1. Introduction

The increasing development of telematics technologies has given rise in the last decades to many interesting applications to the field of transportation. An example is given by the Advanced Travelers Information Systems (ATIS), i.e. innovative technologies aiming at providing travelers with information on network performances in the attempt to facilitate their travel choices. Most of these technologies are conceived to give guidance on en-route travel choices such as route and parking choices, although more recent applications show that the impacts of such systems can also affect other pre-trip choice dimensions such as departure time, trip destination and so on.

According to the temporal nature, we can distinguish the information in three categories (Ben Akiva et al., 1991):

- **historical** information, based on the state of the network in the past (e.g. during the previous day);
- **real-time** information, based on the current state of the network and
- **predictive** information, based on the forecasting of the (future) network conditions, which the drivers actually will encounter when travelling within the system.

It is clear that the best information to provide should be a reliable predictive information. However providing this kind of information is very difficult, especially in case of congestion. In congested network, future traffic performance (that is, what information should tell) depends on future path flows which in turn depend on information provided, since drivers who receive guidance may change their path as a result of information. Guidance generation therefore can be seen as a fixed-point problem (Bottom, 1998).

The solution of such a problem is crucial to any procedure aiming at generating reliable travel guidance, in order to prevent from those potential adverse impacts of information provision known in literature as overreaction and concentration (Ben Akiva et al., 1991). Concentration occurs when information reduces the variations among drivers and increases the uniformity of perception of network conditions. Overreaction occurs when drivers’ reaction to information shifts congestion from one road to another because too many drivers react in the same way to information.

In facts, to avoid these adverse effects, information should take into account the behavioral response of travelers. Although different modeling framework for the simulation of ATIS, following either equilibrium (Al-Deek and Kanafani, 1993; Yang, 1998) or dynamic approaches (Ben Akiva et al., 1997; Jayakrishnan et al., 1994; Emmerink, 1996; Van Berkum and van der Mede, 1994), have been proposed in the literature, to authors’ knowledge the only
one which allow to simulate predictive information consistent with the behavioral response of drivers, is the DYNAMIT (Ben Akiva et al., 1997). The already mentioned fixed-point problem of consistency between information provided and actual network condition is here solved by means of an algorithm similar to the MSA method for Stochastic User Equilibrium Assignment. At a given instant, according to actual network performance, drivers are provided with information; a pre-trip demand simulator, then, allows predicting users’ path choices. A traffic meso-simulator propagates path flows on the network, allowing the calculation of the resulting network performance (Path performances). Finally, the network performance predicted by the ATIS are compared and updated with the performances deriving from propagation of the path flows estimated by the pre-trip demand simulator, until consistency is achieved. Apart from the problems of existence and uniqueness of the above fixed point, whose study is currently underway, providing predictive consistent information has a further difficulty. In facts, for operational reasons, the algorithm for the generation of the information should converge in a very low computational time. Despite all these “still-unsolved” problems relative to the generation of predictive consistent information, it is worth noting that, under particular conditions, information provision can be effective (i.e. meaning that can better off system performances) even if it is not generated, consistently with the behavioral response of drivers. In this paper after having presented a doubly dynamic assignment model aiming at the simulation of road networks in presence of Drivers Information Systems (DIS), the results of some applications to test network, aiming to investigate the range of effectiveness of predictive not-consistent information, are presented.

2. The overall model framework

The overall framework of the models system consists of:

- the Travel Behaviour Simulator, simulating how drivers day by day update their knowledge of network performances, based on different sources of information (namely past experiences, word of mouth, information provided,…), and accordingly adjust their path and departure-time choices;
- the Traffic Simulator which allows real-time estimation of network performances;
- the simulator of the Drivers Information System, which based on the current network condition generates and provides drivers not yet departed from the origin, with predictive information (en-route guidance here are not dealt with).

The day-to-day dynamic process of choice adjustment and of learning from past experience and from information is simulated by means of exponential smoothing (Cascetta and Cantarella, 1995). Drivers are grouped into classes defined according to the degree of knowledge of the network (habitual and occasional users), to the availability of information (informed and not-informed users) and to the desired departure-time from the origin. The reference period is subdivided into temporal subintervals which are assumed to coincide with the available departure time alternatives. To each subinterval a characteristic time instant \( t \) in which departure are concentrated, is associated. For the generic user class \( i \), at the generic day \( t \), the state of the system is defined by the path flows vector, \( h^{i,t} \), and by the vector of the expected path times, \( TT_{exp}^{i,t} \), in the different sub-intervals.

The system of equations which simulates the day-to-day dynamic process is the following one (Cascetta et al., 2000):
\[ TT^i_{exp} = \lambda^i \cdot TT^i_{info} + (1 - \lambda^i) \cdot \left[ \beta^i \cdot TT^i_{act} - \lambda^i \cdot TT^i_{exp} \right] \quad \forall i \]
\[ P^i_j = P^i_j \left[ V^i_j \left( X^i_j \right) \right] \quad \forall i \]
\[ h^i_j = \alpha^i \cdot P^i_j \cdot d^i + (1 - \alpha^i) \cdot h^i_{-j} \quad \forall i \]

where:

- \( TT^i_{exp} \) is the \((n_{KJ} \times 1)\)-dimension vector of expected path times for drivers of class \( i \) in the different departure time intervals, at day \( t \) (being \( n_{KJ} \) the number of (path, departure time) pairs available);
- \( TT^i_{act} \) is the \((n_{KJ} \times 1)\)-dimension vector of the (average) actual path times in the different departure time intervals at day \( t \);
- \( TT^i_{info} \) is the \((n_{KJ} \times 1)\)-dimension vector of path times provided by the Drivers Information System at day \( t \);
- \( V^i_j \) is the \((n_{KJ} \times n_{OD})\)-dimension matrix of the systematic utility related to path and to departure time interval for drivers of class \( i \) at day \( t \) (being \( n_{OD} \) the number of Origin-Destination pairs);
- \( P^i_j \) is the \((n_{KJ} \times n_{OD})\)-dimension matrix of the probability of choosing each path-departure time alternative available, relative to drivers \( i \) at day \( t \);
- \( h^i_j \) is the \((n_{KJ} \times 1)\)-dimension vector of path flow of drivers of class \( i \) in the different interval at day \( t \);
- \( d^i \) is the \((n_{OD} \times 1)\)-dimension vector of demand flow of drivers of class \( i \);
- \( \alpha^i, \beta^i, \lambda^i \) are the control parameters which govern the day-to-day updating process of the path-departure-time choices and of the expected costs.

The probability of choosing each path departure-time pair is estimated through a Logit model. The systematic utility function consists of the path travel time, the early scheduled delay with respect to desired departure time and the commonality factor (Cascetta et al., 1996) which implicitly allows to introduce a covariance between path sharing same links. The systematic utility, \( V^i_{kj} \), relative to path \( k \) and to departure time \( j \), at day \( t \) for drivers of class \( i \), is given by:

\[ V^i_{kj} = \beta_{TT} TT^i_{kj,exp} + \beta_{CF} CF_k + \beta_{EDP} EDP_k(\tau_j, \tau_o) + \beta_{LDP} LDP_k(\tau_j, \tau_o) \]

where:

- \( \tau_j \) is the characteristic time instant of subinterval \( j \);
- \( \tau_o \) is the desired departure time instant;
- \( TT^i_{kj,exp} \) is the expected travel time on path \( k \) in the interval \( j \);
- \( CF_k \) is the commonality factor (Cascetta et al., 1996) given by:

\[ CF_k = \ln \left( 1 + \sum_{h:h \neq k} \frac{TT^0_{hk}}{TT^0_{hk} \cdot TT^0_{k}} \right) \]

being \( TT^0_{hk} \) the sum of the travel times on the links shared by path \( h \) and \( k \), \( TT^0_{h} \) and \( TT^0_{k} \) the path travel times respectively on path \( h \) e \( k \);
- \( EDP(\tau_j, \tau_o) \) is the penalty related to early departure with respect to \( \tau_o \) departing in \( \tau_j \), usually considered only if the early departure is above a minimum threshold \( \Delta_e \):

\[ EDP(\tau_j, \tau_o) = \tau_o - \Delta_e - \tau_j \quad \text{if } \tau_o - \Delta_e - \tau_j > 0 \]
\[ = 0 \quad \text{otherwise} \]

3
• **LDP** \( (\tau_j, \tau_o) \) is the penalty related to a delay with respect to \( \tau_o \) departing in \( \tau_j \), usually considered only if the delay is above a minimum threshold \( \Delta_l \):

\[
LDP(\tau_j, \tau_o) = \begin{cases} 
\tau_j - \tau_o - \Delta_l & \text{if } \tau_j - \tau_o - \Delta_l > 0 \\
0 & \text{otherwise}
\end{cases}
\]

• \( \beta_{TT}, \beta_{CF}, \beta_e \) and \( \beta_l \) are calibrated parameters.

Provided that, within a given reference period (day \( t \)), network performances largely vary due to over-saturation sub-periods of supply characteristics, a dynamic traffic simulator is embedded in the models system to better estimate actual path travel times. This consists of a within-day dynamic network flow propagation model (Cantarella et al, 1999), based on a representation of the transportation network through links and nodes and on the aggregation of drivers into “packets”. The model ensures the respect of the FIFO rule and is designed to simulate the spill-backs of queues when users on link exceed the storage capacity.

Link performances are calculated through a speed-density Greenshield’s relationship (Cascetta, 2000) duly modified in order to assure that over the critical density the link outflow equals the link **exit capacity**:

\[
v_a[j] = \begin{cases} 
v_{0,a} - \Theta \cdot x_a[j] & \text{se } x_a[j] < x_{a,\text{crit}} \\
\frac{Q_a}{x_a[j]} & \text{se } x_{a,\text{crit}} < x_a[j] < x_{a,\text{max}}
\end{cases}
\]

being:

• \( x_a[j] \) the occupancy of link \( a \) in the subinterval \( j \), i.e. the average number of vehicles which run the link during interval \( j \);

• \( v_{0,a} \) the free-flow speed of link \( a \);

• \( Q_a \) the **exit capacity** of the link \( a \) during interval \( j \), i.e. the maximum number of vehicle per time unit which can exit from the link;

• \( x_{a,\text{crit}} \) e \( x_{a,\text{max}} \) respectively the critical and the maximum density of link \( a \) during interval \( j \);

• \( \Theta \) a parameter calibrated in order to guarantee the continuity of the function.

The network model allows the simulation of temporary reduction of the entering capacity of a set of link of the network due to not-recurrent events (i.e. accident) occurring during one or more temporal sub-interval \( j \).

The third component of the modeling framework is the simulator of the Drivers Information System which generates and provides information. The kind of information simulated in the proposed framework is **pre-trip descriptive**: **pre-trip** since information are available only before starting the trip; **descriptive** because information are provided through network performance indicators (i.e. path travel time) and not through explicit guidance on what to do. Under free-flow condition, the DIS simulator provides informed drivers respectively with the path free-flow travel times; under condition of recurrent congestion, it provides the averages of the path travel times in all the previous days for any give subinterval \( j \). In case of not-recurrent congestion, for instance in case of accident at the generic subinterval \( j-1 \), the model starts a “parallel” simulation of the system, starting from network condition at \( j \), supposing that no users knows about the accident. Path travel time computed in this hypothetical situation (i.e. with no information available), will be then transmitted to the informed users in the “real-world” simulation (previously stopped at time \( j \)).
3. Applications

As said in the previous section, since in the proposed modeling framework, consistency between information provided and actual network performance is not guaranteed, the predictive information provided by the DIS to the drivers may differ from what they actually experience. Nevertheless the information provision could better off system performances. This point is strictly connected to the level of congestion on the network and to the number of informed users (market penetration), as shown through the following application to a test network.

At a given day $t$, we make an accident occur on a link, which causes delay on some paths of the test network considered. As results, informed drivers switch onto alternative paths. The analysis has been carried on for different levels of demand flows in terms of total travel time on the network and in terms of average travel time for two classes of drivers: informed (info) and not-informed (no-info) drivers.

![Graph showing travel time percentage reductions due to information provision](image)

**Fig. 1** – Travel time percentage reductions due to information provision (lowly congested network).

It can be observed (Fig. 1) that, in case of low demand flows, information provision induces reductions of total travel times at any level of market penetration, while, in case of highly congested network, there are ranges in which system performances better off and ranges in which it worst off. In the case studied, it can be observed (Fig. 2) a reduction of total travel time until a certain thresholds of market penetration (i.e. 10%). After this threshold the reduction of total travel time decreases until a null value around 90% of market penetration, after which an increasing of total travel time on the network occurs (i.e. network performances worst off due to information provision).

Analogously, it can be observed that in case of low demand flows the reduction of travel time for informed drivers is always higher than the reduction for not-informed drivers. Conversely in case of highly congested networks, the benefits of informed drivers is higher than the benefits for not-informed ones until the threshold of 65% of market penetration after which it becomes smaller. This is due to an overreaction of drivers which generates a delay on the alternative paths (i.e. those not including the link with the accident) bigger than the delay due to the accident itself.
Fig. 2 – Travel time percentage reductions due to information provision (highly congested network).

4. References


Yang H. (1998), Multiple equilibrium behaviors and advanced traveler information system with endogenous market penetration. Vol. 32B, Transportation Research.