3, we note that the choices are mainly dominated by the minimum on-board time (88%) and early/late arrival time (86%).

For the above reasons, we report, in the following, multinomial and mixed logit models (with normal distribution of parameters). Although all the attributes displayed in the *eq. (1)* were tested, only those reported in Table 6 were statistically significant. The models of Table 6 were obtained using all the 150 observations collected in the 2-alternative survey. We can see that 2-alternative model predict at least the 93% of the chosen paths.

Table 4. Model estimation using 4-alternative set

Model	Attributes	Parameter value	t-st
Logit $\rho^2 = 0.71$ *84%-of-right* *99%-of-right* considering the first and the second suggested path alternatives	Waiting time on bus	-0.439	-4.06
	On-board time (train)	-0.078	-1.30
	On-board time (metro)	-0.336	-1.64
	On-board time (bus)	-0.426	-3.24
	Early and late arrival time	-0.291	-3.41
Mixed Logit $\rho^2 = 0.72$ *84%-of-right*	Waiting time on bus	-0.469	-3.93
	On-board time (train)	-0.088	-1.38
	On-board time (metro)	-0.327	-1.45
	On-board time (bus)	-0.447	-3.12
	Early and late arrival time	-0.306	-3.30
	Standard deviation of early and late arrival time	0.179	1.77

Table 5. Path alternatives chosen in 2-alternative scenario

Path	**Path attributes**		
	Chosen	***Present in a scenario***	***Success share***
1	33	70	47.1%
2	73	75	97.3%
3	9	77	11.7%
4	35	78	44.9%

Also in this case, the random parameters were selected assuming that all parameters, included in logit models, are random and then examining their estimated standard deviations, with a zero-based *t*-test for individual parameters and the likelihood-ratio test to establishing the overall contribution of the additional information. In this way, only the on-board time on bus was selected as random parameter. Implementing this model to reproduce the choices revealed in the 4-alternative dataset, the *81%-of-right* was obtained. These results allow us to conclude that scenarios with only two options can be used at the first stage and satisfactory results can be also obtained. In this way, the possibility that user become bored, when he fills in the system, can be reduced.

Table 6. Model estimation using 2-alternative set

Model	Attributes	Parameter value	t-st
Logit $\rho^2 = 0.80$ *93%-of-right* *81%-of-right* in reproducing 4-alternatives	Waiting time (total)	-0.386	-3.66
	On-board time (train)	-0.285	-3.16
	On-board time (metro)	-0.485	-2.03
	On-board time (bus)	-0.538	-3.40
	Early and late arrival time	-0.223	-2.47
Mixed Logit $\rho^2 = 0.82$ *%-of-right*=96%	Waiting time (total)	-0.594	-2.66
	On-board time (train)	-0.439	-2.43
	On-board time (metro)	-0.741	-1.78
	On-board time (bus)	-0.902	-2.45
	Standard deviation of on-board time (bus)	0.185	2.15
	Early and late arrival time	-0.414	-2.08

3.3. The initial parameter estimation

Much attention was paid to the initialization phase, which must be not too long, because the user could become bored and then the quality of data could not be adequate. Therefore, the investigation referred to the minimum number of alternatives to be suggested (2 or more), minimum number of scenarios to be proposed to user, minimum number of attributes that can be used in the initial path utility functions.

The maximum *%-of-right* (in the simulation of choices revealed in the 4-alternative dataset) that it is possible to reach was investigated according to the minimum number of usable observations and number of parameters. A maximum *81%-of-right* can be reached using 115 observations and 5 parameters, because of the complexity of the experimental multi-service transit network. The model specification (i.e. number of attributes for estimating the systematic utility) can also vary according to the number of available observations. These results revealed also that with 10 observations it is possible to reach a *79%-of-right* using a logit model with 2 alternatives, and 95% if the second best path is also considered.

3.4. The user preference up-dating process

Starting from the above results, the up-dating process was simulated, too. The parameters of utility function were estimated varying the number of attributes and the number of observations. The parameter up-dating was performed including, in the Maximum Likelihood estimation procedure, 10 new observations (from 4-alternative set) at a time (i.e. batch updating). The first results (Tables 7) showed that about 30 observations could be necessary to obtain a statistically good model (two attributes and satisfactory values for both ρ^2 and *%-of-right*).

Table 7. Updating process: parameters and model performances with 10 initial SP observations

# of obser.	**Total on board time (minutes)**	**Total waiting time (minutes)**	**Early/late time (minutes)**	**metro and railway on board time (minutes)**	**bus on board time (minutes)**	**railway on board time (minutes)**	**metro on board time (minutes)**	**ρ^2**	**%-of-right**	**%-of-right (best and the 2nd best)**
0	-0.275							0.56	79%	93%
10	-0.456							0.77	79%	93%
20	-0.571							0.82	79%	93%
30	-0.640	-0.359						0.84	79%	95%
40	-0.369	-0.101						0.70	79%	95%
50	-0.407	-0.208	-0.446					0.75	80%	97%
60	-0.366	-0.338	-0.491					0.70	80%	98%
70		-0.356	-0.416	-0.097	-0.355			0.71	80%	98%
80		-0.367	-0.378	-0.082	-0.352			0.71	80%	98%
90		-0.368	-0.369	-0.092	-0.328			0.71	80%	98%
100		-0.373	-0.362	-0.081	-0.332			0.79	85%	98%
110		-0.358	-0.294	-0.081	-0.305			0.76	85%	98%
120		-0.459	-0.327		-0.454	-0.064	-0.315	0.77	85%	98%
130		-0.481	-0.336		-0.481	-0.060	-0.348	0.77	85%	99%
140		-0.465	-0.304		-0.451	-0.071	-0.372	0.72	85%	99%
150		-0.446	-0.304		-0.445	-0.085	-0.367	0.72	85%	99%

4. CONCLUSIONS AND FURTHER DEVELOPMENTS

This paper presented the results of an in-progress research aiming at developing a Traveler Tool that gives dynamic real-time information to user about travel alternatives on a multimodal transport network. The focus was on the investigation of model to be used for suggesting the best paths perceived by each user. Both the initialization and the up-dating process were analyzed pointing out the choices made in an empirical experiment.

A method was tested to incorporate users' preferences learning in a multi-modal advisor system, starting from the statement that user may be diverse when he/she evaluates travel options according to his/her preferences, attitudes, travel scope and contexts. Then, the ability to learn user's utility parameters may significantly improve the quality of offered services. Although Bayesian methods have been studied for that purpose, we proposed a method based on Maximum Likelihood procedure that allows the parameter updating by a reduced pre-fixed number of SP initial observations.

The presented results are encouraging. Even if, for the extensive scale application, further investigations need, some preliminary conclusions can be given. The obtained results show that the initialization phase (performed by SP interviews) can be short (10 observations) and the estimated parameters of path utility function allow to suggest with a good reliability the path preferred by user, also using a minimum number of alternative scenarios. On the other hand, in relation to the up-dating process, we tested that the process can be quite slow and too many observations are required before reaching a statistically significant stability of utility function, but a small number of revealed observations can be enough to give suggestions with an acceptable *%-of-right*.

The general conclusion is that the two methods (i.e. initial aggregate parameter estimation with Bayesian updating and Individual SP+RP Maximum Likelihood estimation) could have different fields of applications, with the first to be preferred when a quite complex multi-service transit network is available. Therefore, further analyses are necessary in order to define the specific fields of application, investigating different *od* pairs.

Besides, these results suggest the further developments of research. First, other model forms, able to point out correlation among paths, have to be considered. A procedure that also allows us to capture the variation of user's preferences during usage should be also analyzed. Finally, the methods assume that choice observations are independent of each other. In reality, repeated choices of travelers are often characterized by habituation and therefore procedures that allow us to identify, when new situations occur, how distortion caused by habituation on the parameter estimation can be reduced should be investigated.

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