25th International Conference on Harbor, Maritime and Multimodal Logistic Modeling & Simulation
20th International Multidisciplinary Modeling & Simulation Multiconference

2724-0339 © 2023 The Authors.
doi: 10.46354/i3m.2023.hms.003

Transport demand estimation for traffic simulations. Heuristic approach linked to vehicle counts

Domenico Gattuso[1], Domenica Savia Pellicanò[1,*] and Gaetana Rubino[1]

[1]Mediterranea University, via R.Zehender, Reggio Calabria, 89124, Italy

[*]Corresponding author. Email address: domenica.pellicano@unirc.it

Abstract

A transport system can be defined as the set of those components and their interactions that determine trips among different points of a territory. Its two main interacting components are: the supply system and the demand system. The first one consists of the physical (road infrastructure) and organizational (traffic structure) components that allow for trip; the second one is given by the set of users who, driven by the need to carry out activities in different places, use different modes of transport. Mathematical models for transport systems simulate demand flows, supply performance, their interactions and main effects, constituting a fundamental tool for evaluation and/or planning activities.

In the literature of sector there are many models proposed for the study of transport supply and demand. Estimating the demand for mobility (expressed in terms of Origin/Destination matrix) is generally complex since it is influenced by several factors. Different methodologies, such as direct investigations in the field, or assuming more or less sophisticated models can be applied. The paper proposes an alternative approach for transport demand estimation aimed at traffic simulations; the approach is of a mixed type and integrates the modeling approach with the results of direct surveys, passing through the determination of Origin/Destination sub-matrices in terms of movement of people and vehicles. The paper proposes the methodological path taken and an application relating to an urban context.

Keywords: Transport System; Demand model; Traffic simulations; Vehicle counts; Origin/Destination matrix; Heuristic approach

1. Introduction

A transport system can be defined as the set of those components and their interactions that determine trips among different points of a territory. It consists of two strongly interacting main components: the transport supply and the mobility demand. The supply is made up of the physical (infrastructures) and organizational (services, fares, traffic rules, etc.) elements that allow for trip; the demand is given by the set of users who, driven by the need to carry out activities in different places, use different modes of transport. The characteristics and relevant aspects of a transport system can be reproduced in a synthetic and simplified way through the construction of a simulation model (Bruzzone et al., 2022; Gattuso and Pellicanò, 2022; Montanari et al., 2022). In general, it is based on a model capable of representing the main characteristics of the supply system, a demand model reproducing the users behavior and a demand/supply interaction model (or assignment model) to simulate traffic flows on the network.

Transport planning decisions affect land use. Given a territory, it is possible to distinguish a transport system and a system of activities (socio-economic) that interact with each other (Figure 1). The activity system influences the transport demand and, in turn, is influenced by the structure of the transport system, through accessibility. Indeed, a good transport system improves accessibility to the area. The interactions between transport and land use are also part of a complex framework that includes economic, political, demographic and technological changes.

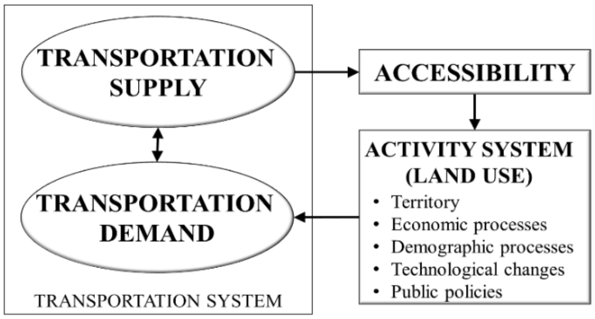

Figure 1. Transport - territory interaction (Elaboration from Cascetta, 2006).

The model approach is very useful for overcoming the difficulties associated with carrying out experiments on the real system and predicting the impacts of the interventions, also considering the complexity of mobility phenomena.

In the scientific literature there are many models proposed for the study of transport supply and demand. The model representation of the supply follows consolidated practices, based on the Graph Theory and on the identification of the dimensional and functional characteristics of the network elements; the definition of the transport demand, in term of Origin/Destination (O/D) matrix, is more complex since it is influenced by many factors that are not easy to identify and quantify.

He et al. (2022) have recently built a framework of studies in the sector literature. Traditionally, the proposed studies address the problem by resorting to the use of a 4-steps model that allows to have a long-term O/D matrix (Profillidis and Botzoris, 2018; Cardozo et al., 2012). The approach is complex due to several parameters involved in the long time horizon. Traditionally, however, to obtain a short-term O/D matrix, reference is made to collected traffic data; however, with this approach there is the risk of not capturing all the trips in the reference period.

Other methods proposed in the literature concern the estimation of static and dynamic demand. In the static case, Casey (1955) used a gravity model; Vardi (1996) referred to traffic investigations. Some researchers have developed statistical methods for estimating the O/D matrix by traffic counts and surveys, such as Cascetta (1984) and Bell (1991), who proposed a least squares method, or like Maher (1983) who used a Bayesian approach. Other authors have suggested the O/D matrix estimation for public transport systems through ICT (Chu, et al., 2020; Goulet-Langlois et al., 2016; Jere et al. 2014; Munizaga and Palma, 2012). The estimation of the dynamic O/D matrix was addressed by some researchers through algorithms based on Kalman filters also using traffic surveys (Chen et al., 2011; Yong et al., 2003). Hurk et al. (2012) proposed a linear statistical model, the autoregressive integrated moving average (ARIMA). Others proposed a neural network approach; Qian et al. (2008) presented a method based on Recurrent Neural Network (RNN); Zhang et al. (2021a) introduced the Channel Attentive Split Convolutional Neural Network (CAS-CNN); Zhang et al. (2021b) proposed a neural architecture named Dynamic Node-Edge Attention Network (DNEAT); Chen et al. (2020) presented a combined model based on multitasking learning and the Graph Convolutional Neural Network (GCN) to predict urban taxi mobility demand; Li et al. (2020) and Toqúe et al. (2016) based their approach on Long Short-Term Memory (LSTM) networks. Wang et al. (2019) proposed a unified model, Grid-Embedding based Multi-task Learning (GEML), based on spatial and temporal information. Ke et al. (2021) proposed a deep learning model named Spatio-Temporal Encoder-Decoder Residual Multi-Graph Convolutional Network (ST-ED-RMGC) to predict the ride-sourcing demand of several O/D pairs.

In the sector literature, there is no found research that introduces a simplified method for estimation of O/D demand that allows to overcome the limits of models or of the surveys. The paper proposes a heuristic approach for transport demand estimation aimed at traffic simulations. The approach is of a mixed type and integrates a modelling approach with results deriving from direct surveys, in terms of traffic counts, making it possible to estimate the O/D sub-matrices relating to a given urban area both in terms of people movements and vehicles.

The paper is structured as follows: Section 2 presents the definition of the O/D matrix and the most popular methods to calculate it; Section 3 introduces the proposed methodological approach; Section 4 proposes an application to a real context of an Italian small city; Conclusions are in the Section 5.

2. Origin/Destination matrix

Users moving in a given area represent the mobility demand linked to the transport services offered by a given territory. The study of demand plays a central role in the modeling and analysis of transport systems since the infrastructures and services to study and design are closely connected to the need of satisfying the mobility requirements expressed by users.

The mobility demand can be defined as the set of user components with specific characteristics that use a transport service, in a pre-established slot time. To define the transport demand, some relevant characteristics have to be considered, such as:

- the category of user (i); choice behaviors change in relation to the category of user; for simplicity, users with homogeneous characteristics (sex, age, occupation, income, etc.) are aggregated in groups;

- the reason of the trip (s); the trip can be systematic or non-systematic and can be home-based (e.g., home-work, home-school) or related to other reasons (e.g., work-shopping, school-leisure);
- the time dimension (h); the considered time slot depends on the analysis purpose, generally, the reference is an hour and a distinction is made between peak hours and soft hours;
- the spatial dimension (o, d); trips are characterized by place of origin (o) and destination (d) and are represented by O/D matrices;
- the modal characterization (m); reference is made to the mode or the sequence of modes of transport (car, foot, collective transport, etc.);
- the path followed (k); a sequence of links connecting each O/D on the network represents a path on the transport supply for mode m.

The spatial dimension of the demand leads to the construction and definition of the O/D matrices (Figure 2). These matrices have a number of rows and columns equal to the number of zones (internal and external) into which the study area is preliminarily divided. The generic element of the matrix supplies the number of trips originating from a zone O and destined for a zone *D*. The elements of the matrix can be classified in relation to the type of origin and destination area; it is therefore possible to identify 4 specific sub-matrices:

- sub-matrix of internal-internal trips (I-I) in which the origin and destination of the trips are within the study area (internal sub-matrix);
- sub-matrix of internal-external trips (I-E) in which the trips origin is inside the study area, instead the destination is outside (exchange sub-matrix);
- sub-matrix of external-internal trips (E-I) in which the trips origin is outside the study area, instead destination is inside (exchange sub-matrix);
- sub-matrix of external-external (E-E) or crossing trips in which both the origin and the destination of the trips are external to the study area, but they cross it (crossing sub-matrix).

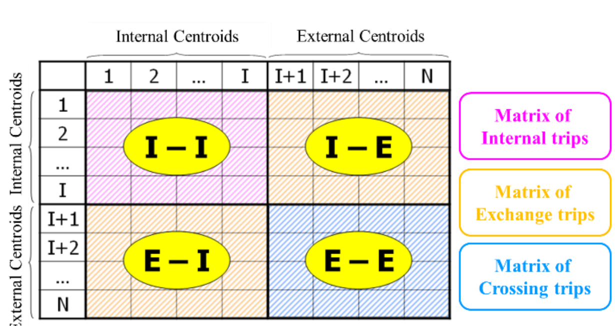

Figure 2. O/D Matrix and sub-matrices.

Analyzing, managing or planning an action on transport systems requires the estimation of the current demand and/or the forecast of the future one, because the supply and therefore the system configuration depend on the transport demand. The estimates can be based on different sources of information and statistical tools. As an alternative to traditional information sources, there are sources using Big Data that work thanks to the availability of data shared on the network; although this method is very simple, however, it could lead to considerable errors in the estimation as it does not allow to have the real trips of the users.

The most common estimation methods are:

- model estimation: the transport demand is evaluated using suitably specified, calibrated and validated models;
- direct estimation: surveys are used, typically interviews carried out on a sample of users, from which the transport demand can be traced using inferential statistics techniques;
- estimation based on mixed methods, i.e., through a combination of the two previous techniques.

2.1. Demand estimation models

In the modeling approach for the estimation of the O/D matrix, a 4-steps model is typically adopted, i.e., divided into 4 sub-models. The model assumes that the transport demand, expressed by users of category i who request to move from the origin o to destination d, for reason s, in time slot h, with mode m, following the path k, can be evaluated as (Cascetta, 2006):

$$d^i_{od}(s,\ h,\ m,\ k) = d^i_o[sh] \cdot p^i[d|osh] \cdot p^i[m|oshd] \cdot p^i[k|oshdm] \quad (1)$$

The $d^i_o[sh]$ emission/generation model provides the average number of trips, made by users of i category, from the o origin, in the h time slot, for the s reason:

$$d^i_o[sh] = N^i[o] \cdot m^i[osh] \quad (2)$$

where $N^i[o]$ represents the number of users of i category located in o zone, $m^i[osh]$ represents the average emission rate for the user of i category and the s reason.

The $p^i[d|osh]$ distribution model gives the rate of users of i category who starting from o zone go to d destination for the s reason, in h time slot. It can be obtained considering a gravitational model as:

$$p^i[d/osh] = \frac{exp(\beta_1 A_d - \beta_2 C_{od})}{\sum_{d} exp(\beta_1 A_{d'} - \beta_2 C_{od'})} \quad (3)$$

where A_d is a typical attractive variable considered for the s reason; C_{od} is the distance as the crow flies between the representative centroids (barycenters) of *o* and *d* zones; β_1 and β_2 are parameters of the model.

The $p^i[m|oshd]$ modal choice model provides the rate of users of *i* category who, moving from *o* to *d*, for the *s* reason, in the *h* time slot, use the *m* transport mode. The modal choice models used almost always have a behavioral interpretation. The Multinomial Logit model is among the most frequently used:

$$p^i[m/oshd] = \frac{exp\left(V^i_{m/oshd}\right)}{\sum_{m'} exp\left(V^i_{m'/oshd}\right)} \tag{4}$$

where the $V^i_{m/oshd}$ systematic utilities are calculated using the service level attributes related to trip for reason *s* between *o* and *d* in the time slot *h* and the socio-economic attributes related to user categories *i*.

The $p^i[k|oshdm]$ path choice model provides the rate of users of *i* category who, moving from *o* to *d* for the *s* reason, in the *h* time slot, with the *m* transport mode, follow the *k* path among the many alternatives (possible or more efficient). Using a Links-Paths-O/D incidence matrix, it is possible to obtain the so-called path flows that represent the mobility demand on each path, for each O/D pair and for each transport mode.

The modelling approach has some limitations; a first element concerns the knowledge of the parameters involved in the model. These values should be determined by calibrations which presuppose experimental investigations; it is possible to use the values present in the sector literature, if they are adaptable to the real context. Furthermore, these parameters may vary over time and therefore not be well determined. The matrix obtained from the model is a composition of matrices relating to different types of trips reasons. It is possible that the analysis doesn't consider some reasons leading to estimation. Another problem is related to the emission model; this generally provides the trips generated by the internal zones, but not those emitted by the external ones. It is also necessary to consider a suitable definition of the average vehicle occupancy rate in order to have O/D matrices in homogenous vehicle units.

2.2. Direct demand estimation

The mobility demand is the result of the aggregation of trips made in a given reference period (for example a typical day or a part thereof) by people on a given territory. Exact knowledge of demand would therefore require information on the characteristics of the trips made by all users. Furthermore, this information should be collected repeatedly, for example on different days, in order to derive an average value.

A census-type knowledge of the question is neither practicable nor necessary: the survey costs would in fact be such as to make the operation not feasible in practice. For these reasons, the estimates of the current transport demand are of the sample type, i.e., determined on the basis of information relating to a sample of system users. The sample surveys aimed at the direct estimation of the transport demand in a given study area, also known as O/D surveys, can be of different types in relation to the characteristics and quality of the desired information.

Two main classes of investigations can be distinguished, those based on investigations *on board* by intercepting users aboard their vehicles, or *home investigations* (at homes or business places). In on board surveys, a sample of users of one or more transport modes is interviewed; the interviews can be carried out on the roadside for car drivers and their passengers, on the vehicle or at terminals (stations, airports, ports, stops) for users of collective transport systems. The sample of users is obtained by interviewing, at random, a pre-established rate of the users who use the considered mode; in the case of surveys conducted in specific points of the system (road sections, stations, etc.) it is therefore necessary to count the total number of users in transit (universe) and interview a predetermined number through a random selection mechanism. When on board surveys are carried out to estimate the exchange and crossing demand, they are called cordon surveys. The data obtained from the sample can be brought back to the universe through an expansion coefficient equal to the reciprocal of the sampling rate. In general, the information obtained with these surveys is relatively simple as the interview has to be conducted in a limited time during the trip, and usually refers only to the trip or trip in progress.

In home surveys, a sample of families or people residing within the study area is interviewed, appropriately distributed by traffic zone. In the case of household interviews, the sample is drawn randomly from all households in the entire area (simple random sample) or from that of households residing in each traffic area (stratified random sample). The members of the families belonging to the sample are questioned about the trips they have made in a pre-established reference period, generally the day before. The same approach can be used for interviewing residents. This type of survey is quite expensive, although it provides generally accurate and reliable results thanks to the direct interaction between the interviewee and the interviewer; telephone surveys are also very widespread, which make it possible to reduce execution costs even if at the cost of simpler and less precise information collected.

In professional practice, there are many other types of sample surveys such as destination surveys, in which users are interviewed at the travel destinations (workplaces, schools, shops, etc.), postal or internet surveys in which users are interviewed by e-mail. All of the latter types of surveys, although less expensive than home surveys, can produce distorted estimates due to the systematic absence of responses from some market segments.

The number of elements to be interviewed depends on the purposes for which the survey is carried out and on the precision of the estimates to be obtained. Usually, surveys aimed at directly estimating current demand require a much larger sample than that needed to calibrate the demand models.

In applications, the most frequent case is that the various components of transport demand are surveyed with different surveys, for example surveys at the cordon for exchange and crossing mobility and at home for the internal one. Direct surveys involve high costs and a complex preparation and processing process.

3. Mixed methodological approach

The proposed methodological approach provides the estimate of the O/D matrix starting from the 4-steps model (up to the third level) integrated with the results of direct investigations, in particular, vehicular traffic counts carried out at the cordon with reference to peak time slots. The Exchange (E-I) and Crossing (E-E) trips can be evaluated using direct estimation based on cordon surveys. Internal-Internal (I-I) and Internal-External (I-E) trips can be obtained with a Model-Survey combination. The operating procedure is shown below, also briefly illustrated in Figure 3:

- the demand generated by internal zones is determined by the emission model; the number of trips is expressed by the EM_i element;
- the overall demand emitted and attracted by the external zones, $EM_{O.}$ and $AT_{.D}$, is respectively equal to the values of the I^{IN} and I^{OUT} flows detected at the cordon;
- the AT_j^{IE} total demand attracted by the external zones starting from internal origins is calculated as the difference between the flows I^{OUT} detected at the cordon and the known AT_j^{EE} demand.
- the X_{ij}^{IE} elements of the exchange sub-matrix I-E are obtained starting from the value AT_j^{IE}, distributed in proportion to the Ad_i percentage of employees per zone;
- the EM_i^{IE} total demand generated by the internal zones towards the external destinations is obtained by the sum per line of the X_{ij}^{IE} elements;
- the EM_i^{II} total demand generated by the internal zones towards internal destinations is calculated as the difference between the EM_i total trips emitted by each internal zone and the EM_i^{IE} demand. The X_{ij}^{II} elements of the I-I sub-matrix are calculated starting from the EM_i^{IE} value, distributed in proportion to the P_i percentage of population in the zone;
- the AT_j total demand attracted by the internal zones is obtained as the sum of AT_j^{II} and AT_j^{EI}. This last operation makes it possible to verify the correctness of the procedure since the AT_j values are already known.

The procedure has been elaborated in order to integrate models estimation results with real traffic counts in a coherent way. The traffic flows of exchange I-E and E-I become strong constraints and assure the validity of an important part of the matrix; the sub matrix E-I is a result of a statistical estimate from interviews with a sample of drivers of vehicles entering the study area through the cordon; the distribution of mobility is linked to significant weights of land as the number of inhabitants per zone (sub matrix I-I) and as the number of employees per zone (sub matrix I-E). The method assures effectiveness in the assessment and a significant goodness estimation of the mobility spatial distribution. In fact, the simulation (demand assignment) gives realistic traffic flows on a set of the network links, in relation to available traffic counts.

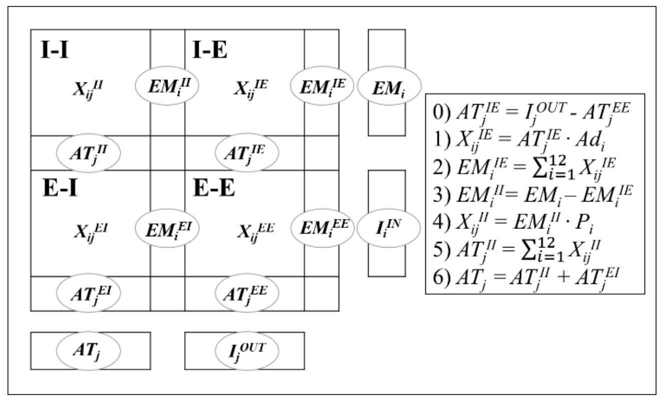

Figure 3. O/D matrix estimation procedure using the combined model-survey method.

4. A case study: estimation of the O/D matrix for an Italian city

An application to a real case is proposed. The study area corresponds to the urban area of the Lecce city, in Southern Italy; the peripheral area is not considered; the ring road is excluded from the service road network, which drains most of the crossing traffic. The study area has been divided into 25 internal zones (aggregation of census parcels with homogeneous characteristics) and 12 external zones (grouping of municipalities located on a traffic route and represented by centroids placed on the cordon of the study area) (Figure 4). The urban area is the center of a municipality which covers an area of about 239 km² and has 95,141; it is in a Region which includes many medium and large municipalities.

To estimate the exchange and crossing demand, a survey of traffic flows has been carried out on the 12 cordon sections arranged close to and inside the ring road, as well as, on 9 strategic road sections on the internal urban network. Sections in some radial road infrastructures on the North-South direction (sea) have not been considered because frequented by modest levels of users and therefore negligible. While the cordon surveys have been used for the construction of the O/D matrix, those on the internal pass sections represented a tool for verifying the congruence of the simulated flows with the final matrix.

The flow survey has been carried out with reference to three peak time slots (8am/9am; 1pm/2pm; 5pm/6pm). Table 1 shows the traffic volumes recorded, in vehicle units, on the 12 sections, in the maximum peak time slot (8am/9am).

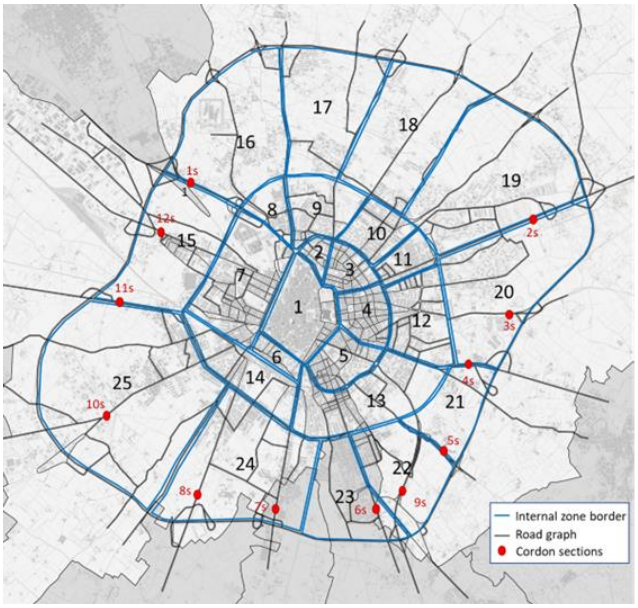

Figure 4. Study area: network graph, traffic zones, cordon centroids.

Table 1. Vehicle units on the cordon sections (8am/9am)

Cordon Section	Entry	Exit
1	1,768	1,110
2	368	325
3	682	401
4	659	451
5	323	239
6	615	486
7	618	407
8	640	505
9	1,218	862
10	618	370
11	335	324
12	572	501
Total	**8,416**	**5,981**

For the estimation of the demand emitted by the urban traffic zones, an emission model has been considered which made it possible to obtain the number of total trips generated by the internal zones for different reasons (home-work H-W, home-school H-S and home-others reasons H-OR) with a motorized vehicle. Table 2 shows the total trips emitted by the internal zones in the maximum peak time slot (8am/9am) and for different reasons, as well as the total, in terms of users/hour; to obtain the flows in vehicle units, an average filling factor of 1.4 (Total vehicles a) has been considered. A correction factor of 1.2 has been also adopted to take into account other trips reasons not considered in the model (Total vehicles b). These values have been chosen considering the average of the values present in the sector literature and in relation to the experience of the authors in the field. In Italian urban context rarely, the average number of persons per vehicle is more than 1.5. The factor 1.2 gives an increase in mobility in order to consider travels related to unusual motivation (as from work place to shop or recreational movements).

Table 2. Total number of trips emitted by internal zones, for different reasons of travel (8am/9am)

	H-W TRIPS	H-S TRIPS	H-OR TRIPS	TOTAL USERS	TOTAL VEHICLES (a)	TOTAL VEHICLES (b)
1	1,396	302	27	1,725	1,232	1,478
2	319	66	6	391	279	335
3	709	143	13	865	618	742
4	1,992	409	36	2,437	1,741	2,089
5	1,188	243	22	1,452	1,037	1,245
6	358	75	7	439	314	377
7	2,221	433	39	2,693	1,923	2,308
8	313	60	5	378	270	324
9	1,030	183	16	1,229	878	1,054
10	1,304	236	21	1,562	1,116	1,339
11	2,587	477	42	3,107	2,219	2,663
12	1,720	317	28	2,065	1,475	1,770
13	240	46	4	291	208	249
14	488	94	8	590	421	505
15	1,224	224	20	1,468	1,048	1,258
16	509	90	8	607	433	520
17	297	51	5	353	252	303
18	639	114	10	763	545	654
19	2,004	330	29	2,363	1,688	2,026
20	1,229	225	20	1,474	1,053	1,263
21	137	25	2	164	117	140
22	95	15	1	111	79	95
23	118	14	1	133	95	114
24	1,099	190	17	1,306	933	1,120
25	877	164	15	1,056	754	905
TOT	**24,090**	**4,527**	**402**	**29,020**	**20,728**	**24,875**

Concerning the trips emitted for the H-S and H-OR reasons, from each internal traffic zone, it has been hypothesized that they have been all directed within the study area. Another assumption is that 26% of the trips emitted for the H-W reason has been directed outside the study area (internal-external trips). This rate has been determined on the basis of overall statistical data (year 2011). The distribution of trips with internal origin among the zones has been carried out in proportion to some attraction parameters which have been translated into a weighting factor in the model. For the I-E exchange trips, the employees per area have been considered; for internal trips I-I the population of the area has been considered.

Starting from the vehicular flows resulting from the traffic surveys leaving the cordon, the procedure reported in the methodological approach has been applied which allowed to obtain the vectors in Table 3 (part a refers to internal zones; part b refers to external zones). While the outgoing surveys have been the input of the algorithm adopted, the incoming surveys have allowed to verify the correctness of the matrix and in particular the resulting E-I sub-matrix.

Table 4 summarizes the numbers of total trips emitted and attracted for large territorial areas and the exchanges among the same areas (I-E, E-I exchange O/D and E-E crossing matrices) as well as the total number of internal trips (I-I matrix). The detail matrices are not reported for reasons of space. Considering that there are 92,020 inhabitants in the study area, each inhabitant makes about 0.36 trip.

Table 3a. Vectors of the O/D matrix from internal zones, in vehicles/hour (8am/9am).

Int	EM_i^{II}	EM_i^{IE}	EM_i	$(AT_j^{II})^T$	$(AT_j^{EI})^T$	$(AT_j)^T$
1	398	1,080	1,478	1,119	1,385	2,504
2	253	82	335	242	109	351
3	710	31	742	556	255	811
4	1,998	91	2,089	1,587	1,068	2,655
5	643	602	1,245	937	952	1,889
6	81	295	376	271	205	476
7	1,948	360	2,308	1,723	495	2,218
8	217	107	324	256	22	278
9	834	220	1,054	807	217	1,024
10	1,057	281	1,339	1,035	229	1,264
11	2,556	106	2,663	2,067	274	2,341
12	1,437	333	1,770	1,378	336	1,714
13	49	200	249	193	396	589
14	398	107	505	386	377	763
15	1,203	55	1,258	997	127	1,124
16	415	105	520	422	19	441
17	250	53	303	250	3	253
18	653	1	654	522	0	522
19	1,572	454	2,026	1,615	169	1,784
20	958	306	1,263	1,104	556	1,660
21	140	0	140	110	3	113
22	94	1	95	75	141	216
23	113	1	114	90	25	115
24	884	235	1,120	907	385	1,292
25	505	400	905	719	195	914
TOT	**19,367**	**5,508**	**24,875**	**19,367**	**7,943**	**27,310**

Table 3b. Vectors of the O/D matrix, from external zones, in vehicles/hour (8am/9am).

Ext	EM_i^{EI}	EM_i^{EE}	I_i^{IN}	$(ATj^{IE})^T$	$(ATj^{EE})^T$	$(Ij^{OUT})^T$
1	1,680	88	1,768	1,064	46	1,110
2	347	21	368	317	8	325
3	682	0	682	368	33	401
4	549	110	659	431	20	451
5	317	6	323	219	20	239
6	561	54	615	447	39	486
7	600	18	618	368	39	407
8	600	40	640	466	39	505
9	1,170	48	1,218	817	45	862
10	577	41	618	348	23	370
11	329	6	335	302	23	324
12	531	41	572	361	140	501
TOT	**7,943**	**473**	**8,416**	**5,508**	**473**	**5,981**

Table 4. Global values of the final O/D matrix in vehicles/hour (8am/9am).

I-I 19,367	I-E 5,508		EM-I 24,875
E-I 7,943	E-E 473		EM-E 8,416
AT-I 27,310	AT-E 5,981		TOT 33,291

The results obtained by applying the proposed approach have been verified by comparing the estimated traffic flows with the real traffic flows (survey). In the specific case it has been analysed the relative difference for a limited number of internal network links, obtaining not relevant values (less than 30%); obviously the flows on the cordon sections (links of entry and exit) are equal to the detected traffic (0% of difference), being bound a priori.

5. Conclusions

The paper has proposed a mixed methodological approach for the estimation of the O/D matrix of trips aimed at traffic simulations on a city network, considering the application of models and direct investigations. The proposed approach aims to overcome the limitations of demand estimation through the exclusive use of models (knowledge of the parameters, knowledge of all trips reasons, trips emitted from external areas, etc.) or by carrying out surveys (high costs, complex preparation and processing process). The method has been applied to a real context which has allowed to obtain the O/D matrix for the car mode in three reference peak time slots. The O/D matrix obtained proved to be reliable in relation to compliance with the double constraint on the exchange flows through the cordon, but also in relation to the good fitness between vehicular flows detected on the strategic sections inside the city area and the corresponding simulated flows obtained through the assignment model (supply/demand interaction) having found differences of no more than 30%.

The model could be extended by considering the other mobility components or adapted to allow an estimate of the user component of public transport, also with the aid of on-board interviews.

References

Bell, M. G. H. (1991). The Estimation of Origin-Destination Matrices by Constrained Generalised Least Squares. Transportation Research Part B, 25 (1): 13–22.

Bruzzone, A. G., Massei, M., Sinelshchikov, K., Giovannetti, A., Ferrari, R., De Paoli, A., Gadupuri, B., Reverberi, A., Fancello, G., Frosolini, M., Vairo, T., Piroddi, G., Gaborit, F., and Paoli, J. (2022). Innovative Virtual Lab for Improving Safety and Port Operations. In Proceedings of the Int. Conf. on Harbor Maritime and Multimodal Logistics M&S, 072.

Cardozo, O. D., García-Palomares, J. C., and Gutiérrez, J. (2012). Application of geographically weighted regression to the direct forecasting of transit ridership at station-level. Applied geography, 34: 548-558.

Cascetta, E. (1984). Estimation of Trip Matrices from Traffic Counts and Survey Data: A Generalized Least

Squares Estimator. Transportation Research Part B, 18 (4–5): 289–299.

Cascetta, E. (2006). Modelli per i sistemi di trasporto: teoria e applicazioni. Ed.UTET.

Casey, H. (1955). The Law of Retail Gravitation Applied to Traffic Engineering. Traffic Quarterly, 9(3): 313–321.

Chen, X., Guo, S., Yu, L., and Hellinga, B. (2011). Short-term forecasting of transit route OD matrix with smart card data. In 2011 14th International IEEE Conference on Intelligent Transportation Systems (ITSC), 1513-1518, IEEE.

Chen, Z., Zhao, B., Wang, Y., Duan, Z., and Zhao, X. (2020). Multitask learning and GCN-based taxi demand prediction for a traffic road network. Sensors, 20(13): 3776.

Chu, K. F., Lam, A. Y., and Li, V. O. (2019). Deep multi-scale convolutional LSTM network for travel demand and origin-destination predictions. IEEE Transactions on Intelligent Transportation Systems, 21(8): 3219-3232.

Gattuso, D., and Pellicanò, D. S. (2022). Advanced management in a logistics platform equipped with automated handling means. In Proceedings of the Int. Conf. on Harbor Maritime and Multimodal Logistics M&S, 001.

Goulet-Langlois, G., Koutsopoulos, H. N., and Zhao, J. (2016). Inferring patterns in the multi-week activity sequences of public transport users. Transportation Research Part C: Emerging Technologies, 64: 1-16.

He, Y., Zhao, Y., and Tsui, K. L. (2022). Short-term forecasting of origin-destination matrix in transit system via a deep learning approach. Transportmetrica A: Transport Science, 1-28.

Hurk, E., Kroon, L. G., Maróti, G., and Vervest, P. (2012). Dynamic forecasting model of time dependent passenger flows for disruption management. In S. Voss, & J. C. Munoz (Eds.), CASPT.

Jere, S., Dauwels, J., Asif, M. T., Vie, N. M., Cichocki, A., and Jaillet, P. (2014). Extracting commuting patterns in railway networks through matrix decompositions. In 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), 541-546, IEEE.

Ke, J., Qin, X., Yang, H., Zheng, Z., Zhu, Z., and Ye, J. (2021). Predicting origin-destination ride-sourcing demand with a spatio-temporal encoder-decoder residual multi-graph convolutional network. Transportation Research Part C: Emerging Technologies, 122, 102858.

Li, D., Cao, J., Li, R., and Wu, L. (2020). A spatio-temporal structured LSTM model for short-term prediction of origin-destination matrix in rail transit with multisource data. IEEE Access, 8: 84000-84019.

Maher, M J. (1983). Inferences on Trip Matrices from Observations on Link Volumes: A Bayesian Statistical Approach. Transportation Research Part B, 17B (6): 435–447.

Montanari, R., Bottani, E., Volpi, A., Solari, F., Lysova, N., and Bocelli, M. (2022). Warehouse Design and Management: a simulative approach to minimize the distance travelled by pickers. In Proceedings of the Int. Conf. on Harbor Maritime and Multimodal Logistics M&S, 034.

Munizaga, M. A., and Palma, C. (2012). Estimation of a disaggregate multimodal public transport Origin–Destination matrix from passive smartcard data from Santiago, Chile. Transportation Research Part C: Emerging Technologies, 24: 9-18.

Profillidis, V. A., and Botzoris, G. N. (2018). Modeling of transport demand: Analyzing, calculating, and forecasting transport demand. Elsevier.

Qian, F., Hu, G., and Xie, J. (2008). A recurrent neural network approach to traffic matrix tracking using partial measurements. In 2008 3rd IEEE Conference on Industrial Electronics and Applications, 1640-1643, IEEE.

Toqué, F., Côme, E., El Mahrsi, M. K., and Oukhellou, L. (2016, November). Forecasting dynamic public transport origin-destination matrices with long-short term memory recurrent neural networks. In 2016 IEEE 19th international conference on intelligent transportation systems (ITSC), 1071-1076, IEEE.

Vardi, Y. (1996). Network Tomography: Estimating Source-Destination Traffic Intensities from LinkData. Journal of the American Statistical Association. 91(433): 365–377.

Wang, Y., Yin, H., Chen, H., Wo, T., Xu, J., and Zheng, K. (2019). Origin-destination matrix prediction via graph convolution: a new perspective of passenger demand modeling. In Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining, 1227-1235.

Yong, L., YuanLi, C., and YongXuan, H. (2003). Kalman filtering based dynamic OD matrix estimation and prediction for traffic systems. In Proceedings of the 2003 IEEE International Conference on Intelligent Transportation Systems, 2: 1515-1520, IEEE.

Zhang, D., Xiao, F., Shen, M., and Zhong, S. (2021b). DNEAT: A novel dynamic node-edge attention network for origin-destination demand prediction. Transportation Research Part C: Emerging Technologies, 122: 102851.

Zhang, J., Che, H., Chen, F., Ma, W., and He, Z. (2021a). Short-term origin-destination demand prediction in urban rail transit systems: A channel-wise attentive split-convolutional neural network method. Transportation Research Part C: Emerging Technologies, 124: 102928.