EWGT2013 – 16th Meeting of the EURO Working Group on Transportation

High Speed Rail (HSR) induced demand models

Ennio Cascetta[a], Pierluigi Coppola[b],*

[a] Dept. of Transportation Engeneering - University of Naples "Federico II", Via Claudio 21- 80125 Napoli (Italy)
[b] Dept. of of Enterprise Engineering University of Rome "Tor Vergata", Via del Politecnico 1, Roma 00133, Italy

Abstract

Recent High Speed Rail (HSR) investments in Italy, together with the entrance in the HSR market of a new private operator competing with the national incumbent, create the conditions for a unique case study, to investigate the behaviour of long-distance passengers. In this paper a modelling framework developed to forecast the national passenger demand for different macroeconomic, transport supply, and HSR marketing scenarios is presented, focusing on the sub-models forecasting induced demand.

1. Introduction

HSR demand forecasting requires the evaluation of three components (Table 1): the diverted demand, which derives from the travelers' mode choice diversion toward HSR either from other modes (e.g. Auto, Air) or other rail services (e.g. Intercity); the economy-based demand growth, which is linked to the trends of the National and International economic systems, under the assumption that the more the people are wealthy the more they travel; and the induced demand which depends either "directly" on the generalized travel cost, i.e. changes in travel choices such as trip frequency , destination or activity pattern, e.g. the trip becomes more frequent because traveling with HSR is faster, cheaper and/or more comfortable, or "indirectly" due to modifications of the travelers' mobility or lifestyle choices, e.g. travelers start commuting (i.e. making more frequent trips) due to the relocation of the residence or of the workplace, and partly due to changes in land use, e.g. new residents, jobs and activities interconnected thanks to HSR.

* Corresponding author. Tel.: +39-06-72597059; fax: +39-06-72597053
E-mail address: coppola@ing.uniroma2.it

Table 1. taxonomy of the HSR generated demand.

DIVERTED DEMAND	from other modes	*e.g. shift from air/auto to HSR*	*endogenous factors*
	from other rail services	*e.g. shift from Intercity to HSR*	
INDUCED DEMAND	direct	*e.g. changes of trip frequency, destination or related activity pattern*	
	indirect	*e.g. increase of mobility due to change in life-styles and land use*	
(ECONOMY-BASED) DEMAND GROWTH		*e.g. increase of the overall mobility due to economic growth*	*exogenous factors*

To forecast the impacts of the new HSR services, a general modelling architecture has been developed (Ben-Akiva et al., 2010) consisting of the following integrated models:

• the "National demand growth" model, which projects the base year total OD volumes to future years, according to assumed macroeconomics trends;

• the "mode/service/run choice" model, which estimates the market share of different inter-urban transportation modes, including alternative rail services, such as Intercity, High-Speed, 1st and 2nd class and different HSR operators (i.e. competition within HSR mode) characterized by different fares, different timetables, different on-board services and other "brand-related" characteristics;

• the "induced demand" model which estimates the additional HSR demand due to the improvement of HSR level of services (i.e. new services, travel time reductions, etc.);

• the stochastic assignment model which loads the multimodal and multiservice (diachronic) network to estimate the flows on the individual trains and flights.

Such models system has been calibrated over the Italian national case study, which represents an interesting field of application. In fact, the HSR in Italy is still under development meaning that the travel times station-to-station, which have already been reduced by about 30-40%, are expected to be further reduced with the completion of the new underground bypass-stations in Bologna and Firenze that will allow the speeding up of the service in such dense urban areas. Moreover, starting from 2012 the new HSR operator "Nuovo Trasporto Viaggiatori" (NTV) entered the HSR market competing with the incumbent Trenitalia, giving rise to the first case in the World of competition among HSR operators on the same line, i.e. multiple operators on a single infrastructure (for further details see Cascetta and Coppola, 2013). In this respect the Italian HSR system represents an ideal test site to estimate and validate long-distance passengers demand model.

In this paper we will focus on the sub-models developed to estimate the specific component of the induced demand related to how trip-frequency varies with level of HSR service, i.e. HSR travel time, cost and service frequency. The paper is organized as follows. In Section 2 the state of the art of national demand models developed for forecasting HSR demand is presented and a models classification is proposed. Section 3 the trip-frequency models estimates, based on panel data gathered in 2012 on the Italian multimodal transportation system, are presented. Section 4 sums up conclusions and identifies further research areas.

2.   HSR generated demand forecasting: models review

Recent openings of HSR lines worldwide are showing outstanding increases of passenger demand (see for instance, the Italian case study presented in Cascetta et al., 2013). This is not only due to increased HSR modal share, but significantly due to also the additional demand induced by HSR. In fact, induced demand depends either "directly" on the generalized travel cost, i.e. changes in travel choices such as trip frequency, destination or activity pattern, e.g. the trip becomes more frequent because traveling with HSR is faster, cheaper and/or more comfortable, or "indirectly" due to modifications of the travelers' mobility or lifestyle choices, e.g. travelers start commuting (i.e. making more frequent trips) due to the relocation of the residence or of the workplace, and partly due to changes in land use, e.g. new residents, jobs and activities interconnected thanks to HSR.

HSR demand forecasting models can be distinguished in aggregate and disaggregate. Aggregate models forecast railways demand based on aggregate demand elasticity values to GDP variations, car and railway travel times, fuel costs, car ownership, population and so on. Such models make use of large data sets obtained from recorded ticket sales and from travel surveys, as well as from national statistics. They have successfully predicted the rail demand growth (see for instance Wardman, 2006), but their capabilities are limited when there are big technological and economic changes. Moreover, aggregate demand forecasting models by definition cannot simulate flows on individual rail segment or trains, i.e. estimates needed to design and assess both infrastructures and services.

Disaggregate models can be mono-modal and multi-modal (Table 2). Mono-modal models, typically conceived to simulate demand in urban context, focus on a specific mode and forecast the impact of a new technology or an operational improvement on the demand and the overall performances on that modes; an example for HSR can be found in Hsu and Chung (1997) or in Couto and Graham (2008). On the other hand, disaggregate (mainly behavioral) modeling structures simulate explicitly the competition between Rail and other modes (multi-modal models) and/or between rail services, e.g. Intercity and HSR (multi-service models). Such models have been applied to forecast HSR demand in Germany (Mandel et al., 1997), Sweden (Froidh, 2005; 2008), Spain (Roman et al., 2007; Martin and Nombela, 2007), Japan (Yao e Morikawa, 2005), Korea (Park et al., 2006) and Italy (Cascetta and Coppola, 2012). Most of these models focus on the competition between Air and HSR (long distance passenger models) some of them deal also with auto competition and very few include the competition between rail services and operators (see for instance Ben-Akiva et al., 2010).

Table 2. classification and review of HSR disaggregate demand models.

		FREQUENCY BASED	SCHEDULED-BASED
MULTI-MODAL	**Multi (Rail) service**	Ben-akiva et al (2010)	Cascetta and Coppola (2012)
	Single (Rail) service	Roman et al. (2007) Yao and Morikawa (2005) Froidh (2008)	
MONO-MODAL	**Multi (Rail) service**	Couto and Graham (2008) Hsu and Chung (1997)	
	Single (Rail) service	Urban case studies	Urban case studies

Concerning the modeling approach to the simulation, it is well known that the common practice in modeling scheduled transport systems, both at the urban and intercity levels, involves the representation of services as lines, with the time dimension taken into account through the average line frequency, through which the average on-board loads and performances can be calculated (*frequency-based approach*). This approach is not

satisfactory in many applications, typical of low-frequency systems and/or operational planning (e.g. timetable design), in which we have to take into account time-dependent characteristics of the service and of the demand and we need to analyze the loads on each vehicle. In such cases, scheduled services can be better represented by individual vehicle trips which define individual connections within a given timetable. The modeling framework, in which all its components (demand, supply, path choice and assignment) account explicitly for the timetable, is defined as the schedule-based approach (Wilson and Nuzzolo, 2004).

All the models presented in the literature to forecast HSR demand, follow a frequency-based approach. Cascetta and Coppola (2012) developed a mode/service/run choice model for HSR demand forecasting, following a schedule-based approach. The core of this model is based on the simulation of the competition between transportation modes (i.e. air, auto, rail), railways services (intercity vs. High Speed Rail) and HSR operators using an explicit representation of the timetables of all competing modes\services (schedule-based assignment). This requires, in turn, a diachronic network representation of the transport supply for scheduled services and a Nested Logit model of mode, service, operator, and run choice. To authors' knowledge this represents the first case of elastic demand, schedule-based assignment model at national scale to forecast HSR demand.

Among the above modeling framework, the models developed to estimate the demand changes induced directly by modification of HSR level of services (i.e. travel time and cost, service frequency, etc.) refer to the individual user or users classes, and are typically called "*trip-frequency*" models.

Trip-frequency models estimate the average number of trips, $m^i[osh]$, made by the generic individual "i", from the generic zone of residence "o" in the time interval "h", for the trip purpose "s". The total number of trips in period h by zone o can therefore be expressed as follows.

$$d_o\,[h] = \sum_i \sum_s n^i[o]\,m^i[osh]$$

where $n^i[o]$ is the number of users in zone "o" belonging to class "i".

These models are called *behavioral* (or more properly, *random utility models*) if they derive from explicit assumptions about users' choice behavior, and *descriptive* if they capture the relationships between travel demand and activity and transportation supply-system variables without making specific assumptions about decision-makers' behavior.

2.1. Descriptive Models

"*Classification tables*" are the simplest descriptive generated demand models (see for instance Cascetta, 2009). For each user class i, assumed to be homogeneous with respect to a given trip purpose, the average number of trips $m^i[osh]$ for purpose s in period h is directly estimated, most commonly from travel survey data. The main limitation of such approach is that demand levels are not expressed as functions of socioeconomic variables other than those used to define the users classes. In addition, limitations in data availability and the difficulty of forecasting the future number of users generally keep the number of classes relatively small, even when a more detailed breakdown could be appropriate.

"*Trip rate regression models*" are more sophisticated. These models express the trip rate $m^i[osh]$ for a user of class i and for purpose s, as a function, typically linear, of variables corresponding to user class and origin zone:

$$m^i[osh] = \sum_j \beta_j\,X_{jo}{}^i \tag{1}$$

The attributes $X_{jo}{}^i$ are usually the mean values of socioeconomic variables such as income, number of cars owned, and so on, but they may also include level-of-service attributes such as zonal accessibility. The name trip

rate regression is derived from the statistical model, linear regression, which is used to specify the variables Xj and to estimate the coefficients βj.

2.2. *Behavioral Models*

The behavioral models, normally associated with an individual approach, are built on the assumption that the user of the transport system is a rational decision-maker, who tends to maximize his/her perceived utility, derived from activities related to transportation: the demand for transport is thus directly derived from assumptions about the socio-economic characteristics of users, the attributes of the existing transport and economic systems, and of the physical environment. These models are often referred to as *Random Utility Models (RUM).*

In a random utility framework, the trip rate m^i[osh] can be expressed as:

$$m^i \, [osh] = \sum_x x \, p^i \, [x/osh] \tag{2}$$

or

$$m^i \, [osh] = \sum_x \sum_d x \, p^i \, [x/odsh] \tag{3}$$

where p^i[x/osh] and p^i[x/odsh] represent respectively the probability that a user undertakes "x" trips for purpose s in period h, starting from zone o ("*origin-based models*") and the probability that a user undertakes "x" trips for purpose s in period h , on the specific Origin-Destination (OD) pair "od" ("*OD-based models*").

Such probabilities depend on variables related either to households or individuals. Household-level variables include, for example, total income and household size, whereas individual-level variables include occupational status, gender, family role, age, and so on. Other variables include the level of service which in origin-based models is related, in an aggregate manner, to the origin zone by mean for example of accessibility measures (see for instance Coppola and Nuzzolo, 2011), while in the OD-based models can be expressed by attributes related to the specific modes of transport available on the given OD pair.

3. **The proposed modeling specifications**

The proposed trip-frequency models belong to the class of behavioral (random utility) OD –based models. We here focus on ex-province trips. The probability p^i[x/odsh] in equation (3) is estimated through a Logit model with three alternatives. i.e. no (ex-province) trips, one (ex-province) trip per week, and more than one trip per week:

$$p^i(x|odsh) = \frac{e^{V^i(x|odsh)}}{\sum_{x\prime=0,1,2+} e^{V^i(x\prime|odsh)}} \tag{4}$$

The reference period is indeed assumed to be equal to the winter week. In the context of ex-province trips, this is long enough to let the aggregation of the alternatives of making more than one trip in one single alternative be acceptable. Therefore, the choice set consists of the above three frequency classes: $x = 0,1,2+$.

The average number of trips undertaken by each individual is obtained as a weighted average of the number of trips, x, corresponding to each frequency class respectively equal to 0, 1, and 2,2 (i.e. the average number of trips for those travelling out of the province of residence more than 1 times per week, estimated by the sample), with weights given by the probability of choosing each frequency class (see Equation 3).

The systematic utility functions, $V^i(x|odsh)$ in equation (4), have the following expressions (in which the functional dependence of the attribute on user "i",on the OD pair "od", on the travel purpose "s" and on the reference period "h" are omitted, for sake of simplicity):

$$\mathbf{V}(x = 0) = ASC_0$$

$$\mathbf{V}(x = 1) = \beta_{ADD1} * Add_{res}(o) + \beta_{maschio1} * maschio + \beta_{laurea1} * laurea + \beta_{occ_{alto1}} * Occ_{alto} + \beta_{logsum2} \\ * Logsum(o, d) + \beta_{sogliaT_{min120_1}} * sogliaT120(o, d) + ASC_1$$

$$\mathbf{V}(x = 2+) = \beta_{ADD2} * Add_{res}(o) + \beta_{maschio2} * maschio + \beta_{laurea2} * laurea + \beta_{occ_{alto2}} * Occ_{alto} + \beta_{Logsum2} \\ * Logsum(o, d) + \beta_{sogliaT_{min120_2}} * sogliaT120(o, d)$$

where
- $Add_{res}(o)$ is the total employment in the residence province "o" of user i;
- maschio is a dummy variable equal to 1 if user i is male, 0 otherwise;
- laurea is a dummy variable equal to 1 if user i possesses a degree, 0 otherwise;
- Occ_{alto}, is a dummy variable equal to 1 if user i is employed in high professional condition;
- Logsum(o,d) is the inclusive variable of the level of service attributes on the given OD pair (o,d), estimated using the frequency-based mode choice model (Ben-Akiva et al., 2010);
- sogliaT120(o,d) is a dummy variable equal to 1 if the OD minimum (across all the available modes) travel time on the given OD pair (o,d) is below the threshold of 120 minutes, 0 otherwise;
- ASC0 and ASC1 are the Alternative Specific Constant of the alternative x=0 and x=1.

The attributes in the systematic utility functions are the socioeconomic characteristics of the traveler (gender, professional status, degree possession) and the inclusive variable associated with level or service on the OD pair (o,d) (i.e. mode-choice logsum variable). As it can be seen all the attributes are specific attributes of the alternatives.

Several model specifications have been estimated, through the Maximum Likelihood method, for two different travel purposes: Business and non-Business. These models estimates are based on the Mo.Vi. (Pragma, 2012), i.e. a survey of national mobility gathered between July and November 2012 consisting of 26.000 (CATI) interviews, on the characteristics of trips longer than 50 km made by respondents in the previous week.

The model estimates returned values of β correct in the sign (Table 3). For instance, the negative value of the parameter of the "self-attractivity" variable (i.e. total employment in the province, "Add_{res}") in the systematic utility of alternative 1 and 2+ , reflects the relatively small need to carry out activities outside the province for individuals who, other things equal, live in areas with more opportunities satisfying their needs. As well, the positive values of the parameters of gender, degree possession and professional condition reflect the users classes with more propensity to undertake ex-province trips are male, graduated and employed in high professional condition. The latter attribute, however, is not significant for non-Business purposes.

The Logsum variable, depending on the level of service of modes available on the OD pair, appears to be very significant with a positive parameter (as expected). This is significantly greater than others parameter provided that the level of service on the OD pair is the main determinant in trip-frequency decision making (see models b) in Table 3).

In model specification c) (Table 3), the dummy variable "SogliaT_min" has been introduced. The positive and significant value of the parameter of such attribute proves that under certain threshold of OD travel time there is a strong increase of mobility (i.e. trip-frequency) due to agglomeration effects between the zones (O and D) which strongly do increase economic and social trades and, thus, also the mobility. Several travel time thresholds have

been tested between 60 and 180 minutes. The threshold of minimum time that returned the most significant values was 120 minutes.

Table 3. Estimated model parameters for business and non-business purposes.

Parameters	Unit	Business			Non-Business		
		a)	b)	c)	a)	b)	c)
b_add1	100.000	-0,160*	-0,134	-0,148	-0,203	-0,141	-0,140
		(1,77)	(-1,98)	(-1,95)	(-2,87)	(-2,02)	(-2,01)
b_add2+	100.000	-1,34	-2,30	-1,96	-0,919	-1,49	-1,44
		(-4,15)	(-5,75)	(-5,60)	(-3,00)	(-4,61)	(-4,52)
b_laurea1	1/0	0,49	0,498	0,580	0,480	0,509	0,508
		(4,08)	(4,14)	(4,22)	(5,69)	(6,01)	(6,00)
b_laurea2+	1/0	1,04	1,02	1,04	1,04	1,06	1,06
		(5,17)	(5,06)	(5,17)	(4,61)	(4,68)	(4,68)
b_cond_prof1	1/0	0,307*	0,338*	0,348*	-0,201**	-0,134**	-0,136**
		(1,74)	(1,82)	(1,84)	(-0,53)	(-0,35)	(-0,36)
b_cond_prof2+	1/0	0,985	1,10	1,10	0,950*	1,10*	1,09*
		(1,93)	(2,13)	(2,15)	(1,60)	(1,86)	(1,84)
b_maschio1	1/0	0,497	0,503	0,501	0,283	0,290	0,289
		(4,83)	(4,88)	(4,86)	(3,87)	(3,95)	(3,94)
b_maschio2+	1/0	1,30	1,31	1,30	1,13	1,14	1,14
		(6,47)	(6,50)	(6,47)	(5,11)	(5,13)	(5,12)
b_logsum_Bus1	min		5,04	1,64		4,76	4,37
			(21,82)	(4,11)		(37,29)	(17,69)
b_logsum_Bus2+	min		7,29	2,90		6,33	4,64
			(19,29)	(4,87)		(15,36)	(6,04)
b_soglia_Tmin120_1	1/0			1,89			0,261
				(13,11)			(1,87)
b_soglia_Tmin120_2+	1/0			2,97			1,12
				(10,60)			(2,59)
b_asc0	1/0	8,95	9,31	10,2	11,5	11	10,9
		(-46,31)	(-45,69)	(-39,52)	(30,36)	(-38,01)	(-36,89)
b_asc1	1/0	1,34	1,48	2,12	3,30	3,02	2,94
		(-6,29)	(-6,66)	(-7,66)	(8,49)	(-10,08)	(-9,64)
Init log-likelihood		-611726,0	-611726,0	-611726,0	-612251,1	-612251,1	-612251,1
Final log-likelihood		-4163,4	-3918,2	-3789,5	-6766,1	-6047,4	-6042,3
Number of observations		556817	556817	556817	557295	557295	557295

** statistically significant at level of 90%; ** parameter not statistically significant*

Furthermore, comparing models b) versus c), a significant reduction in magnitude of the parameter of the Logsum variable can be observed. This indicates that trip-frequency is highly non-linear in the OD level of service (e.g. OD travel time). To verify such conjecture, a piecewise linear function of the minimum travel time on the OD pair (minimum among the available transport modes) has been introduced instead of the Logsum (models d) in Table 4). This variable on the one hand, allows to overcome the problems of discontinuity of the utility function using the threshold variable "soglia_Tmin120"; on the other hand, confirm the non-linearity of

trip-frequency with respect to OD travel time. Indeed, the estimated parameters, negative as expected, yield a dis-utility function increasing slope varying with travel times, greater beyond the threshold value of 120 minutes (Table 4).

Table 4. estimated model parameters with piecewise linear function of minimum OD travel time.

Parameters	Unit	Business d)	Non-Business d)
b_add1	100.000	-0,184	-0,134
		(-1,90)	(-1,96)
b_add2+	100.000	-1,87	-1,31
		(-5,18)	(-3,96)
b_laurea1	1/0	0,528	0,520
		(4,39)	(6,16)
b_laurea2+	1/0	1,07	1,08
		(5,31)	(4,76)
b_cond_prof1	1/0	0,337	-0,165
		(0,82)	(-0,43)
b_cond_prof2+	1/0	1,07	1,03
		(2,08)	(1,74)
b_maschio1	1/0	0,504	0,291
		(4,89)	(3,98)
b_maschio2+	1/0	1,30	1,14
		(6,48)	(5,13)
b_time 1 (Tmin < 120)	min	-0,00248	-0,00192
		(-1,98)	(-2,09)
b_time 2+ (Tmin < 120)	min	-0,00974	-0,00324*
		(-2,44)	(-1,67)
b_time 1 (Tmin > 120)	min	-0,0173	-0,0185
		(-16,29)	(-23,77)
b_time 2+ (Tmin > 120)	min	-0,0345	-0,0319
		(-8,38)	(-8,01)
b_asc0	1/0	5,90	6,89
		(16,86)	(13,18)
b_asc1	1/0	0,108**	1,84
		(0,81)	(3,33)
Init log-likelihood		-611725,9	-612251,1
Final log-likelihood		-3722	-6824,7
Number of observations		556817	557295

* statistically significant at level of 90%; ** parameter not statistically significant
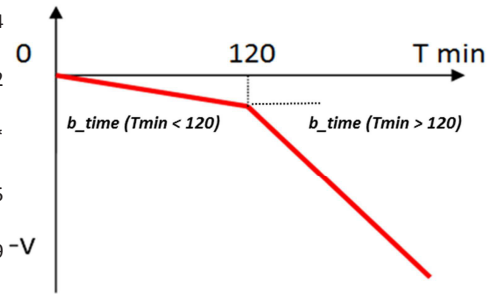
3.1. Model elasticity values

Model demand direct elasticities with respect to HSR level of service attributes are reported in Table 5, by trip purpose and for several OD pairs at different distance. It can be observed that elasticities for Business travel purpose are generally lower than those for Non-Business trips, reflecting the fact that the trip-frequency choices of people travelling for business are less flexible and more constrained than those moving for other purpose (e.g. leisure, personal care, etc.). Furthermore, it can be observed the shorter the OD distance the greater of elasticity, particularly for HSR service frequency and travel times. This confirms the high degree of non-linearity of trip-

frequency with level of service attributes, due to the fact that under certain thresholds, agglomeration effects trigger and increase the overall levels of mobility.

Table 5. Estimated model elasticities w.r.t. HSR level of service.

Demand Direct Elasticity w.r.t.		HSR travel time				HSR travel cost				HSR service freqeuncy			
		Business		*Non Business*		*Business*		*Non Business*		*Business*		*Non Business*	
OD pair	distance (Km)	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX
FIRENZE – BOLOGNA	79	0,028	0,032	0,030	0,032	0,006	0,007	0,002	0,002	0,023	0,026	0,074	0,079
ROMA – NAPOLI	209	0,036	0,037	0,043	0,044	0,003	0,004	0,015	0,015	0,005	0,005	0,036	0,037
ROMA – FIRENZE	254	0,030	0,032	0,038	0,039	0,009	0,010	0,030	0,030	0,010	0,011	0,038	0,039
ROMA – BOLOGNA	333	0,018	0,019	0,041	0,041	0,008	0,009	0,042	0,043	0,003	0,004	0,022	0,022
ROMA – MILANO	515	0,005	0,005	0,021	0,021	0,003	0,003	0,027	0,027	0,001	0,001	0,010	0,010
NAPOLI – MILANO	720	0,004	0,004	0,015	0,016	0,002	0,002	0,052	0,052	0,001	0,001	0,009	0,009

4.   Conclusions and further research areas

In this paper some models specifications aiming at forecasting the increase of transport demand level, induced by HSR, have been presented. Induced demand may depend either "directly" on the generalized travel cost, i.e. changes in travel choices such as trip frequency, destination or activity pattern, or "indirectly" due to modifications of the travelers' lifestyle choices, and relocation of the residence and/or workplace. Here we focused on trip-frequency induced "direct" effects.

The proposed trip-frequency models belong to the class of behavioral (random utility) OD –based models, which estimate the probability that a user undertakes a given number of ex-province trips for a given purpose in a reference period, on the specific Origin-Destination (OD) pair. The reference period is here assumed to be equal to the winter week. The choice set consists of the three frequency classes: zero, one, and more than one ex-province trip per week.

Several model specifications have been estimated, through the Maximum Likelihood method, for two different travel purposes: Business and non-Business. The model estimates returned values of β's correct in the sign and statistically significant for all the socioeconomic individual attributes (i.e. gender, professional status, degree possession) and for the inclusive variable associated to the level or service on the generic OD pair (i.e. mode-choice logsum variable). In fact, level of service resulted to be the main determinant in trip-frequency decision making. Furthermore, trip-frequency resulted to be highly non-linear in the OD travel time: under a certain threshold of OD travel time there is a strong increase of mobility (i.e. trip-frequency) due to agglomeration effects between the zones (i.e. O and D) which trigger economic and social trades, and, thus, increase mobility. Several travel time thresholds have been tested between 60 and 180 minutes. The threshold of minimum time that returned the most significant values was 120 minutes.

Direct elasticity of demand with respect to changes in HSR travel time, cost and service frequency were computed. Elasticities for Business travel purpose are generally lower than those for Non-Business trips, reflecting the fact that the trip-frequency choices of people travelling for business are less flexible than those who move for other purpose (e.g. leisure, personal care, ...). Furthermore, the shorter the distance the greater of elasticity, particularly for HSR service frequency and travel times.

The estimated trip-frequency models are part of a comprehensive modeling architecture allowing to predicting the impacts on national passenger volumes due to different hypothetical short-term and long-term scenarios. In the long term induced demand forecasting requires the evaluation of the indirect effects on mobility due to modifications of the travelers' lifestyles and/or changes in land use, e.g. new residents, jobs and activities interconnected thanks to HSR. This will be the subject of future research.

Acknowledgements

References

Ben-Akiva M., Cascetta E., Coppola P., Papola A., & Velardi V. (2010). "High Speed Rail demand forecasting in a competitive market: the Italian case study" Proceedings of the World Conference of Transportation Research (WCTR), Lisbon, Portugal.

Cascetta E., & Coppola P. (2013). "Competition on fast track: an analysis of the first competitive market for HSR services" Proceedings of the Euro Working Group on Transportation (EWGT), Porto, Portugal (forthcoming).

Cascetta E., Coppola P., & Velardi V. (2013). "High Speed Rail demand: before and after evidences from the Italian market" disP – The Planning review. ETH, Zurich. (forthcoming)

Cascetta E., & Coppola P. (2012). "An elastic demand schedule-based multimodal assignment model for the simulation of high speed rail (HSR) systems" Euro Journal on Transportation and Logistics, vol. 1, p. 3-27, ISSN: 2192-4376, doi:10.1007/s13676-012-0002-0.

Cascetta E. (2009). Transportation Systems Analysis: Models and Applications Second Edition. Springer.

Coppola P., & Nuzzolo, A. (2011). Changing accessibility, dwelling price and the spatial distribution of socio-economic activities. Research in *Transportation Economics*, 31 (2011), 63-71. DOI: 10.1016/j.retrec.2010.11.009

Couto A., & Graham D.J. (2008). "The impact of high-speed technology on railway demand" Transportation 35 pp. 111–128.

Froidh O. (2008). "Perspectives for a future high-speed train in the Swedish domestic travel market" Journal of Transport Geography 16 (4), pp. 268-277.

Froidh O. (2005). "Market effects of regional high-speed trains on the Svealand line" Journal of Transport Geography 13, pp. 352–361.

Hsu C., & Chung W. (1997). "A model for market share distribution between high-speed and conventional rail services in a transportation corridor" The Annals of Regional Science 31, pp. 121-153.

Mandel B., Gaudry M., & Rothengatter W. (1997). "A disaggregate Box-Cox Logit mode choice model of intercity passenger travel in Germany and its implications for High-Speed Rail demand forecasts" The Annals of Regional Science 31, pp. 99-120.

Martin J.C., & Nombela G. (2007). "Microeconomic impacts of investments in high speed trains in Spain" The Annals of Regional Science 41, pp. 715–733.

Park Y., & Ha H-K. (2006). "Analysis of the impact of high-speed railroad service on air transport demand" Transportation Research E 42 (2), pp. 95-104.

Pragma (2012). Mo.Vi. - Monitor Viaggiatori. Roma, Italy

Roman C., Espino R., & Martin C. (2007). "Competition of high-speed train with air transport: The case of Madrid–Barcelona" Journal of Air Transport Management 13, pp. 277–284.

Yao E., & Morikawa T. (2005). "A study of an integrated intercity travel demand model" Transportation Research A, Volume 39 (4) pp. 367-381.

Wardman M. (2006). "Demand for Rail Travel and the Effects of External Factors" Transportation Research E 42 (3), pp. 129-148.

Wilson, N.H.M., & Nuzzolo, A. (2004). Schedule-Based Dynamic Transit Modeling: theory and applications Kluwer Academic Publisher.