Modeling the dynamic effect of information on drivers’ choice behavior in the context of an Advanced Traveler Information System

Modeling the Dynamic Effect of Information on Drivers' Choice Behavior in an Advanced Traveler Information System Context

Mauro Dell'Orco and Mario Marinelli

D.I.C.A.T.E.Ch. – Technical University of Bari, via Orabona 4, 70125 Bari, Italy

Abstract

In this paper, we present a modeling approach, based on the Fuzzy Data Fusion, to reproduce the drivers' dynamic choice behavior under an Advanced Traveler Information System (ATIS). The proposed model uses the Possibility Theory to model Uncertainty embedded in human perception of information. We have introduced a time-dependent Possibility Distribution of Information to model the users' changing perception of travel time also based on current network conditions. Drivers' choice models are often developed and calibrated by using, among other, Stated Preference (SP) surveys. In this work, we present an experiment to set up an SP-tool based on a driving simulator developed at the Technical University of Bari. The results obtained by the proposed model are analyzed and compared with the dynamic drivers' behavior observed in the experiment.

Keywords: dynamic route choice behavior; Possibility Theory; Data Fusion; Stated Preferences; driving simulator.

1. Introduction

A key issue in evaluating the performance of an Advanced Travelers Information System (ATIS) is understanding the information impact on the travelers' behavior. The analysis of drivers' decision-making in a context of real-time information and of changing traffic conditions requires dynamic models of drivers' behavior. This analysis is a crucial task, to simulate phenomena correctly like compliance with information, route choices in the presence of information, etc. Different conceptual models of drivers' behavior under information provision have been proposed in the literature. These models are based on the idea that each driver updates his/her knowledge of costs of alternatives using provided information. Then, the driver compares the updated costs of alternatives and chooses, among them, the best one from his/her point of view. Since knowledge of alternatives and information are rarely perfect, uncertainty affects single person's decision; therefore, handling uncertainty is an important issue for these models. We can arrange approaches followed by different scientists to face this problem into two main groups, according to how they modeled the uncertainty. Methods in the first group use randomness to represent uncertainty; for a comprehensive review see Ben-Elia and Avineri (2015). For this kind of models, unavailability of full numerical data could limit their reliability; in fact, these models are unable to handle non-numerical values of parameters. On the contrary, models included in the second group can model uncertainty in verbal, incomplete or imprecise data using concepts of the Fuzzy Logic. In fact, fundamental concepts of Fuzzy Set Theory like linguistic variables, approximate reasoning, and computing with words introduced by Zadeh have more understanding of uncertainty, imprecision, and linguistically articulated observations. These concepts support "the brain's crucial ability to manipulate perceptions of distance, size, weight, color, speed, time, direction, force, number, truth, likelihood, and other characteristics of physical and mental objects. A fundamental difference between perceptions and measurements is that, in general, measures are crisp whereas perceptions are "fuzzy" (Zadeh, 1978). First, Teodorović and Kikuchi (1990) proposed a route choice model based on Fuzzy Set Theory.

In this paper, we have examined in detail, through the Uncertainty-based Information Theory, dynamic drivers' compliance with information. In particular, we made the hypothesis that drivers' compliance with information services is a function of Uncertainty and can change over time. Therefore, we have set up a relation between Uncertainty and compliance level, and we have obtained a new, original model. The model is based on a Fuzzy Fusion of the drivers' previous experience and of the perceived information, expressed by a time-dependent Possibility distribution. First, Dell'Orco and Marinelli (2009) introduced a static version of the model. Afterward, Di Pace et al. (2011) have used that version of the model to evaluate drivers' risk perception in ATIS context. Recently, the model has also been used to represent drivers' choice behavior when data come from different information sources (Marinelli et al., 2015). In this work, we have introduced a new dynamic formulation of the model and a better parameters' description and evaluation.

Moreover, to validate the proposed model, we have carried out a Stated Preference (SP) experiment at the Technical University of Bari (Italy), using a PC-based driving simulator. The road network employed in the experiment reproduces a real one existing in the city of Bari. The respondents recruited for the experiment were travelers more or less familiar with the network. To evaluate the dynamic effect of information, the road network proposed to respondents simulates different arrival times with two different, randomly generated, messages. In this way, we were able to reproduce different congestion levels and travel times, accordingly with their statistical distribution in the real world.

The paper is structured as follows. The next section presents a literature review. In section 3, the modeling approach, based on the Possibility Theory and the Data Fusion, is described. In section 4, a numerical application is proposed to explain how the proposed model works. In section 5, we have described the SP experiment designed to acquire information about drivers' choice behavior through a driving simulator. In section 6, we have reported results of the proposed model are carried out and, in the last section, conclusions.

2. Literature review

Drivers' travel choice behavior under information provision has been deeply investigated in the past. Recently, Ben-Elia and Avineri (2015) have proposed a review focusing on the individual travel behavior as well as network studies involving collective responses. Different models can be set up, depending on the fact that the study of choice behavior is static or dynamic. In fact, in the static case, pre-trip decisions are made for transport mode, route and time departure. In this case, the decisions are influenced by drivers' experience and by pre-trip information. Instead, in the dynamic case, en-route switching decision is made by the perception of current conditions of the network. In both cases, three factors are involved in routing decision (Adler and Blue, 1998): historical experience; current perception of the network conditions; information given by an informative system.

Horowitz (1984) modeled dynamic route choice by adaptive learning based on utility maximization. Arentze and Timmermans (2003) have proposed a reinforcement learning-based approach for dynamic travel choice modeling. Lo et al. (2006) suggested a route choice model based on the concept of travel time budget. They postulated that travelers perceive the variability of route travel times based on experience and other different factors as travel time budget, which every traveler wants to minimize. They formulated a multi-class mixed-equilibrium mathematical program to capture the route choice behaviors of travelers with different risk aversions or requirements on punctual arrivals. To extend stochastic route choice models, Mirchandani and Soroush (1987) proposed a generalized traffic equilibrium problem on stochastic networks (GTESP) that incorporates in the path choice process both probabilistic travel times and variable perceptions. Siu and Lo (2006) formulated a stochastic equilibrium to address uncertainty in the actual travel time, due both to incomplete traffic information about link capacity degradations and to the perception of variations in the travel time budget. To address the effect of other parameters on drivers' route choice, Aashtiani and Iravani (1999) incorporated signalized and un-signalized delay to the deterministic traffic assignment. They proposed some delay functions based on HCM manual and included these functions to the link delay function. Some experiments indicated that the learning and adaptive process of commuters' route choice might take a long time, partly because of the feedbacks from the traffic system. Indeed, complex switching resulting from the provision of better information (Hu and Mahmassani, 1995; Mahmassani and Cheng, 1986; Mahmassani and Liu, 1999) can lengthen the process. Gao (2012) studied the impacts of real-time information on drivers' routing choices in time-dependent networks where random incidents are the source of stochasticity. The author formulated a fixed–point problem of the user equilibrium solved through a method of successive average heuristic. Kucharski and Gentile (2016) proposed a probabilistic model to represent the process of spreading information to the drivers via multiple information sources. They embedded the model in a macroscopic dynamic traffic assignment (DTA) of a simulation framework providing a dynamic forecast of informed drivers in road networks. Li et al. (2017) proposed an optimization model with different types of traveler knowledge in an advanced traveler information system context. Some works proposed solutions based on Variable Speed Limit (VSL) systems to manage traffic flow (Abuamer et al., 2016; Demiral and Celikoglu, 2011; Li et al., 2015; Muller et al., 2016; Sadat and Celikoglu, 2017; Soriguera et al., 2017; Yang et al., 2017).

Khattak et al. (1993) used multinomial logit models to analyze drivers' en route diversion and return choices. They identified that: information can indeed encourage drivers to divert from their regular routes; information on travel times should be supplied on many alternative routes; drivers are sensitive to the quality of the information: the more precise the information on the location of the congested sections, the more likely drivers are to divert. The conceptual frameworks for analyzing the effects of traffic information on driver behavior should take explicit account of the process of information acquisition and use. Also, the linkage between this process and observed driver behavior should be considered (Ben-Akiva et al., 1991; Polak and Jones, 1993; Mahmassani and Jayakrishman, 1991). Hato et al. (1999) proposed a route choice model that takes account of drivers' behavior in the acquisition and use of traffic information from multiple sources. The model has been validated using observed data on driver behavior.

Several authors have used in the literature other frameworks than random utility for modeling route choice behavior. For example, Lotan and Koutsopoulos (1993), Lotan (1997), Henn (2000) and Rilett and Park (2001) proposed different models based on fuzzy logic. Dougherty (1995) gives a review of work using artificial neural networks and Yamamoto et al. (2002) use decision trees for modeling the route choice between two alternatives. Dia and Panwai (2010) have modeled compliance to information through a comparative evaluation of discrete choice and artificial neural networks. They have highlighted how artificial neural networks can represent an alternative tool for modeling reactive behavior with imperfect information.

In this field of research, where the availability of revealed preference data is so limited, driving simulators have frequently been used to collect data. In general, the most adopted approach for collecting data is the Stated Preference (SP). Two main types of tools for SP in ATIS contexts are the most popular: driving-simulators (DSs) and travel-simulators (TSs). Both methods are computer-based. DSs are characterized by a better realism if the respondents are asked to drive to implement their travel choices, as it happens in the real world. Bonsall et al. (1991) reported on the results obtained by two EU DRIVE I projects, while Koutsopoulos et al. (1995) pointed at the inherent biases related to using travel simulators. Bonsall (1995) modeled the impact of variable message sign information using the VLADIMIR route-choice simulator. He found that the importance of phrasing the message should not be underestimated, as drivers in the sample appeared to be very sensitive to different types of message telling the same things. In most cases, data have been collected by using TS, as for instance in (Ben-Akiva et al., 1991; Mahmassani and Jou, 1998; Avineri and Prashker, 2006; Chorus et al., 2007). In TS, respondents enter travel choices after having received a description of travel alternatives and associated characteristics, without any driving. Only a limited number of studies have been carried out by adopting DSs (Bonsall and Parry, 1991; Bonsall and Firmin, 1997; Koutsopoulos et al., 1994; Katsikopoulos at al., 2002; Tian et al., 2012).

In this work, we have designed a Stated Preference experiment where we provide the information by variable message signs (VMSs). These signs, as an advanced traffic guidance system, can provide real-time traffic information in urban road networks to help drivers choose the routes with lower traffic volumes. Thus, the vehicles can be distributed reasonably in road networks to improve the performance of a transportation system (Emmerink et al., 1996). VMS effectiveness is dependent on drivers' route choice behavior, and VMS design and position may influence lane changing and speed control behaviors. The responses represent the drivers' perception of the guidance information and the degree of confidence in the information. Zhong et al. (2012) have studied the effects of different factors on drivers' compliance with information on road condition shown on a graphic VMS. They constructed a method to calculate the compliance rate of each driver by considering the relation among the suggested path of VMS, the chosen path, the experiential path of the driver, and the driver's trust degree in VMS. Yan and Wu (2014) investigate whether and how VMS position and VMS information format influence drivers' behaviors, based on a driving simulation experiment. Recently, Chang et al. (2017) have studied the drivers' response to dynamic travel information with VMS. They proposed a classification and regression trees (CAT) model constructing a hierarchical structure of driver compliance from different factors evaluated from a Stated Preference Survey.

In this paper, we propose a model able to reproduce the drivers' dynamic compliance with real-time information, thus definitely different from the previous static models. The proposed model, as described in details in the following sections, takes into account, through Possibility Theory, uncertainty embedded in the human perception of travel time. Moreover, we have added a Stated Preference experiment, based on a driving simulator, to evaluate drivers' perceptions. Finally, we have calibrated the proposed model through a Genetic Algorithm, validated by questionnaires' data.

3. Modeling the dynamic perception

An Advanced Traveler Information System (ATIS) may provide to users *pre-trip* information (before drivers begin the trip) or *en-route* information (while drivers are moving). In the first case, static choice models are involved; in the second case, dynamic ones. Usually, in both cases, travelers combine information with their previous experience to obtain a prediction about the cost of each path and to choose the most convenient from their point of view.

We assume that drivers have some experience about the attributes of the transportation system. They use the information to update their experience and to choose an alternative accordingly.

Considering that the drivers' knowledge about the transportation system could be imprecise or vague, we need an appropriate theory to express the way they perceive information. For this reason, we have introduced in our model the Possibility Theory, presented by L.A. Zadeh (1978). This theory, closely related to Fuzzy sets theory, allows dealing with uncertainties embedded in imprecise or vague knowledge. Moreover, it represents a mathematical tool able to assess the possibility of occurrence of an event, even without any knowledge about the probability of this occurrence.

According to the Possibility Theory, let us now consider two sets A and B, containing respectively information released by the informative system, and information perceived by the drivers. Note that, although delivered information can be accurate or vague, human mind always processes it approximately. Therefore, a relation between the sets A and B should not be precise. In Figure 1, the 45°-straight dotted line represents the relationship between information released and completely and correctly perceived. The function $\Pi(B)$ is called Possibility of B and expresses to which extension the event B, related to a released information A, is possible according to the drivers' perception. In other words, considering the vagueness of human perception, information "A" released by the informative system corresponds to an interval "B" perceived by travelers. Each value of B has its Possibility, whose maximum is 1. In this way, the straight line does not represent anymore the actual relationship between A and B; instead, the irregular area shaded in Figure 1 is a correct representation. As a result, Possibility can express both drivers' knowledge and information, like in Figure 2, where we have considered a triangular-shaped fuzzy set. We recall that one can represent fuzzy sets and Possibility distributions in the same way.

place Fig. 1 about here

place Fig. 2 about here

In the updating process of their knowledge, drivers combine data coming both from their experience and from information provided by an information system like ATIS. Note that the impact of information on drivers' choices can change over time: when information is released, drivers can perceive it differently as the time goes on, even related to the perception of the current conditions of the network. At the beginning of an event, e.g. few minutes after an accident, drivers' compliance with the information system could be quite small, due to an initial short queue and an acceptable speed reduction. After a while, drivers perceive a significant change in the network status and their compliance with information possibly increases. In time, the users update the perceived delay according to the perceived network status even if the released information does not change. As a result, the percentage of drivers shifting on alternative routes changes accordingly.

This dynamic impact of information on drivers' behavior has been introduced in our model considering a time-dependent possibility distribution of information I at time t $\Pi(I,t)$ (Figure 3). Assuming that the drivers' experience does not change over short time periods, we can formulate this distribution as follows:

$$
\Pi(I,t) = \begin{cases} \dfrac{\tau - a(t)}{b(t) - a(t)}, & a(t) \le \tau < b(t) \\ \dfrac{\tau - c(t)}{b(t) - c(t)}, & b(t) \le \tau \le c(t) \\ 0, \text{ otherwise} \end{cases} \tag{1}
$$

where a and c are respectively leftmost and rightmost limits of the triangular distribution, while b is the so-called center point, related to the maximum Possibility value. This Possibility distribution can adequately represent approximated evaluations in human reasoning, like "travel time is b minutes", which means "in my opinion, travel time is approximately b minutes, from a to c minutes". These parameters are time-dependent, according to the change over time of the perceived information.

place Fig. 3 about here

The aggregation of experience and information could be not always meaningful since data coming from different sources can be far from each other, and thus not compatible. Therefore, a suitable aggregation function should also include a measure of compatibility.

In the proposed model, we have considered the compatibility measure introduced by Yager and Kelman (1996), and extended it considering the time-dependence of information perception:

$$
R[x_1(t), x_2(t)] = \begin{cases} 0 & if \ |x_1(t) - x_2(t)| > k \\ 1 - \dfrac{1}{k}|x_1(t) - x_2(t)| & if \ |x_1(t) - x_2(t)| \le k \end{cases} \tag{2}
$$

where k is a parameter related to the information perception and its value should be assigned carefully to obtain a proper compatibility measure.

At each time t, we have used the *Ordered Weighted Average* (OWA) operator and the compatibility function R, defined in (1), to fuse data coming both from perception and experience.

Given a set $A=\{a_1, a_2,\dots,a_n\}$ and a fusion function F, an OWA operator is a weighting vector $W=[w_1,\dots,w_n]$ such that:

- $w_i \in [0,1]$;
- $\Sigma_i \, w_i = 1$;
- $F(a_1, a_2,\dots,a_n) = \Sigma_i \, b_j \, w_j$

in which b_j is the j-th largest element of A. By adjusting the weighting vector, we can represent different drivers' attitudes: when W favors the smaller valued arguments in the aggregation process, it reflects an *aggressive* driver. Otherwise, it reflects a *cautious* driver.

In this work, we have used the method by O'Hagan (1990) to calculate the weights w_i ($i = 1,\dots,n$) at time t through the following mathematical programming problem:

$$
Max \quad -\sum_{i=1}^{n} w_i \cdot \ln(w_i)
$$

subject to (3)

$$
\sum_{i=1}^{n} w_i \cdot h_n(i) = \beta(t)
$$

$$\sum_{i=1}^{n} w_i = 1$$

$$w_i > 0 \qquad \forall i$$

where $h_n(i) = \frac{n-i}{n-1}$, and β(t) $\in$[0,1] is a coefficient representing, in our case, drivers' cautiousness related to the dynamic perception of information. Note that, if at time *t* the fusion involves only two sets, then $h_2(1) = 1$, $h_2(2) = 0$. Thus, from the constraints of previous program (Eq. 3):

$$w_1 = \beta(t) \tag{4}$$

$$w_2 = 1 - \beta(t) \tag{5}$$

To set up a value of $\beta(t)$, the primary hypothesis of this model is that drivers' cautiousness is a function of uncertainty related to the perceived information. Let us make an example of this concept. Assume that, at a certain time *t*, the shorter one of two alternative paths is temporarily closed by barriers. In this case, information "path is closed" is not uncertain, that is $U(I) = 0$, and drivers must choose the longer path. Thus, the OWA operator should favor the largest value, that is $w_1 = 1$, and consequently $\beta(t) = 1$ from (4). Conversely, if instead of barriers there is an information system that provides very vague information about the condition of the path, uncertainty $U(I)$ is very large, and drivers should prefer to rely on their own experience. In this case, the OWA operator favors the smallest value, w_2 approaches 1 and thus, from (5), β approaches 0. From this example, it appears that the parameter β can be interpreted also as drivers' compliance with information. In fact, $\beta = 1$ means that the driver is totally compliant with information, $\beta = 0$ means the opposite.

In this study, we have assumed that:

- drivers' compliance with information decreases with increasing of uncertainty. Thus, the relative elasticity of compliance on uncertainty is negative.

  In analytical terms: $\frac{d\beta(t)/\beta(t)}{dU(I,t)/U(I,t)} < 0$;

- the increase of compliance with additional information is greater in the case of ignorance than in the case of complete knowledge. That is, the relative elasticity is a function of uncertainty itself.

By these hypotheses, the following linear relationship between relative elasticity and uncertainty level has been carried out:

$$\frac{d\beta(t)/\beta(t)}{dU(I,t)/U(I,t)} = -\gamma(t) \cdot U(I,t) \tag{6}$$

and hence, at time *t*:

$$\beta(t) = \frac{1}{e^{\gamma(t) \cdot U(I,t)}} \tag{7}$$

where γ is another parameter related to the information perception, which takes into account individuals' attitude in perceiving information in time.

We have incorporated the compatibility concept in the fusion of fuzzy sets using the method suggested by Yager and Kelman (1996). Therefore, let

- $A_{i,t}$ (i= 1,…n) be a collection of fuzzy sets at time t;
- $B_t = F(A_{i,t})$ be the result of aggregation at time t;
- $A_{i\alpha,t}$=[$l_{i\alpha,t}$, $r_{i\alpha,t}$] be the α-cut associated with $A_{i,t}$;
- $l^*_{\alpha,t} = \max_i[l_{i\alpha,t}]$ be the largest lower bound of any α-cut;
- $r^*_{\alpha,t} = \min_i[r_{i\alpha,t}]$ be the smallest upper bound of any α-cut;
- $U^*_{\alpha,t} = \inf\{\tau \mid R(l^*_{\alpha,t}, \tau) \geq \alpha\}$ be the smallest value compatible with $l^*_{\alpha,t}$ at level α;

- $V^*_{\alpha,t} = \sup\{\tau \mid R(r^*_{\alpha,t}, \tau) \geq \alpha\}$ be the largest value compatible with $r^*_{\alpha,t}$, at level α.

Provided that $U^*_{\alpha,t} \leq r^*_{\alpha,t}$ and $V^*_{\alpha,t} \geq l^*_{\alpha,t}$, the α-cut of B can be calculated as:

$$B_{\alpha,t} = [F(d_{1\alpha,t}, \ldots, d_{n\alpha,t}), F(e_{1\alpha,t}, \ldots, e_{n\alpha,t})] \tag{8}$$

where:

$$d_{i\alpha,t} = \begin{cases} l_{i\alpha,t} & \text{if } l_{i\alpha,t} \geq U^*_{\alpha,t} \\ U^*_{\alpha,t} & \text{otherwise} \end{cases} \qquad e_{i\alpha,t} = \begin{cases} r_{i\alpha,t} & \text{if } r_{i\alpha,t} \geq V^*_{\alpha,t} \\ V^*_{\alpha,t} & \text{otherwise} \end{cases} \tag{9}$$

The information fusion model incorporates important aspects, such as:

- the dynamic nature of information integration. The user's previous experience influences the perception of travel time of an alternative;
- the accuracy of the informative system. The more accurate information is, the more important is the effect on the drivers' perception;
- the nonlinear relationship between information and perception. The parameter β itself is a function of information so that the updated cost is a nonlinear function of information.

After aggregating experience with information, drivers compare the resulting perception with the experience related to other alternatives. As stated above, the concept of Possibility is useful in representing decision maker's uncertainty about the perception of alternatives; however, it cannot be used directly in calculations. For this reason, to compute drivers' choices, we have transformed Possibility into Probability values.

The transformation procedure is based on the probabilistic normalization ($\sum_i p_i = 1$), along with the Principle of Uncertainty Invariance, systematized by Klir and Wang (1992). This principle specifies that Uncertainty in a given situation should be the same, whatever is the mathematical framework used to describe that situation.

Under the requirement of the probabilistic normalization and the Uncertainty Invariance, we should use a transformation having two free coefficients. Thus, according to Geer and Klir (1992), we have used the "log-interval" scale transformations having the form:

$$\Pi_{i,t} = \delta \cdot (p_{i,t})^{\alpha} \tag{10}$$

where $\Pi_{i,t}$ is Possibility and $p_{i,t}$ Probability of the ith alternative at time t; α and δ are positive constants.

From (10) we obtain: $p_{i,t} = (\Pi_{i,t}/\delta)^{1/\alpha}$ and, applying the probabilistic normalization, $\delta = \left(\sum_i \Pi_{i,t}{}^{1/\alpha}\right)^{\alpha}$ whence, setting $\varepsilon = 1/\alpha$:

$$p_i = \Pi^{\varepsilon}_{i,t} \Big/ \sum_j \Pi^{\varepsilon}_{j,t} \tag{11}$$

We use the Principle of Uncertainty Invariance to calculate ε. At time t, given an ordered Possibility distribution $\{\Pi_{1,t}, \Pi_{2,t}, \ldots, \Pi_{i,t}, \Pi_{i+1,t}, \ldots, \Pi_{n,t}\}$ for which is always the case that $\Pi_{i,t} \geq \Pi_{i+1,t}$, the possibilistic counterpart of the probabilistic uncertainty, called U-Uncertainty, is given by the following function:

$$U = \sum_{i=1}^{n} \left(\Pi_{i,t} - \Pi_{i+1,t}\right) \cdot log_2(i) \tag{12}$$

while the so-called Shannon Entropy gives the probabilistic uncertainty:

$$E = -\sum_{i=1}^{n} p_{i,t} \cdot log_2\left(p_{i,t}\right) \tag{13}$$

According to the Principle of Uncertainty Invariance, Probabilistic Uncertainty E, and Possibilistic Uncertainty U, must have the same value:

$$-\sum_{i=1}^{n} p_{i,t} \cdot log_2(p_{i,t}) = -\sum_{i=1}^{n} \Pi_{i,t}^{\varepsilon} \Big/ \sum_{j} \Pi_{j,t}^{\varepsilon} \cdot log_2\left(\Pi_{i,t}^{\varepsilon} \Big/ \sum_{j} \Pi_{j,t}^{\varepsilon}\right) = \sum_{i=1}^{n} (\Pi_{i,t} - \Pi_{i+1,t}) \cdot log_2(i) \tag{14}$$

where $\Pi_{n+1} = 0$ by definition.

The proposed model can evaluate the drivers' dynamic choice behavior, starting from information released at a particular time by an information system. In time, the model updates the perceived information through a time-dependent Possibility distribution and fuses it with the drivers' experience. Then, a comparison of experiences related to other different alternatives is carried out, to obtain the dynamic choice. Figure 4 presents a block diagram of the proposed model.

place Fig. 4 about here

3.1. Calibration of the model

As described above, the parameters k and γ characterize the proposed model. A proper tuning of these parameters can adapt the model to simulate a particular drivers' compliance with information. We can calibrate the parameters using data coming from Stated Preference (SP) experiments. In this work, we have considered Genetic Algorithms (GA) to calibrate the model for their good performances in solving complex nonlinear optimization problems.

In the calibration procedure, we aim to minimize the root mean square error (RMSE) between the choice percentages observed in the SP experiments p_i and probabilities computed by the model $\hat{p}_i(k,\gamma)$ for each alternative i, defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}[p_i - \hat{p}_i(k,\gamma)]^2} \tag{15}$$

where N is the number of the choice alternatives. An individual chromosome has been coded as a concatenation of two parameters' sets K and Γ, defined as:

$$K = [k_1, \dots, k_S] \tag{16}$$

$$\Gamma = [\gamma_1, \dots, \gamma_S] \tag{17}$$

where S is the number of respondents in SP experiments. Thus, a single gene represents a single parameter k or γ as characteristics of each participant. The aim of the calibration process is to find the best parameters k and γ able to reproduce the observed choice behavior at each time t. At each iteration (generation) at time t, the algorithm executes all the steps reported in Figure 4 to evaluate the objective function (15).

In the following, we first present a test application to route choice, and a driving simulator-based Stated Preference experiment to calibrate the proposed model and carry out the validation.

4. Numerical application to the route choice

A simple test network with a single origin-destination pair (i, j) and two paths a and b have been considered (Figure 5) to evaluate the outcomes of the proposed model.

Let us assume that:

- drivers have experience that travel time, on average, on the path *a* is “about 17 minutes”, ranging from 12 to 22 minutes, while on the path *b* is “about 25 minutes”, ranging from 20 to 30 minutes;
- at time $t = 0$, a Variable Message Signal (VMS) at the origin node *i* displays real-time traffic information like, for example, “congestion ahead”, “3 km queue”, “minor accident”.

place Fig. 5 about here

The resultant possibility distributions, based on the assumptions that drivers have an imperfect knowledge of travel times for paths *a* and *b*, are shown in Figure 6. In the beginning, when ATIS doesn’t provide information, drivers make a comparison between travel times only by their experience on the path *a* (t_a) and path *b* (t_b).

According to Possibility Theory, we can evaluate the comparison by the relations:

- Possibility that $t_a < t_b = \Pi(t_a < t_b)= \max\left(\min\left(\Pi(t_a), \Pi(\leq t_b)\right)\right)$
- Possibility that $t_b < t_a = \Pi(t_b < t_a)= \max\left(\min\left(\Pi(t_b), \Pi(\leq t_a)\right)\right)$

where $\Pi(t_i)$ and $\Pi(\leq t_i)$, $i = \{a, b\}$, are the Possibilities that travel time is t_i or smaller than t_i, respectively. In our example, from fig. 3 the results of comparison are:

- $\Pi(t_b < t_a) = 1$
- $\Pi(t_b < t_a) = 0.2$

Through equation (14), we can then calculate the probability p_i of choosing the route *i* without information about traffic conditions. In our case, we have obtained: $\varepsilon = 2.14$, $p_a = 0.97$, $p_b = 0.03$.

place Fig. 6 about here

Now, assume that, at time t = 0, the variable message sign (VMS) releases the message “queue on the path a”. Initially, the information provided by the VMS makes the drivers update the perceived travel time always as “approximately 22 minutes”, ranging from 12 to 30 minutes. As the network status changes, drivers process information in a different way. Considering the dynamic effect of information, we can assume that the parameters a, b and c related to the information possibility distribution $\Pi(I, t)$ (see Figure 3) change over time according to the following linear functions:

$$\begin{cases} a(t) = 3/10 \cdot t + 12 \\ b(t) = 3/5 \cdot t + 22 \\ c(t) = 4/5 \cdot t + 30 \end{cases}$$

The resulting time-dependent possibility distribution for $0 \leq t \leq 10$ minutes is represented in Figure 7. We can observe how the support of the distributions ($c(t) - a(t)$), strictly related to the uncertainty in drivers’ perception of information, increases over time. In this way, we can capture the propensity of drivers to perceive an increasing uncertainty related to the travel time, as soon as the state of the network worsens. The resulting U-Uncertainty, calculated by using Eq. (12), is reported in Figure 8 as a function of time.

place Fig. 7 about here

place Fig. 8 about here

To apply the Fuzzy Fusion method, we have to assign the respective values to parameters k in equation (2) and γ in equation (7), both related to the drivers' compliance with the provided information. For example, setting k = 20 and γ = 0.2, from the fuzzy fusion we obtain the $\Pi(t_f)$ reported in Figure 9a, related to the information perception at time t = 0 ($\Pi(I,0)$). The resulting set $\Pi(t_f)$ is a *subnormal* fuzzy set because its height h_f is 0.85, thus is less than 1. $\Pi(t_f)$ must be redefined as follows (Klir and Wang, 1992), to transform this fuzzy set in a normal one ($\Pi(r_f)$) preserving information:

$\Pi(r_f) = \Pi(t_f) + 1 - h_f$

In this case, we have increased the Possibility values of t_f by the same amount of 1-h_f = 0.15. Figure 9b reports the result of this redefinition.

Thus, the comparison is now carried out between r_f and t_b, and gives:

- $\Pi\left(r_f < t_b\right) = 1$
- $\Pi\left(t_b < r_f\right) = 0.586$

Using again the Principle of Uncertainty Invariance, we can calculate now: ε = 3.39, p_a = 0.86, p_b = 0.14. Therefore, in the presence of information "queue on the path a" provided by the VMS, about 11% of the total number of drivers shift from the path *a* to path *b* at time t = 0, just when the information is provided considering a medium level of compliance.

place Fig. 9 about here

Moreover, setting time t = 0, we can also assess changes in probabilities of route choice depending on different levels of drivers' compliance with information. Figure 10 shows the probabilities p_a of choosing the path *a* as a function of the parameters k and γ, representing the drivers' compliance: for high values of k and γ, the probability p_a (light gray) is around 96%. In this case, the model represents drivers with a low level of compliance, like drivers without information. Instead, we have obtained a high level of compliance with high values of k and low values of γ. In this case, p_a decreases to about 72% (dark gray).

place Fig. 10 about here

Finally, let us assume that at the beginning drivers show a low compliance level and that the compliance level gradually increases in time, due to the worsening of network conditions. We can model this behavior setting k = 50 and $\gamma(t) = 3 * e^{-10*t}, 0 \leq t \leq 10$. The resulting probabilities of route choice are shown in Figure 11. In this Figure, the proposed model appears also able to evaluate the drivers' dynamic behavior, considering the switch of the path preference in time. In fact, 8 minutes after the release of information by the VMS, drivers start to prefer the path *b* to path *a*, although path *a* was the fastest one in their experience.

place Fig. 11 about here

5. The SP experiment

To validate the proposed model, we have designed a Stated Preference (SP) experiment using a PC-based driving simulator of Technical University of Bari (Figure 2).

We have used the software UC-win/Road as a driving simulator. The simulation system worked on a single computer provided with NVidia Graphic Card (1 GB of graphic memory) and a Quad-Core CPU, which guarantees good real-time rendering and computation performances. For the simulation, we have used a steering wheel (Logitech™ MOMO Racing Force Feedback Wheel), able to provide force feedback, as well as six programmable buttons (ignition, horn, turn signals, etc.). Additionally, we have used a wide-screen monitor to have a good field of view, also showing internal car cockpit with tachometer and speedometer. Environmental sounds are reproduced to create a more realistic situation.

During the experiment, respondents have been asked to choose a route among three alternatives. We have configured the context in such a way that the respondents could make a choice as a (possible) shift from the natural alternative. In this experiment, respondents were familiar with the experimental context. The simulated network was a part of the real network in Bari, a medium-sized city in Southern Italy (Figure 3). The choice set consisted of i) the main route (route 1, R1); ii) the route 2 (R2); iii) the route 3 (R3). The route 1 was the natural choice in case of free flow conditions; the route 2 was the detour option, in the case of moderate traffic congestion; the route 3 was an earlier detour in the case of high traffic congestion.

Before starting the simulation, respondents were asked to drive along each alternative route of the choice set, without ATIS and in free-flow traffic conditions, to get familiarity with the driving simulator. After this training step, respondents made six successive trials, grouped in three driving sessions. At each session, respondents drove twice, starting from a different simulation time. The Variable Message Signs (VMSs) representing the ATIS could be randomly active or not. The activation of the ATIS was a consequence of an accident occurrence, perturbing the standard traffic pattern to an extent depending on the accident severity.

place Fig. 12 about here

place Fig. 13 about here

place Table 1 about here

The trials were called "*without information*" when the VMSs were not activated; otherwise, trials were called "*with information*". Moreover, ATIS provided two possible messages: 'queue' and 'accident', displayed randomly during all trials. VMSs located on the main road, as reported in Table 1, provided respondents with information.

The first VMS was placed 300 meters before the first diversion node (Exit 13A-Mungivacca, toward route 3); the second VMS was 1250 meters before the second diversion node (Exit 12-Carrassi, toward route 2), and the third VMS was 150 meters before the second diversion node. A queue started in all cases 900 meters after the last diversion node and 500 meters before the exit ramp of Exit 11-Poggiofranco. Different congestion levels were obtained starting the simulation at time t_0 equal to 3, 6 or 9 minutes after the event occurrence and information provision. In this way, we have simulated the impact of the network status on drivers' perceptions by using different arrival times from event occurrence. In this scenario, VMSs display the presence and the position of a queue, neither the queue length nor the estimated queuing time. At the end of each trial, respondents were asked to answer a questionnaire, in which they stated the chosen route, the perception of a possible delay by the provided information (minimum, most expected and maximum time value), and the perceived travel time on that route. These data were required to define the parameters (a, b, c) of the triangular fuzzy numbers related to their perceptions, and to apply the model of Data Fusion previously described.

6. Results

The SP experiment has been carried out over a period of six months with a sample size of 20 respondents. The experiment sample is almost heterogeneous since it is composed of 50% of male and 50% of female respondents. The 80% of them are students and the remaining 20% are administrative staff. Each respondent has performed six trials in random virtual scenarios as described above. At the end of the experiment, we have obtained a dataset of 120 records corresponding to the total number of completed trials and related questionnaires.

Table 2 reports the average values of the respondents' experience as the fuzzy parameters (a, b, c). In trials with information, a respondent perceives a delay as he/she reads the message provided by the VMSs and evaluates the traffic conditions. This perception of delay depends not only on subjective factors but also on the content of the information itself. Table 3 shows, for each arriving time t_0, the perceived travel time as triangular fuzzy numbers, respectively for messages 'queue' and 'accident'. We can observe that the perceived travel time for the message 'queue' is lower than that for the message 'accident'. This result is reasonable because the awareness of an accident is more effective than a queue as delay perception. Moreover, the information perception changes as the network status changes; in particular, for both messages 'queue' and 'accident', the more the perception of the status of the network is affected by congestion, the more the value of the parameter c (maximum travel time is estimated T_{max}) increases. Correspondingly, an increase in the support $(c - a)$ of the perceived travel time occurs, meaning that the drivers' uncertainty increases in time.

Table 4 reports the resultant route choice probabilities for each arriving time t_0. The choice behavior varies according to the message displayed on the VMSs. This result is consistent with the perception of possible delays, consequent from the provided information. In fact, the perception of a possible greater delay increases the propensity to abandon the usual path, turning over other available alternatives. Note that in the case of message 'queue', no respondent chooses the route R3, while in the case of message 'accident' no respondent chooses the route R1. In both cases, the majority of drivers prefer the intermediate route R2.

place Table 2 about here

place Table 3 about here

place Table 4 about here

To validate the model and estimate the dynamic effect of information on drivers' choice behavior, we have computed time-dependent functions, related to the information perception parameters (Table 3) through the following quadratic regression:

$$\text{message 'queue'} \quad \begin{cases} a(t) = 0.26 \cdot t^2 - 2.98 \cdot t + 18.2 \\ b(t) = 0.21 \cdot t^2 - 2.178 \cdot t + 19 \\ c(t) = 0.38 \cdot t^2 - 3.03 \cdot t + 24.1 \end{cases} \qquad 3 \le t \le 9$$

$$\text{message 'accident'} \quad \begin{cases} a(t) = -0.15 \cdot t^2 + 2.31 \cdot t + 8.25 \\ b(t) = -0.03 \cdot t^2 + 0.9 \cdot t + 17.25 \\ c(t) = -0.02 \cdot t^2 + 1.51 \cdot t + 21 \end{cases} \qquad 3 \le t \le 9$$

Similarly, to estimate the drivers' choice probabilities within the observation interval $t \in [3, 9]$, we have considered the following quadratic regression functions obtained from experiment average values (Table 4):

message 'queue' $\begin{cases} p_{R1}(t) = 0.03 \cdot t^2 - 0.38 \cdot t + 1.5 \\ p_{R2}(t) = -0.026 \cdot t^2 + 0.38 \cdot t - 0.5 \\ p_{R3}(t) = 0 \end{cases}$ $3 \leq t \leq 9$

message 'accident' $\begin{cases} p_{R1}(t) = 0 \\ p_{R2}(t) = 0.002 \cdot t^2 - 0.04 \cdot t + 0.95 \\ p_{R3}(t) = -0.002 \cdot t^2 + 0.04 \cdot t + 0.05 \end{cases}$ $3 \leq t \leq 9$

As previously described, the parameters k and γ (Eq. 2 and 7) are used to calibrate the drivers' compliance with the information system; setting a high value of parameter k and varying γ we can model different drivers' compliance. In this case, having set k = 10000 both for 'queue' and 'accident' messages, we have calculated through the Genetic Algorithm (GA) the values of parameter γ that minimized the root mean square error (RMSE) between observed choices and predictions of the model. Figure 14a and 15a report the estimated values of parameter γ obtained by calibration for message 'queue' and 'accident' respectively. In Figure 14b and 15b, the results of the choice probability estimation $\hat{p}_{Ri}$ are reported. The estimated dynamic choice behavior is compared to average observed values p_{Ri} reported in Table 4. It is possible to see that, in the case of message 'queue', the drivers' compliance with information is medium at the beginning and increases over time (γ decreasing). Instead, in the case of message 'accident', the drivers' compliance is always very high corresponding to very low γ values, on average $1.2 \cdot 10^{-4}$.

Figure 16 reports the resulting RMSE obtained by the model in the observation interval. In the case of 'queue' message, the RMSE value is 5.36% on average, lower than the case of 'accident' message, which is 10.0% on average. Thus, the proposed model can reproduce the overall behavior correctly and, therefore, the dynamic effect of information on users' choices.

place Fig. 14 about here

place Fig. 15 about here

place Fig. 16 about here

7. Conclusions

In this paper, the emphasis was on capturing the dynamic reasoning process of drivers making en-route choices in the presence of traffic information. We have modeled the influence of uncertainty in updating the knowledge of attributes of a transportation system, like expected travel time on a path, using the concept of compatibility between experience and current information. The presented model points out the relevant role of the Possibility Theory in calculating uncertainty and thus drivers' compliance with delivered information. We have extended the model considering a time-dependent Possibility distribution to deal with the dynamic nature of drivers' perception. The proposed modeling framework includes a Fuzzy Data Fusion method to represent drivers' peculiarity in combining data coming both from their experience and from information provided by an information system like ATIS. We have presented a numerical application to observe the capability of the model in quantifying users' compliance with information and realistically updating the expected travel time. Two parameters, k, and γ, both concerning the drivers' compliance level, characterize the model. By assigning these parameters appropriately, we can assess the dynamic drivers' route choice behavior.

A Stated Preference (SP) experiment has been designed using a driving simulator to validate the model. We developed a virtual scenario in the city of Bari (Italy) and proposed it to respondents in different conditions, obtained by combining arrival time and message type using VMSs. In particular, to reproduce the dynamic choice behavior, different arrival times (3, 6, 9 minutes) after the occurrence of an event ('queue' or 'accident') have been simulated. Data acquired through questionnaires have been used to parameterize the proposed model and to reproduce the drivers' perceptions and choice behaviors. We have measured the effectiveness of the model through the RMSE values between observed and calculated preferences. The proposed model has resulted very effective in reproducing dynamic drivers' preferences under information provision (5.36% RMSE on average for the message 'queue'; 10.0% RMSE on average for the message 'accident'). Further developments will deal with the impact of different types of information (experiential, descriptive and prescriptive) to analyze perceptions' variation of drivers.

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Abstract

In this paper, we present a modeling approach, based on the Fuzzy Data Fusion, to reproduce the drivers' dynamic choice behavior under an Advanced Traveler Information System (ATIS). The proposed model uses the Possibility Theory to model Uncertainty embedded in human perception of information. We have introduced a time-dependent Possibility Distribution of Information to model the users' changing perception of travel time also based on current network conditions. Drivers' choice models are often developed and calibrated by using, among other, Stated Preference (SP) surveys. In this work, we present an experiment to set up an SP-tool based on a driving simulator developed at the Technical University of Bari. The results obtained by the proposed model are analyzed and compared with the dynamic drivers' behavior observed in the experiment.

Keywords

Dynamic route choice behavior
Possibility Theory
Data Fusion
Stated Preferences
Driving simulator

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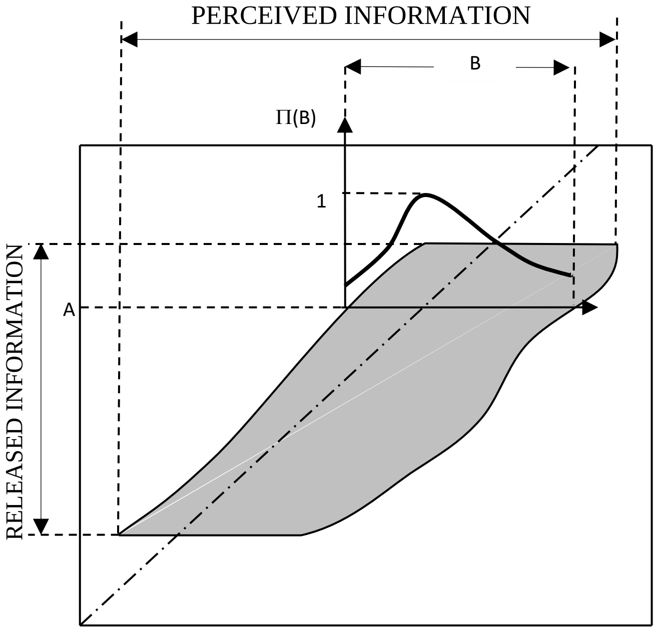

Fig. 1. The relationship between released and perceived information.

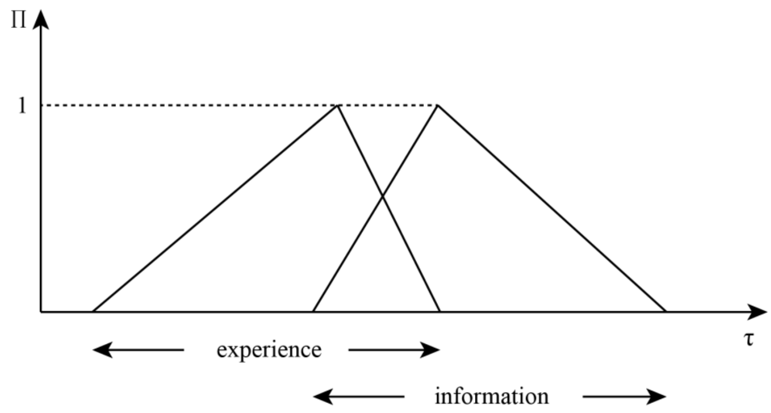

Fig. 2. Possibility distributions of experience and information perception.

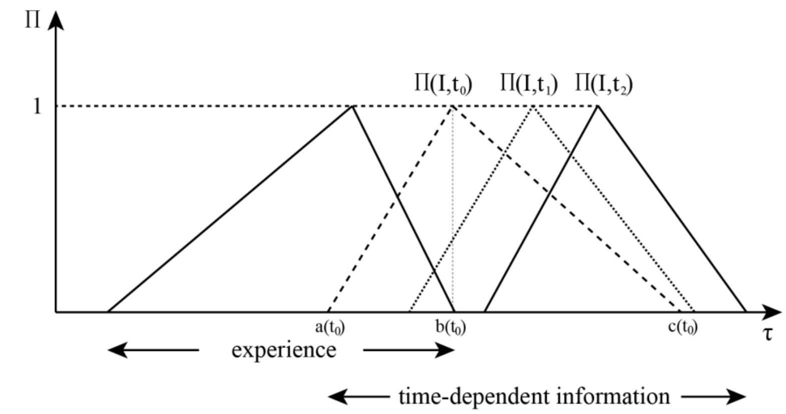

Fig. 3. Possibility distributions of experience and time-dependent information perception.

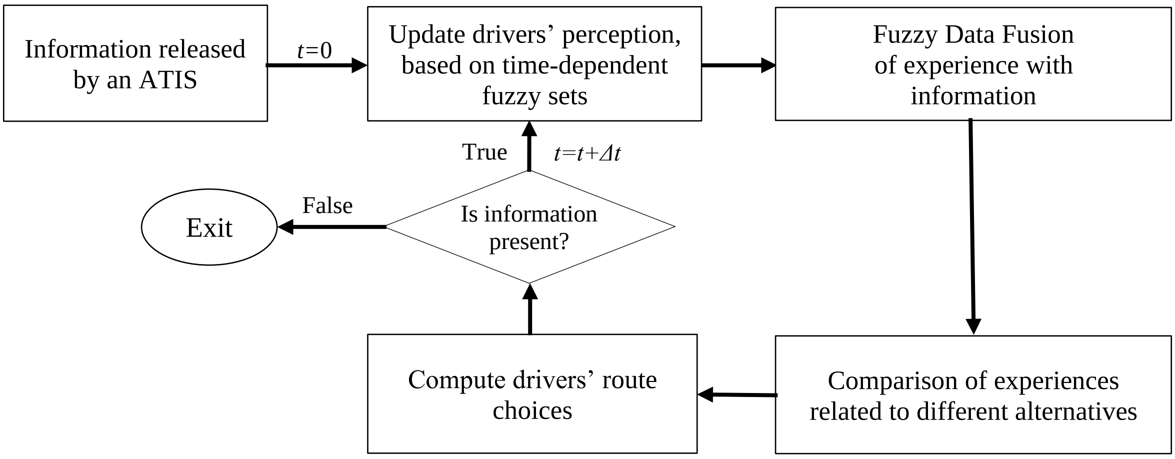

Fig. 4. Block diagram of the proposed model.

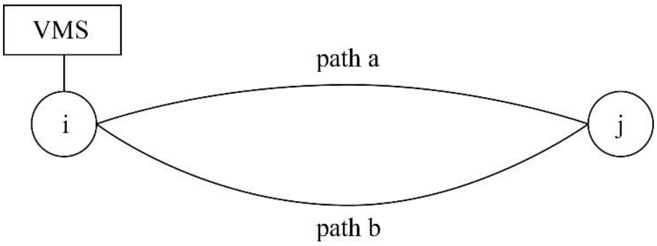

Fig. 5. Test network.

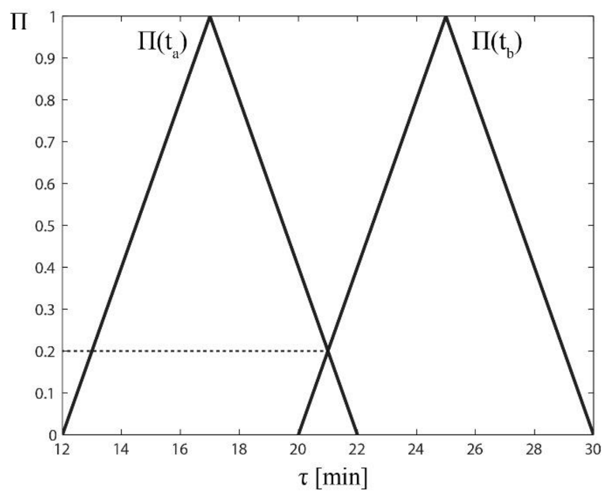

Fig. 6. Fuzzy sets related to the travel time experienced on the path *a* (t_a) and path *b* (t_b).

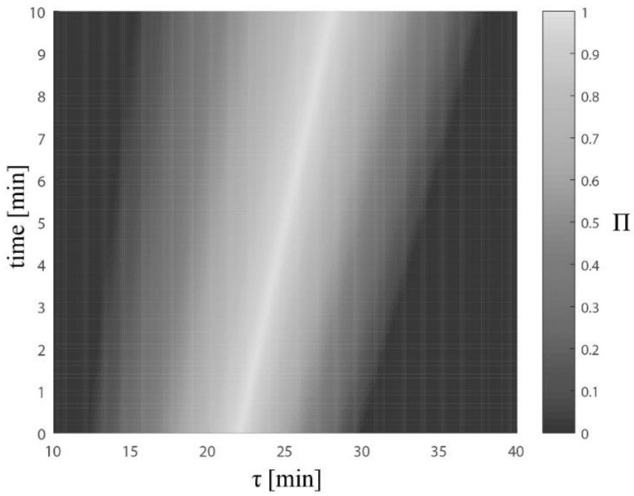

Fig. 7. Possibility distribution over time considered in the numerical application.

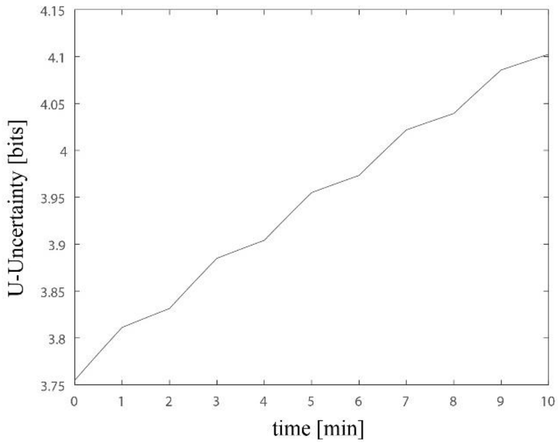

Fig. 8. U-Uncertainty over time of the considered possibility distributions.

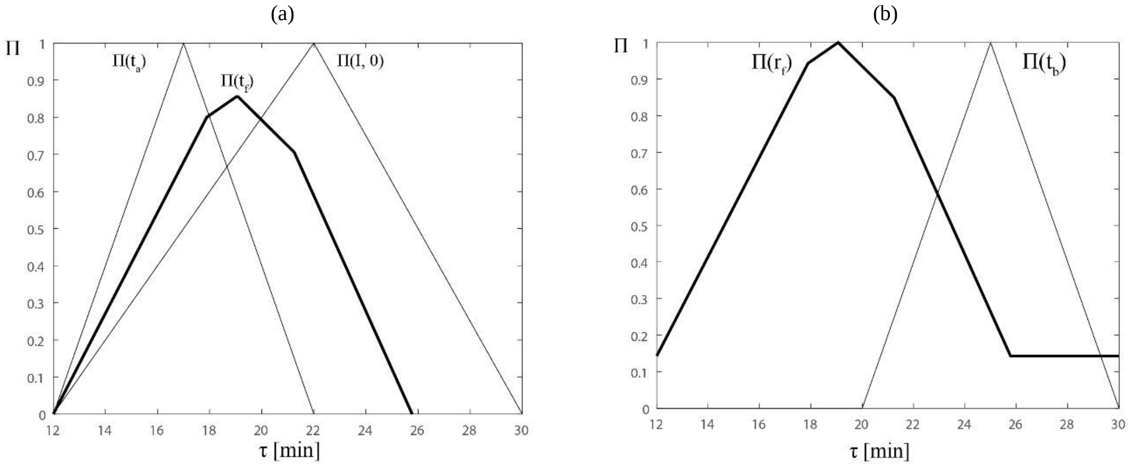

Fig. 9. (a) Resulting data fusion (t_f) between travel time experienced on the path a (t_a) and VMS message perception at time $t = 0$; (b) comparison between normalized data fusion (r_f) and travel time experienced on path b (t_b).

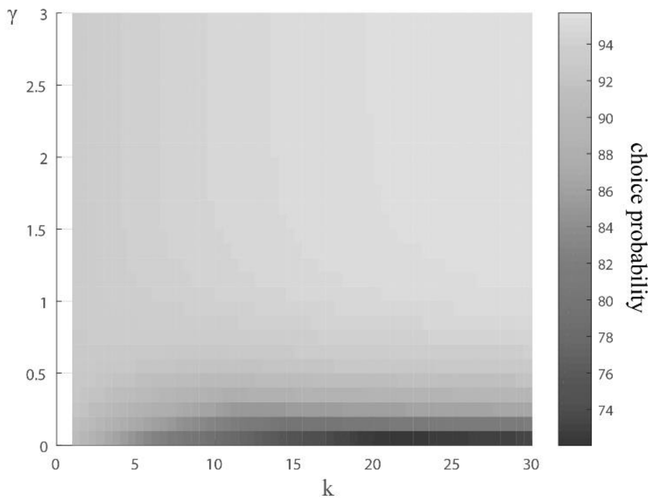

Fig. 10. Choice probabilities of the path a (p_a) at time t = 0, for different values of k and γ.

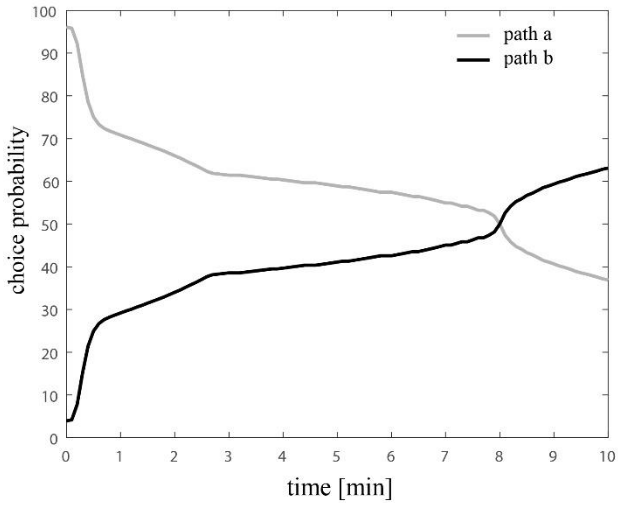

Fig. 11. Choice probabilities of path *a* and path *b* during the time.

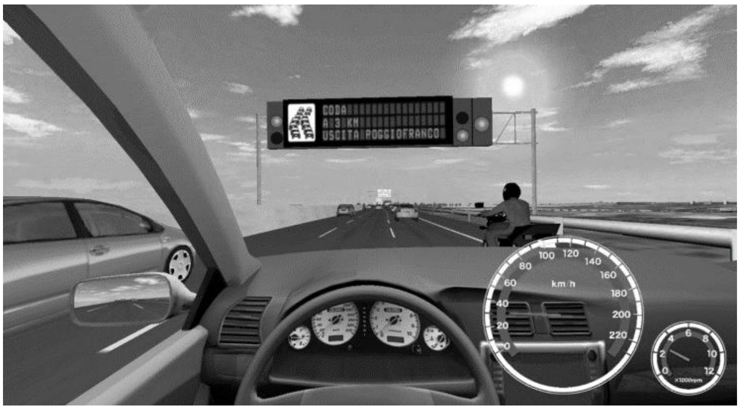

Fig. 12. Screenshot of the Driving Simulator.

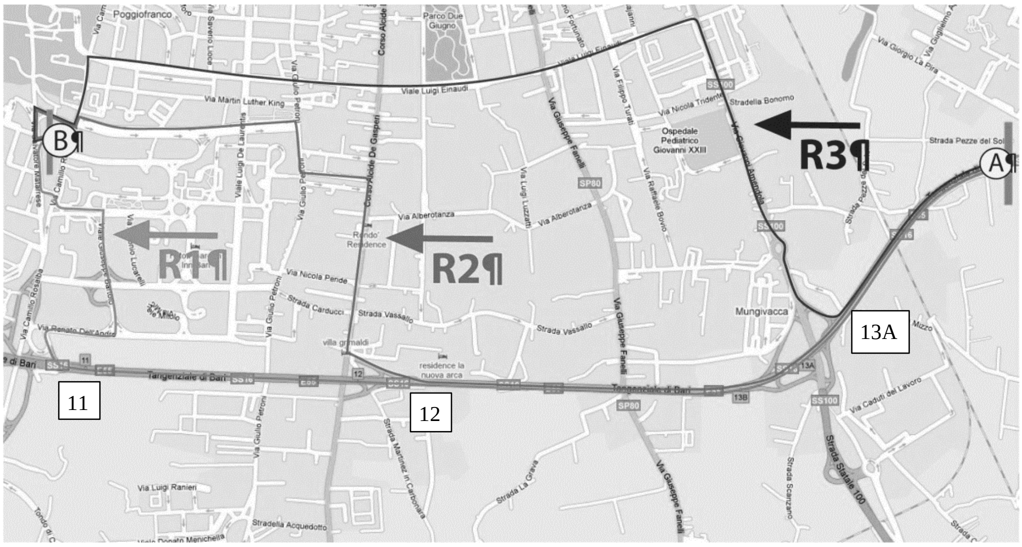

Fig. 13. Map of the considere d network (Bari, Italy).

(a)

(b)

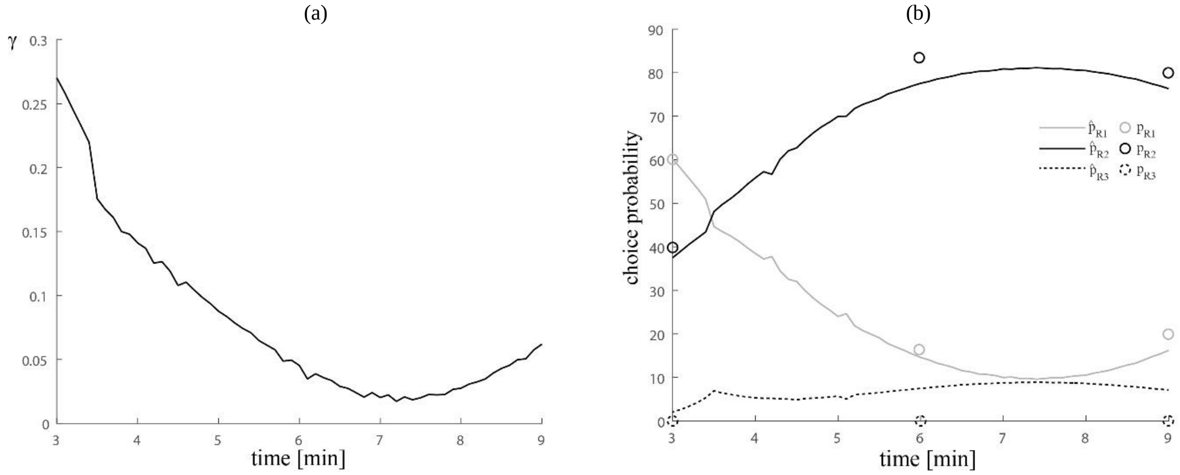

Fig. 14. Message 'queue': (a) resulting values of parameter γ after calibration; (b) resulting choice probabilities obtained by the model $\hat{p}_{Ri}$ compared to observed probabilities p_{Ri} (circles).

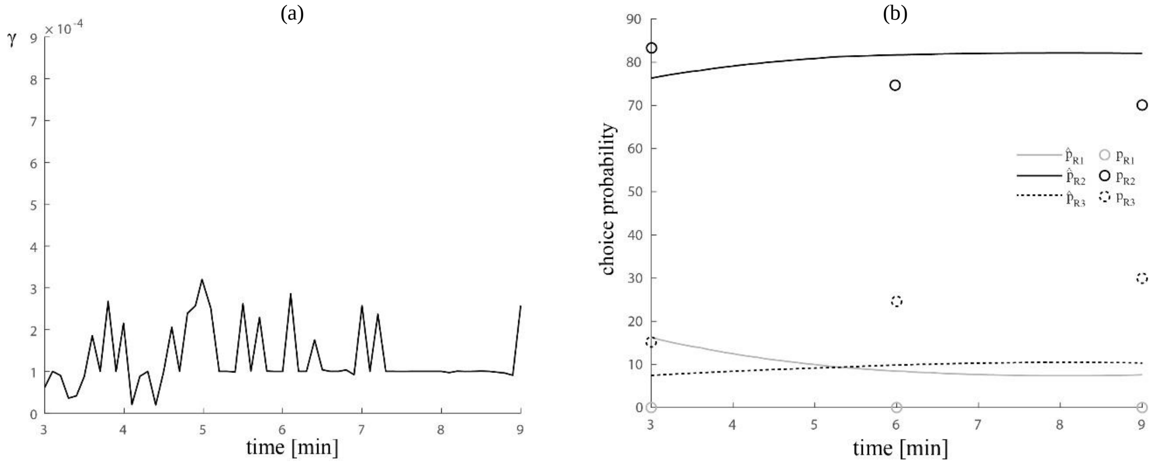

Fig. 15. Message 'accident': (a) resulting values of parameter γ after calibration; (b) resulting choice probabilities obtained by the model $\hat{p}_{Ri}$ compared to observed probabilities p_{Ri}(circles).

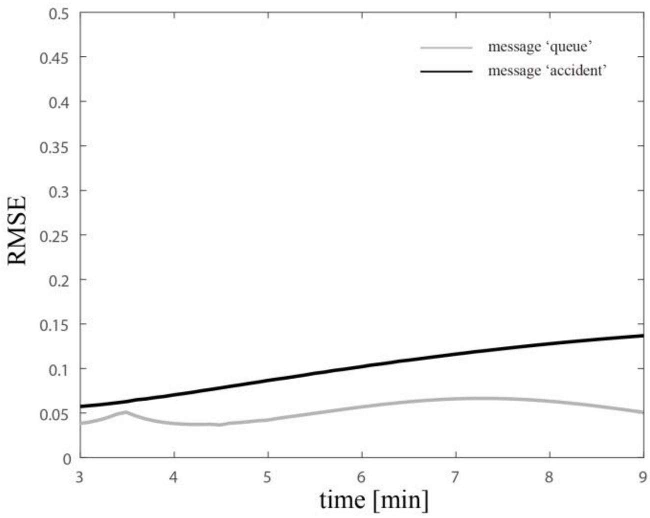

Fig. 16. RMSE obtained by the proposed model for message 'queue' and 'accident' in the observation interval.

Table 1

Location of VMSs and main ramps.

From	To	Distance (m)
Entrance (A)	1st VMS	400
1st VMS	1st Diversion, Exit 13A-Mungivacca	300
1st Diversion, Exit 13A-Mungivacca	2nd VMS	700
2nd VMS	3rd VMS	1100
3rd VMS	2nd Diversion, Exit 12-Carrassi	150
2nd Diversion, Exit 12-Carrassi	Queue/Accident	900
Queue	Exit 11-Poggiofranco	500

Table 2

Perceived travel time related to drivers' experience for each route.

Route	T_{min} (*a*)	T (*b*)	T_{max} (*c*)
R1	7.87	10.32	13.72
R2	11.38	14.45	18.70
R3	15.27	18.58	22.47

Table 3

Perceived travel time related to provided information for each arriving time.

	Message 'queue'			Message 'accident'		
t_0 [min]	**T_{min} (*a*)**	**T (*b*)**	**T_{max} (*c*)**	**T_{min} (*a*)**	**T (*b*)**	**T_{max} (*c*)**
3	11.6	14.4	18.4	13.83	19.67	25.33
6	9.67	13.67	19.5	16.75	21.5	29.25
9	12.4	16.8	27.4	17.0	22.75	32.75

Table 4

Observed route choice for each arriving time.

	Message 'queue ' Choice %			Message 'accident' Choice %		
t_0 [min]	R1	R2	R3	R1	R2	R3
3	60.0	40.0	0.0	0.0	83.0	17.0
6	17.0	83.0	0.0	0.0	75.0	25.0
9	20.0	80.0	0.0	0.0	70.0	30.0