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Urban freight demand forecasting: A mixed quantity/delivery/vehicle-based model

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ABSTRACT

The research germinates from the statement that the cities have to solve the impacts due to freight transport in order to improve their sustainability implementing sets of city logistics measures. But city logistics measures involve several actors and choice dimensions. It is therefore important to have methods and models able to assess the effectiveness of the measures to be implemented. The current models were mainly developed to simulate some aspects of urban freight transport, and are not able to forecast many impacts of implementing traffic and transportation measures at an urban scale.

This paper presents a modelling approach that tries to point out the relations existing among city logistics measures, actors and choice dimensions. It comprises three model sub-systems to estimate the quantity O–D matrices by transport service type (e.g. retailer on own account or wholesaler on own account or by carrier), the delivery O–D matrices by delivery time period, and the vehicle O–D matrices according to delivery tour departure time and vehicle type.

This modelling system is a multi-stage model and considers a discrete choice approach for each decisional level. It was first tested using some data collected in the inner area of Rome, including traffic counts and interviews with retailers and truck-drivers. The model estimations were also compared with the experimental ones, and quite satisfactory results were obtained.

1. Introduction

Local administrators are looking at city logistics measures in order to reduce the negative effects of freight transport within their cities (Russo and Comi, 2011; Lindholm and Behrends, 2012). Freight transport is the result of choices made by several stakeholders, and in particular by transport and logistics operators (retailers, wholesalers and carriers). Feasible solutions thus also have to be an optimal compromise between the various interests concerned (Dablanc, 2007; Stathopoulos et al., 2011; Holguín-Veras and Wang, 2011).

It is therefore important to have methods and models able to consider the behaviour of actors involved in the urban freight transport process (Friesz et al., 2011; Holguín-Veras, 2011; Muñuzuri et al., 2012). In this context, a key role is played by freight demand models that have to satisfy the requirements described in Section 2.

Analysis of the state-of-the-art (Section 2) shows that many of the proposed models do not use a general and mixed framework approach that considers actors and their choice dimensions. It is thus difficult to forecast the effects of implementing city logistics measures.

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In order to find a feasible solution that allows these identified limits to be overcome, we present a system of models (Section 3) that was calibrated by using some surveys carried out in the inner area of Rome. The surveys were based on interviews with retailers and food-and-drink outlets, and truck drivers, and included commercial traffic counts. The models are specified within the quantity/delivery/vehicle mixed modelling approach and are integrated in a unified modelling framework. Although, as described in Section 4, the results of this first calibration phase are satisfactory, further developments, including the analysis of transferability, are in progress as described in Section 5.

2. Freight demand model requirements

2.1. The system to be modelled

The first step of the simulation procedure is to identify the components of urban freight transport, seeking to link choice behaviour and city logistics measures. In urban and metropolitan areas, freight transport is mainly related to the distribution of final products from producers, wholesalers and distribution centres to the businesses in the area (e.g. shops, food-and-drink outlets, offices, consulting firms). For examples, in Rome it represents more than 80% of total quantity and delivery daily movements. In particular, urban distribution can be represented through the functional scheme of freight distribution as pictured in Fig. 1. Even if the proposed model can be applied to whole urban freight distribution system, this paper will deal with the bold part of Fig. 1, that is the case in which the freight passes through a retailer or a food-and-drink outlet before arriving at the end-consumer. As confirmed by several surveys (Ambrosini and Routhier, 2004), this flow represents the main component of freight moved to the centre of urban areas (e.g. in Rome, it represents the 70% of daily delivery flows), where most of the freight transport impacts are concentrated (Ibeas et al., 2012; NCFRP, 2012), and most of the city logistics measures are implemented. Besides, in these areas the measures are quite different from the rest of the city, where they mainly refer to road safety.

As regards the restocking of retailers and food-and-drink outlets, urban freight transport is characterised by different actors which act to move freight. In particular, actors can be grouped according to three classes:

- *wholesalers*, that are sometimes responsible for planning and managing the physical distribution of products; below, we assume that this class also includes producers, distributors and logistics operators which consolidate/deconsolidate freight during the transportation chain up to consumers; this class of actors can decide the transport service type, time, vehicle and possible intermediate facilities (e.g. urban distribution centres), as well as delivery tour;
- *carriers*, which include the actors responsible for transport that decide how to provide transport; we also include transport operators and express companies (couriers);
- *retailers* and food-and-drink outlets, that sell goods to end consumers and can decide how much and how to restock, from where, what time, which vehicle, which delivery tour has to be used.

Referring to the choice dimensions influenced by more common and effective city logistics measures, we can identify two sets of choices: one related to demand and one related to supply/logistics (Table 1). The former class includes choices relative to: how much to be restocked daily, where to get freight to sell in the shop. The latter class includes choices relative to: which type of transport service to be used (e.g. directly on one's own or using third parties), what time to make the delivery journey, which type of vehicle to be used, which delivery tour (e.g. sequence of pick-ups/deliveries). As summarised in Table 1, each of the previous choices can be modified by more common and effective implementing city logistics measures. These measures can be classified in two levels: strategic and tactical/operational. At *strategic level* (Muñuzuri et al., 2005; van Duin and Quak, 2007; Russo and Comi, 2011), the city logistics measures are mainly addressed to influence land use (e.g. government of urban transformations) and end consumers' behaviours. At the other hand, the *tactical/operational* measures predominantly impact on delivery vehicle journeys. A modelling system able to assess these city logistics measures should thus consider all these choice dimensions.

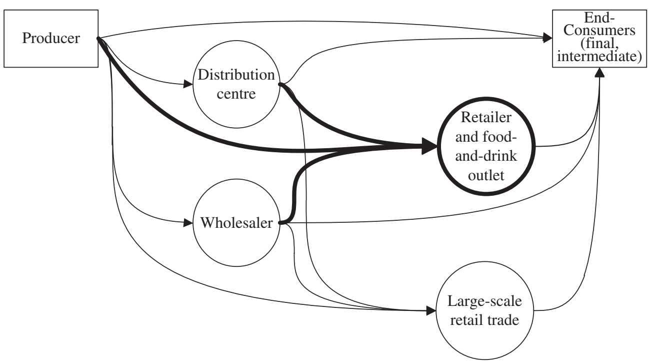

Fig. 1. Structure of urban freight distribution.

Table 1
Choice dimensions, actors and more common/effective city logistics policies/measures.

Choice dimensions	Demand		Supply/logistics			
	How much?	Which acquisition zone?	Which service type?	What time?	Which vehicle?	Which delivery tour?
Actors						
Retailer	x	x	x	x	x	x
Wholesaler			x	x	x	x
Carrier				x	x	x
Measures						
Urban distribution centre/transit point		x	x	x	x	x
Time windows			x	x		x
Weight constraints			x		x	x
Emission constraints/incentives for LEV			x		x	
Road/parking pricing			x		x	x
Incentives for 3P			x		x	x
Government of urban transformations	x	x	x			x

2.2. The characteristics of existing urban freight demand models

The choice of a set of city logistics measures should be based on design tools by simulating the main effects of exogenously specified scenario, verifying their technical compatibility and evaluating their convenience (i.e. *what if* approach).

At strategic level, the models should in-depth highlight the mechanism underlying demand generation. Then, the *quantity* O–D freight flows should be pointed out. For example, land use and zoning decisions at the local level, that determine the location of the origin or destination of goods, often occur without a full understanding or consideration of urban goods movement by commercial vehicles. As a consequence, the logistical needs of businesses and consumers may be degraded, opportunities for economic development may be missed, and freight movements may unnecessarily detract from the quality of life through congestion or emissions (NCFRP, 2012).

At tactical/operational level, the models have to point out the definition of *delivery* tours and hence the vehicle used. In these tools, starting from the *delivery* O–D matrices we can obtain the freight *vehicle* O–D matrices that, interacting within the assignment model, allow us to obtain the link flows and hence to estimate and evaluate link performances and external impacts of a given city logistics scenario.

At the end, the models for the estimation of freight O–D flows should simulate all actors' choices (i.e. wholesaler, carrier and retailer) in relation to city logistics measures at different planning horizons, and thus a general framework able to analyse freight flows in terms of quantities, deliveries and vehicles should be used.

The need to find solutions able to simulate effects of city logistics measures prior to implementation has stimulated research in urban freight demand and different models have been proposed. Although several classifications have been used according to various criteria (Regan and Garrido, 2001; Taniguchi et al., 2001; Ambrosini et al., 2008; Chow et al., 2010; Anand et al., 2012; Gonzalez-Feliu and Routhier, 2012; Comi et al., 2014), in this study the main existing models were analysed and classified in relation to the following requirements (Table 2): *reference unit* (commodity/quantity, delivery, truck/vehicle), transport *actors* (retailer, wholesaler, carrier), *choice dimensions* (see Table 1), integration within a *general framework* and presence of *calibrated parameters*.

From the analysis of these criteria, it may be noted that many of the proposed models do not integrate the three different reference units within a general modelling framework. Few of them allow us to analyse the choice dimensions and relative actors impacted by the implementation of city logistics measures through probabilistic-behavioural models. These models were developed to simulate some aspects of urban freight transport and do not consider all the three recalled reference units (i.e. quantity, delivery and vehicle), that allow the actors' behaviour to be captured. Besides, some of them are based on empirical relations that well describe the current state of the system but they could fail when new city logistics scenarios (before implementation) are simulated and assessed. Some are commodity-based models and hence accurately simulate the mechanism underlying the generation of freight transport demand. Others use delivery units and are more specific for studying the logistic process of restocking, in particular the process of the increasing of delivery number and hence of a major parcelling out. Finally, other studies refer directly to the vehicle unit that is required by road network performance and impact models. In particular, starting from quantity or delivery O–D matrices, the O–D vehicle flows have to be estimated. The translation is not direct, particularly in urban areas where freight vehicles undertake complex routing patterns involving trip chains (tours). In fact, each restocker jointly chooses the number and the location of deliveries for each tour and hence defines his/her tours, trying to reduce the related costs (e.g. using routing algorithm). Then, the paper proposes to obtain the freight vehicle O–D matrices using a two-step procedure: definition of delivery tours from delivery O–D matrices through delivery tour models, and definition of the freight vehicle O–D matrices from the delivery tours. Various types of models have been developed to define delivery tours from known delivery O–D flows (Nuzzolo and Comi, 2013). The main behavioural models consist of partial share models. They give the probabilities that a delivery tour has a given number of

Table 2
Main models for urban freight demand.

Criteria	Reference unit	Actors	Choice dimensions						General framework	Calibrated parameters
			How much?	Which acquisition zone?	Which service type?	What time?	Which vehicle?	Which delivery tour?		
Sonntag (1985)	V	W/C	N	Y	Y	N	N	Y	N	N
Ogden (1992)	Q/T	C	Y	Y	N	N	Y	N	N	Y
Oppenheim (1994)	Q	W/C	Y	Y	N	N	N	N	Y	N
Eriksson (1996)	T	W/C	Y	Y	N	Y	N	Y	N	N
Boerkamps and Van Binsbergen (1999)	Q/T	Q/V	Y	Y	N	Y	N	Y	Y	N
Taniguchi et al. (2001)	Q/T	C	Y	Y	N	N	Y	Y	N	N
Janssen and Vollmer (2005)	T	W/C	N	Y	Y	N	N	Y	N	N
Wisetjindawat et al. (2005)	Q/T	R/W/C	Y	Y	N	N	Y	N	Y	Y
Gentile and Vigo (2006)	D	C	Y	Y	N	Y	N	Y	Y	Y
Hunt and Stefan (2007)	T	C	Y	Y	N	Y	Y	Y	Y	Y
Raothanachonkun et al. (2007)	Q/T	C	N	N	N	N	Y	Y	N	Y
Wang and Holguin-Veras (2008)	Q/T	C	N	N	N	N	N	Y	N	Y
Qureshi et al. (2009)	T	C	N	N	N	Y	N	Y	N	N
Wang and Holguin-Veras (2009)	Q/T	C	N	N	N	N	N	Y	N	Y
Giuliano et al. (2010)	Q/T	C	Y	Y	N	N	N	N	N	Y
Muñuzuri et al. (2010)	D/T	C	Y	Y	N	N	Y	N	Y	Y
Nuzzolo et al. (2010a)	Q/D/T	R/W/C	Y	Y	Y	Y	Y	Y	Y	N
Russo and Comi (2010)	Q/T	R	Y	Y	Y	Y	Y	Y	Y	Y
Nuzzolo et al. (2011)	D/T	R/W/C	N	N	N	N	N	Y	N	Y
Kawamura and Miodonski (2012)	Q	R	Y	N	N	N	N	N	N	Y
Gonzalez-Feliu et al. (2012)	D	C	Y	Y	Y	Y	Y	Y	Y	Y

Q = commodity/Quantity; D = Delivery; T = Truck/vehicle; C = Carrier or transport operator; R = Retailer; W = Wholesaler; Y = Yes; N = No.

stops, a given sequence of stops/deliveries and a given type of vehicle used. They propose to obtain the freight vehicle O–D matrices by an incremental growth approach (Hunt and Stefan, 2007; Wang and Holguin-Veras, 2008) similar to those used for passenger trip-chain simulation: at each stop for a given type of vehicle, the option to come back to the warehouse is considered; if the tour continues, the probability of the next delivery location is calculated. But, this approach implies relevant approximations because the actual choice process is not reproduced, as generally the choices of the number of stops and delivery zone sequence are pre-trip choices. We propose a multi-step approach that defines tours through joint definition of the trip chain order (that is the number of stops in a tour), the type of vehicle used and the delivery location sequence. Once all delivery tours have been estimated, the freight vehicle O–D flows can be obtained through the aggregation of the trips of the tours, as reported in Section 3.3 below. Finally, some of the main models, reviewed and classified in Table 2, are designed without calibration.

Hence it is difficult to analyse the complexity of urban transport systems with actors that make up urban freight mobility and to forecast many of the main impacts of implementing traffic and transportation measures at an urban scale. A unified and mixed structure where freight transport demand is studied in these three reference units should be the focus of investigation. Besides, models should be behavioural and hence derived from explicit assumptions about actors' choices. In this way, they would allow us to simulate the current choices and, in particular, to forecast the future ones according to some network attributes that can be modified by city logistics measures.

A new modelling framework that tries to overcome the limits of current models is presented in Section 3. It considers quantity, delivery and vehicle units and is able to simulate urban goods movements pointing out actors' choices and to take into account several effects on choices due to implementations of more common and effective city logistics measures.

3. General structure of the proposed modelling system

In this section the proposed modelling system is described. It can be classified as a quantity/delivery/vehicle mixed model: quantity is used in order to capture the mechanism underlying the generation of freight demand, delivery to follow the logistic process of restocking, and vehicle to obtain the freight vehicle flows on the network.

This paper presents the integration and the advancement of some works developed by the authors (some of them are also reported in Table 2) in the course of multi-year research.

The model system consists of three model sub-systems that allow us to estimate (Fig. 2):

- the average quantity O–D matrices by transport service type (e.g. retailer on own account or wholesaler on own account or by carrier);
- the average delivery O–D matrices by delivery time period;

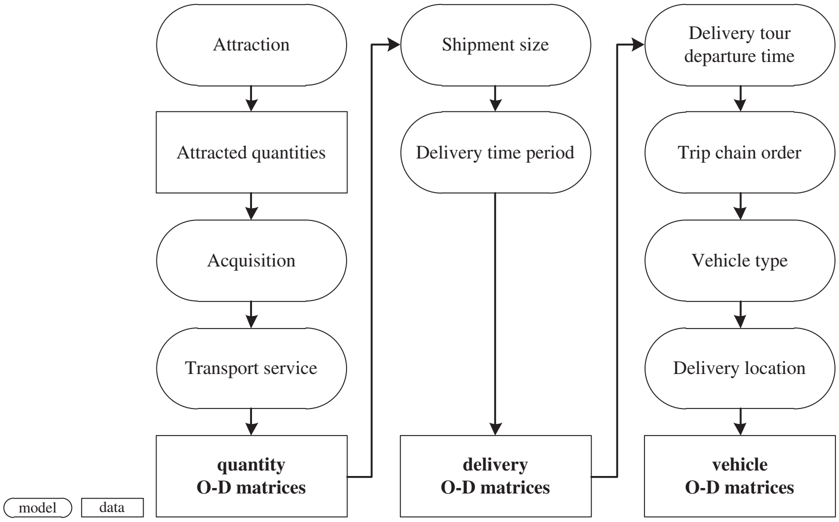

Fig. 2. The proposed modelling system for freight vehicle O–D estimation (Nuzzolo et al., 2010a).

- the average vehicle O–D matrices by delivery tour departure time and vehicle type.

The following sections describe each sub-system.

3.1. *The quantity model sub-system*

The quantity model sub-system allows us to estimate the quantity O–D matrices characterised by freight type *s* and transport service type *r*. The possible transport service types are (Fig. 3):

- retailer on own account;
- retailer by third party (i.e. transport company or courier that offers small size shipment);
- wholesaler on own account;
- wholesaler by third party.

Let $Q_{od}^{sh}[r]$ be the average *quantity* flow of freight type *s* attracted between zone *o* and zone *d* in a time period *h* (e.g. day) with transport service type *r*. For simplicity of notation, the class index *s* (freight type) and *h* (time period) will be taken as understood unless otherwise stated. Thus, the average quantity flow, $Q_{od}[r]$, can be estimated as follows:

$$Q_{od}[r] = Q_{.d} \cdot p[o/d] \cdot p[r/od] \quad (1)$$

where
- $Q_{od}[r]$ is the average quantity flow of freight attracted by zone *d* and coming from zone *o* with transport service type *r*;
- $Q_{.d}$ is the average freight quantity attracted by zone *d* obtained by an *attraction model*;
- $p[o/d]$ is the probability that freight attracted by zone *d* comes from zone *o* (e.g. warehouse location zone); it represents the acquisition share obtained by a discrete choice *acquisition model*;
- $p[r/od]$ is the probability of being restocked by transport service type *r* obtained by a discrete choice *transport service type model*.

3.2. *The delivery model sub-system*

The average delivery O–D flow carried out by transport service type *r* on pair *od* in delivery time period τ, $ND_{od}[\tau r]$, can be determined as follows:

$$ND_{od}[\tau r] = Q_{od}[r] \cdot p[\tau/d]/q[r] \quad (2)$$

where
- $ND_{od}[\tau r]$ is the number of deliveries performed by transport service type *r* on pair *od* in delivery time period τ;
- $p[\tau/d]$ is the probability of having deliveries at the retail destination in delivery time period τ obtained by a *delivery time period model*;
- $q[r]$ is the average freight quantity delivered with transport service type *r* (average *shipment size*).

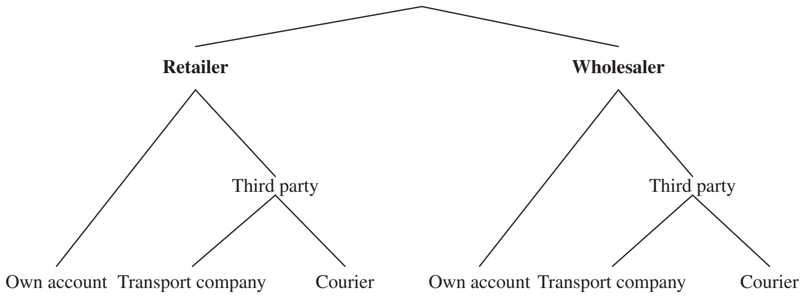

Fig. 3. Transport service type: structure of choice dimensions.

3.3. The vehicle model sub-system

In the proposed modelling framework, the O–D vehicle matrices are obtained using an analytical aggregate multi-step delivery tour model that considers the average behaviour of the restockers (or categories of restockers) starting from the same warehouse zone. The number of tours with n stops for deliveries departing from origin zone o at time t of delivery time period τ and operated by transport service r and vehicle type υ, $T_o[\upsilon nt\tau r]$, is estimated as follows:

$$T_o[\upsilon nt\tau r] = T_o[\tau r] \cdot p[t/\tau ro] \cdot p[n/t\tau ro] \cdot p[\upsilon/nt\tau ro] \tag{3}$$

where

- $T_o[\tau r]$ is the total number of tours departing from origin zone o in delivery time period τ;
- $p[t/\tau ro]$ is the probability that the delivery tours depart at a certain time t from an origin o (i.e. warehouse zone) obtained by a discrete choice *delivery tour departure time model*;
- $p[n/t\tau ro]$ is the probability that deliveries are performed by tours departing from a given zone o with n stops obtained by a discrete choice *trip chain order model*;
- $p[\upsilon/nt\tau ro]$ is the probability that deliveries are performed by vehicle type υ obtained by a discrete choice *vehicle type model.*

The total number of tours $T_o[\tau r]$ can be determined as follows:

$$T_o[\tau r] = ND_{o.}[\tau r]/\bar{n} = \sum_{d'} ND_{od'}[\tau r] / \sum_{n,t} n \cdot p[n/t\tau ro] \cdot p[t/\tau ro] \tag{4}$$

where

- $ND_o[\tau r]$ is the average number of deliveries performed by service transport type r departing from origin zone o in delivery time period τ;
- $\bar{n}$ is the average number of deliveries performed by tours departing from origin zone o in delivery time period τ.

Being able to assume that each tour is performed by a vehicle and given $T_o[\upsilon nt\tau r]$ (see. Eq. (3)), the number of vehicles $VC_{d_i d_j}$ on $(d_i\, d_j)$ pair can be estimated as follows:

$$VC_{d_i d_j}[\upsilon nt\tau ro] = \sum_k VC_{d_i^{k+1} d_j^k}[\upsilon nt\tau ro] = T_o[\upsilon nt\tau r] \cdot \sum_k p[d_j^{k+1}/d_i^k\, \upsilon nt\tau ro] \tag{5}$$

where $p[d_j^{k+1}/d_i^k\, \upsilon nt\tau ro]$ is the probability of delivering in zone d_j the delivery $(k+1)$, conditional upon having previously delivered in zone d_i the delivery k, within a tour with n stops departing from a given zone o obtained by a discrete choice *delivery location model.*

4. Calibration results for the inner area of Rome

The modelling system was calibrated for the inner zone of Rome where, in 2008, the municipal authorities commissioned a study on new policies for urban freight transport that was carried out by academic researchers, with a twofold aim. One was to monitor the effects of a new regulation of freight traffic implemented from 2001 onwards, and the other to develop a modelling framework able to support the *ex ante* assessment of future scenarios (Nuzzolo et al., 2010b; Stathopoulos et al., 2011; Nuzzolo and Comi, 2014). Below, for the sake of readability, the main results will be summarised. For more details, refer to Nuzzolo and Comi (2011).

4.1. The dataset

The study area is the inner city area, of about 6 km^2, with about 50,000 inhabitants and 24,000 employees related to trade. At surveys time, access was not permitted to pre-Euro vehicles and with a gross laden weight of less than 3.5 tonnes. Also vehicles with a gross laden weight under 8.5 tonnes were allowed access only at night-time and were restricted to some specific roads.

The study was supported by some surveys carried out in 2008: traffic counts of commercial and other vehicles at the border of study area, with about 600 interviews of truck drivers in order to investigate the supply chain of freight distribution within the study area, and about 500 interviews of retailers in order to investigate the retail trade in the study area for each freight type.

The study area is a mixed land-use area (CBD, residential, commercial, tourist) which is mainly affected by attraction freight flows (Nuzzolo and Comi, 2014), while the origins of freight flows take place mainly in the peripheral areas of Municipality. The analysis highlights freight movements in the study area amounting to about 15,000 tons per day and more than 66% is destined to shops or food-and-drink outlets. In terms of freight segmentation, 36% consists of foodstuffs (about 16% is dispatched to restaurants and cafe, and 20% to retailers), 61% consists of other end-consumer products (e.g. household and health products), and the remaining 3% are goods related to services. To analyse the system, the area of the municipality of Rome was divided into 99 traffic zones with a level of detail which increases as the inner area was approached. The inner area consisted of 16 traffic zones.

The sub-systems presented in Section 3 above were specified and calibrated, as reported below. The modelling system was specified through easy-to-capture variables (especially for its forecasting use) represented by level-of-service attributes and aggregate socio-economic variables, such as number of employees. The presented models are the result of several specifications and calibrations based on different combinations of possible attributes. In the following, models that performed the best statistical significances are reported. Models were calibrated using Generalised Least Squares (GLS) or the Maximum Likelihood (ML) estimators in relation to the availability of data and to their statistical reliability.

4.2. The quantity model sub-system

Referring to the general architecture described in Section 3, the first model is the *attraction model* which allows us to obtain the average flow of freight that arrives in each zone of the study area in order to satisfy end-consumer demand. In general, each end consumer can purchase the goods required in different shops or, in the case of some freight types, he/she can buy or consume them in commercial concerns such as cafés and restaurants. The attraction model is a regressive model in which the average daily quantity of freight attracted by zone d, $Q_{.d}$, is estimated as follows:

$$Q_{.d} = \beta_{AD} \cdot AD_d + \beta_{ASA} \cdot ASA_d \qquad [t/\text{day}] \tag{6}$$

where

- AD_d is the total number of retail employees in zone d;
- ASA_d is a dummy variable equal to 1 if the proportion of retail employees to inhabitants in the zone d is higher than 35%;
- β_{AD} and β_{ASA} are parameters to be calibrated.

Such models were calibrated according to seven types of goods (Table 3): foodstuffs, home accessories, stationery, clothing, building materials, household and personal hygiene, and other goods. The reported models were calibrated employing

Table 3
Attraction and acquisition: calibration results.

Model	Freight type	Attribute	Parameter (*t–st* value)
Attraction	Foodstuffs	Retail employees	0.06 (1.9)
	(R^2 = 0.91)	ASA_d	599.7 (5.9)
	Home accessories	Retail employees	1.6 (2.5)
	(R^2 = 0.79)	ASA_d	240.7 (2.5)
	Stationery	Retail employees	2.9 (1.9)
	(R^2 = 0.89)	ASA_d	311.3 (4.9)
	Clothing	Retail employees	0.1 (3.0)
	(R^2 = 0.75)	ASA_d	134.5 (3.2)
	Household and personal hygiene	Retail employees	0.1 (1.9)
	(R^2 = 0.59)	ASA_d	41.7 (2.4)
	Building	Retail employees	1.3 (8.9)
	(R^2 = 0.89)		
	Other goods	Retail employees	1.2 (3.5)
	(R^2 = 0.80)	ASA_d	191.1 (3.5)
Acquisition	Foodstuffs	Warehouse employees	2.1 (1.9)
	(R^2 = 0.45)	Travel cost (km)	−0.05 (1.9)
	Remaining goods	Warehouse employees	0.13 (2.6)
	(R^2 = 0.52)	Travel cost (km)	−0.08 (2.8)

the Generalised Least Squares (GLS) method. First, the freight quantity attracted by each traffic zone d was obtained from survey data ($\widehat{Q}_{.d}$), and then the parameters (β) were estimated solving the following expression:

$$\min_{\beta} Q = \sum_{d} [Q_{.d} - \widehat{Q}_{.d}]^2$$

The capability to reproduce the revealed observations was measured by the coefficient of determination R^2 ($R^2 = 1 - SSE/SST$, where SSE is the sum of square errors and SST is the total sum of squares).

All parameters are correct in sign and are statistically significant as shown by t–st values. The ability of the models to reproduce the revealed values is shown by R^2 values similar to those reported in the literature for such models (Washington et al., 2011; Ibeas et al., 2012; Nuzzolo et al., 2013). Results highlight that for all types of freight the variable ASA_d is statistically significant and its weight is not particularly high in the attracted freight estimation.

In order to simulate the origin of freight for each attraction zone within the study area, the *acquisition model* was used. It simulates the choice of an origin among possible alternatives to get the freight to be sold. Random utility models in a gravitational form were specified and calibrated. The share of freight attracted by zone d coming from zone o (e.g. places where production places/firms, distribution centres, warehouses are located) is obtained as follows:

$$p[o/d] = (AI_o)^{\beta_1} \cdot C_{od}^{\beta 2} \Big/ \sum_{o'} (AI_{o'})^{\beta_1} \cdot C_{o'd}^{\beta 2} \quad (7)$$

where

- $p[o/d]$ is the probability that the freight attracted by zone d comes from zone o;
- AI_o is the number of warehouse employees of zone o;
- C_{od} is the travel distance between o and d;
- β_1 and β_2 are parameters to be calibrated (Table 3).

The calibration was performed using the GLS method. On the basis of traffic counts and truck-driver interviews, the quantity O–D flows ($\widehat{Q}_{od}$) were obtained. Then, the parameters (β) were estimated by solving the following expression:

$$\min_{\beta} Q = \sum_{od} [Q_{od} - \widehat{Q}_{od}]^2$$

where Q_{od} ($=Q_{.d} \cdot p[o/d]$) is the simulated quantity O–D flow.

The capability to reproduce the revealed observations was measured by the coefficient of determination R^2.

Even if acquisition models were calibrated for all previous identified freight types, similar results were obtained for freight types other than foodstuffs. Thus, only one acquisition model was calibrated for all freight types other from foodstuffs. For this reason, Table 3 reports two sets of parameters: the first for foodstuffs and the second for the remaining freight types. On analysing the calibration results it emerges that the number of employees has a high weight for foodstuffs, while the weight of travel cost (travel distance) is quite similar. Also in this case, the R^2 values are similar to those reported in the literature for such models (Washington et al., 2011; Ibeas et al., 2012; Nuzzolo et al., 2013).

Once the above two models were specified and calibrated, they were applied to the inner city of Rome in order to test the model's ability to reproduce the revealed quantity O–D flows. Fig. 4 reports a comparison between the revealed and

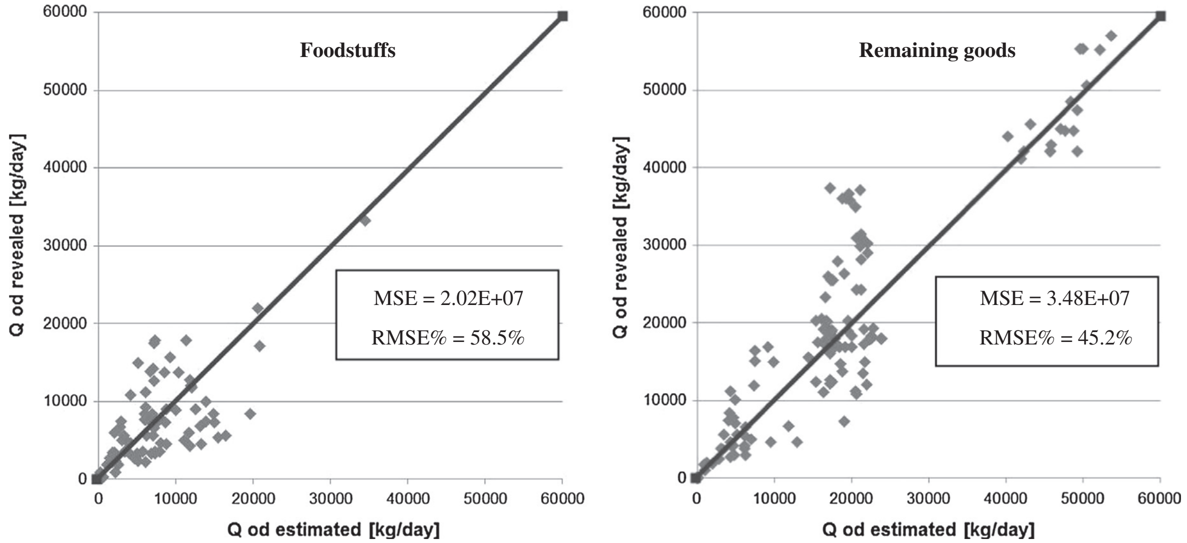

Fig. 4. Revealed vs. estimated freight quantity O–D flows [kg/day].

estimated quantity O–D flows both for foodstuffs and remaining good. The Mean Square Error (*MSE*) and the ratio between the square root of the Mean Square Error and the average demand (*RMSE%*) are also given. The estimates for foodstuffs O–D quantity flows are slightly scattered. However, the model for remaining goods yields better results, particularly because the results are less fluctuating. Further analyses are in progress to verify the dispersion of foodstuff estimates, including other socio-economic data in the acquisition model.

Attraction and acquisition models highlight the spatial distribution of commodity exchanges according to residential, commercial and service activities. In particular, the attraction model gives the freight quantity required in each traffic zone, and further developments are in progress in order to investigate how urban policies, modifying the transportation attributes for passengers or the retail network, can influence customer demand and hence the attracted goods quantity. The acquisition model allows us to evaluate the catchment area of warehouses as well as the urban distribution centres.

The quantity O–D matrices per transport service-type are obtained using a *transport service type model*. From retailer interview data, a binomial logit model was calibrated with two types of transport service: retailers on own account (c_{oa}) and other transport service types (c_{tp}). The calibration was performed by Maximum Likelihood (ML) method and the model capability to reproduce the choice made by sample was measured by ρ^2 statistic. The systematic function of the two identified transport service alternatives was expressed as follows:

$$\begin{aligned} V_{c_{oa}} &= \underset{(1.6)}{0.032} \cdot PC + \underset{(3.4)}{1.008} \\ V_{c_{tp}} &= \underset{(6.3)}{1.97} \cdot PROD + \underset{(7.8)}{2.56} \cdot CD + \underset{(6.4)}{1.82} \cdot WH + \underset{(1.5)}{0.023} \cdot EM + \underset{(1.3)}{0.6} \cdot q \end{aligned} \qquad \rho^2 = 0.21 \tag{8}$$

where

- $V_{c_{oa}}$ is the systematic utility for transport service type c_{oa} (on own account);
- $V_{c_{tp}}$ is the systematic utility for transport service type c_{tp} (by other transport service types);
- *PC* is a dummy variable equal to 1 if the restocked shop is a *food-and-drink outlet* (e.g. café, restaurant), 0 otherwise;
- *PROD* is a dummy variable equal to 1 if the restocked freight arrives from the *producer*, 0 otherwise;
- *CD* is a dummy variable equal to 1 if the restocked freight arrives from a *distribution centre*, 0 otherwise;
- *WH* is a dummy variable equal to 1 if the restocked freight arrives from a *wholesaler*, 0 otherwise;
- *EM* is the number of employees at the shop to be restocked;
- q is the average *shipment size*, expressed in tonnes.

As revealed by surveys, we can see that the probability of being restocked by other transport service types rises if freight comes from a distribution centre. This probability also increases with the number of employees at the shop and with shipment size. For food-and-drink outlets, the probability of restocking on own account is higher than shops. The model allows us to evaluate the impacts due to the implementation of infrastructure (e.g. urban distribution centre) and traffic management measures, such as factors that could modify shipment size.

4.3. The delivery model sub-system

In order to obtain the delivery O–D matrices, the average delivered quantity (*shipment size*), $q[r]$, was estimated. The literature contains some models developed for shipment size, mainly referring to intercity transport (de Jong and Ben-Akiva, 2007; Rich et al., 2009).

As regards retailer interviews, the shipment size for retailer i (i.e. shop or food-and-drink outlet), regardless of the transport service type (i.e. $\forall r$), can be expressed as a linear function of attributes related to socio-economic data as follows:

$$q^i = \underset{(5.3)}{5.83} \cdot EM^i + \underset{(3.8)}{95.17} \cdot STORE + \underset{(1.6)}{32.71} \cdot PC + \underset{(5.2)}{130.63} \cdot MR \quad [\text{kg/delivery}] \quad R^2 = 0.56 \tag{9}$$

where

- q^i is the average quantity delivered to shop i, expressed in kg;
- EM^i is the number of employees at shop i;
- *STORE* is a dummy variable equal to 1 if there is a depot, 0 otherwise;
- *PC* is a dummy variable equal to 1 if the restocked outlet is a *food-and-drink outlet* (e.g. café, restaurant), 0 otherwise;
- *MR* is a dummy variable equal to 1 if the restocking occurs before noon (i.e. in the morning), 0 otherwise.

The model was calibrated through the GLS method. The results show that during the morning the delivered quantity is greater than in the afternoon. Fig. 5 reports a comparison between the revealed and estimated deliveries both for foodstuffs and remaining goods. The results are encouraging: the model reproduces actual delivery movements quite well.

The delivery O–D flows can then be split by delivery time period τ. In many city centres around the world, as confirmed by our test cases and by the literature (Quak and de Koster, 2008; Sathaye et al., 2010), time is constrained by governance regulations: the public authorities define one or two time windows (e.g. one in the morning between 8:00 and 10:00 am and one in the afternoon). For this reason, our *delivery time period model* is statistic-descriptive. In Rome for many freight types, the retailers prefer to be restocked in the morning before opening time (about 60% of interviewees). In fact, purchases of some non-durable goods mainly occur in the morning, whereas durable goods are generally purchased in the afternoon. Thus retailers prefer to receive freight in the morning in order to reduce interference with customers.

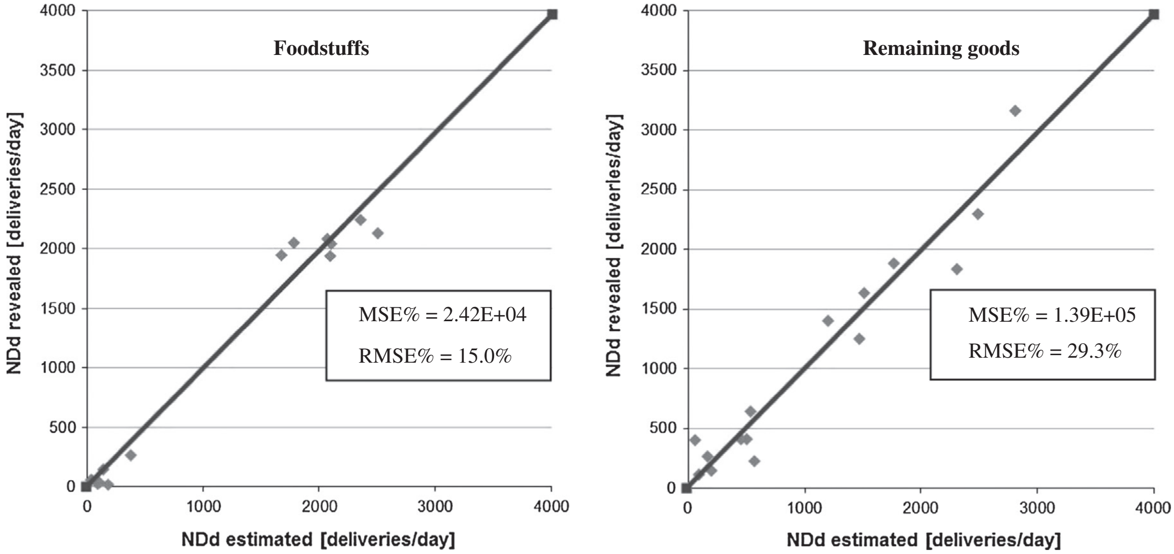

Fig. 5. Revealed vs. estimated attracted delivery flows [deliveries/day].

4.4. The vehicle model sub-system

The delivery O–D matrices now have to convert into vehicle O–D matrices. From survey data and the literature (Figliozzi, 2007, 2010), it emerged that the departure time of a tour is strictly related to the number of stops per tour, the number of stops per tour influences the type of vehicle used, and the type of vehicle is related to shipment size, which in turn depends on the characteristics of the shops of the destination zone. The models are structured to point out these relationships, considering that the choice process can be considered as a hierarchical choice process, where each choice dimension can be influenced by one another.

The survey analysis also pointed out that restockers:

- tend to leave from the warehouse in the early morning to arrive at shops at opening; as shown in Fig. 6, a retailer on own account prefers to restock his/her shop in the morning, while wholesalers and carriers also undertake few journeys in the afternoon;
- have a high number of round trips if they are located in a zone with high level of accessibility because round trips allow them to reduce journey operation planning; generally, retailers prefer round trips, while carriers prefer tours with more than two stops;
- in moving foodstuffs, undertake tours with a large number of stops;
- prefer light goods vehicles for tours with few stops.

In the following using a sequential approach the calibration of the above models (see Section 3.3) is described.

In Rome the distribution of delivery tour departure times follows the pattern of Fig. 6, and the *delivery tour departure time model* in question is a statistic-descriptive model strictly related to network performance (i.e. effects of congestion on travel time).

The *trip chain order model* allows us to define the distribution of deliveries that characterise the tour. While in Nuzzolo et al. (2012a) we find an aggregate logit model (regardless of the transport service type) with three alternatives (i.e. one stop, two and more than two stops), the proposed modelling system includes three different models according to three transport service types: retailer on own account, wholesaler on own account and carrier. For example, the model calibrated for the wholesaler on own account yielded the identification of four classes of tours with one delivery (round trip), two, three and more than three deliveries. A multinomial logit model was calibrated (by Maximum Likelihood method) and the systematic utilities of each alternative were expressed as follows:

$$\begin{aligned}
V_1 &= \underset{(2.5)}{2.430} + \underset{(1.6)}{0.252} \cdot VEH \\
V_2 &= -\underset{(-1.1)}{0.399} \cdot VEH - \underset{(-2.1)}{0.075} \cdot \ln(IAA_o) - \underset{(-1.7)}{0.151} \cdot q + \underset{(2.1)}{0.965} \cdot FGT + \underset{(2.6)}{2.429} \qquad \rho^2 = 0.18 \\
V_3 &= -\underset{(-1.1)}{0.042} \cdot \ln(IAA_o) + \underset{(2.7)}{1.381} \cdot FGT + \underset{(1.8)}{1.788} \\
V_{>3} &= -\underset{(-1.5)}{0.799} \cdot VEH - \underset{(-1.4)}{0.082} \cdot \ln(IAA_o) - \underset{(-1.5)}{0.195} \cdot q + \underset{(3.1)}{2.512} \cdot FGT
\end{aligned} \tag{10}$$

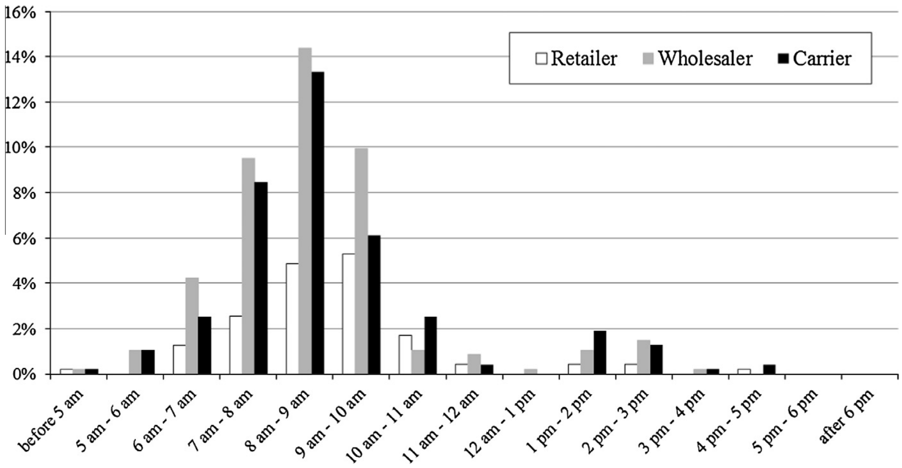

Fig. 6. Departure time from warehouses.

where

- *VEH* is a dummy variable equal to 1 if the vehicle used is a Light Goods Vehicle, 0 otherwise;
- IAA_o is the retailer accessibility index of zone *o*, from which the tour departs (e.g. warehouse location);
- *q* is the average quantity of freight delivered at each stop (i.e. delivery point) along the tour, expressed in tons;
- *FGT* is a dummy variable equal to 1 if the delivered freight belongs to the *foodstuffs* class, 0 otherwise.

The retailer accessibility index IAA_o was calculated as:

$$IAA_o = [AA_o - \min_z(AA_z)]/[\max_z(AA_z) - \min_z(AA_z)]$$

where AA_x is the accessibility of zone *x* estimated as:

$$AA_x = \sum_j (UL_j)^{6.334} \cdot \exp[-3.913 \cdot dist_{xj}]$$

with

- UL_j the number of retail establishments of zone *j* to be restocked;
- $dist_{xj}$ the distance between zone *x* and *j*, calculated on the road network according to the path of minimum generalised travel cost, expressed in km.

This model allows us to assess the city logistics measures impacting on Level-of-Service attributes, and thus the number of deliveries per tour. Implementation of measures affecting types of allowed vehicles could influence the transported load and, thus, the number of deliveries on the delivery tour. The calibration results show the important role of the accessibility of the origin zone; in fact, they have revealed that on increasing accessibility, the number of deliveries per tour decreases. It confirms that the restocker prefers to do round trips if the warehouse is located in a zone with a high accessibility as it allows them to reduce the operational complexity of tour management. The probability of having tours with more than two stops increases for foodstuffs. Finally, as expected, the probability of having round trips increases for Light Goods Vehicles and small delivered quantities. However, the number of stops/deliveries per tour could be modified by the implementation of city logistics solutions pushing towards more efficient transport services in terms of transported loads and generalised travel cost. Such solutions could be as follows:

- time windows modifying accessibility could increase the number of tours, which are usually non-optimised in terms of transported load;
- vehicle constraints (e.g. weight) reducing the transported load could mean tours with few deliveries;
- incentives to carriers (third parties) could lead to optimised tours;
- freight class, city logistics measures should point out foodstuffs restocking tours.

The journeys undertaken coming from zone *o* can then be characterised by vehicle type using a *vehicle type model*. In the literature, we mainly find statistic-descriptive models (Nuzzolo et al., 2010b) or probabilistic-behavioural models for carriers (Wang and Hu, 2012), while from the retail survey results, it was possible to investigate which vehicle is used by the retailer on own account for restocking. Three different types of vehicles were identified:

- car (e.g. SUV, station-wagon);
- goods vehicles with gross loads under 1.5 ton (i.e. LGVs);
- goods vehicles with gross loads between 1.5 and 3.5 tons (i.e. MGVs).

Referring to the transport service type c_{oa} (retailer on own account), a multinomial logit model was calibrated applying the ML method. The systematic utility to use vehicle type v was expressed as follows:

$$\begin{aligned} V_{car} &= \underset{(3.4)}{1.01} \\ V_{lgv} &= \underset{(2.0)}{0.003} \cdot EM + \underset{(2.2)}{0.5} \cdot q + \underset{(3.4)}{0.05} \cdot ASA_{lgv} \qquad \rho^2 = 0.38 \\ V_{mgv} &= \underset{(12.2)}{0.004} \cdot EM + \underset{(3.4)}{3.0} \cdot q + \underset{(1.7)}{0.006} \cdot STORE \end{aligned} \tag{11}$$

where

- V_{car} is the systematic utility of using a *car*;
- V_{lgv} is the systematic utility of using a *Light Goods Vehicle (LGV)*;
- V_{mgv} is the systematic utility of using a *Medium Goods Vehicle (MGV)*;
- EM is the number of employees at the shop;
- q is the average *shipment size*, expressed in tons;
- ASA_{lgv} is the Alternative Specific Attribute equal to 1 for *Light Goods Vehicles*, 0 otherwise;
- $STORE$ is the surface area of store, expressed in m^2.

It has to be noted that retailers with few employees and a small depot prefer to use their car or light goods vehicles with more than one trip per day and bring only freight that is sure to sell in the near future.

Referring to the *delivery location model*, the survey revealed that different behaviour could be followed by a restocker in the choice of the first destination within a tour and in choosing subsequent stops within the same tour. A set of multinomial logit models which include different combinations of independent variables were tested, and the ML method was used. The statistically best results for own-account wholesalers and carriers were obtained considering the systematic utility related to the first zone d_j^1 as follows:

$$V_{d_j^1} = \underset{(3.8)}{0.213} \cdot \ln\left(\mathrm{AD}_{d_j^1}\right) - \underset{(-4.8)}{0.028} \cdot \mathrm{dist}_{\mathrm{od}_j^1} + \underset{(2.1)}{2.03} \cdot \mathrm{DS}_{\mathrm{od}_j^1} + \underset{(9.5)}{7.84} \cdot \mathrm{IAA}_{d_j^1} \qquad \rho^2 = 0.33 \tag{12}$$

where

- $AD_{d_j^1}$ is the number of retail employees in zone d_j;
- $dist_{od_j^1}$ is the distance between zone o and d_j, calculated on the road network according to the path of minimum generalised travel cost and expressed in km;
- $DS_{od_j^1}$ is the share of deliveries on pair od_j with respect to all deliveries departing from zone o;
- $IAA_{d_j^1}$ is the retailer accessibility of zone d_j.

Once again referring to own-account wholesalers and carriers, in order to define the sequence of next delivery location stops, a multinomial logit model was calibrated using ML method. The systematic utility function related to zone d, V_d, was expressed as a linear function of two sets of attributes, variables associated with a destination alternative (e.g. number of employees) and "memory" variables representing the history of the tour (e.g. distance to be covered in order to reach the next location up to the cumulative covered distance):

$$V_{d_j^{k+1}} = \underset{(3.5)}{0.291} \cdot \ln\left(\mathrm{AD}_{d_j^{k+1}}\right) - \underset{(-5.2)}{0.325} \cdot \mathrm{dist}_{d_i^k d_j^{k+1}} + \underset{(3.2)}{8.408} \cdot \mathrm{DS}_{od_j^{k+1}} - \underset{(-4.1)}{1.655} \cdot \ln\left(\mathrm{HT}_{d_j^{k+1}}\right) + \underset{(2.5)}{1.064} \cdot \mathrm{ASA}_{d_j^{k+1}=d_i^k} \quad \rho^2 = 0.25 \tag{13}$$

where

- $V_{d_j^{k+1}}$ is the systematic utility of delivering in zone d_j delivery $(k + 1)$ conditional on having previously delivered in zone d_i delivery k within a tour with n stops/deliveries departing from a given zone o;
- $AD_{d_j^{k+1}}$ is the number of retail employees in zone d_j;
- $dist_{d_i^k d_j^{k+1}}$ is the distance between zone d_i^k and d_j^{k+1}, calculated on the road network according to the path of minimum generalised travel cost and expressed in km;
- $DS_{od_j^{k+1}}$ is the share of deliveries on od_j^{k+1} pair with respect to all deliveries departing from zone o;
- $HT_{d_j^{k+1}}$ is the ratio between the distance to be covered to reach the next delivery location and the current distance covered;
- $ASA_{d_j^{k+1}=d_i^k}$ is a dummy variable equal to 1 if the next stop is within the same current zone, 0 otherwise.

The results show that the probability of choosing for the next delivery a zone that is easy to reach and where many deliveries should be performed is higher. The sign of the memory parameter demonstrates that the systematic utility of choosing a destination is a cost function of the distance from the current location. It implies that destinations far away from the current location are those which have a lower probability of being chosen.

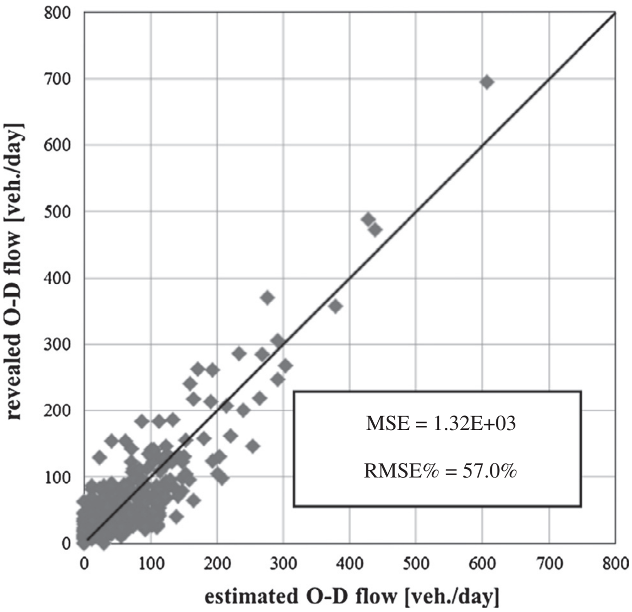

Fig. 7. Revealed vs. estimated freight vehicle O–D flows.

However, the delivery location choice model allows us to detect the impacts due to implementation of city logistics that can modify the generalised travel cost and hence accessibility:

- time windows, pricing and vehicle constraints modify accessibility, driving toward long trips within the same tour;
- transit points or urban distribution centres allow optimised restocking tours to be increased.

Fig. 7 plots the comparison between the revealed and estimated freight vehicle O–D flows. The results confirm the goodness of model framework. In fact, the model quite well reproduces the current O–D flows as confirmed by comparison with the 45° line, and the low values of *MSE*. Further analyses are in progress in order to improve the *RMSE%* value.

The proposed model is used to assess some measures that Municipality of Rome is planning in order to improve the city centre sustainability. For example, it was applied in order to assess a new implementing scenario with no access to Euro 2 vehicles from 2012 and no access to Euro 3 from 2013. The model allowed to obtain the freight vehicle O–D flows, which assigned to the road network provide pollutant emissions in relation to average link flows and average link speed. Even if further *ex ante* assessments are in progress, the preliminary results point out that good result can be obtained in terms of pollutant reductions: 6% of matter particulate reduction in 2012, and 33% from 2013.

5. Conclusions and further developments

This paper presented a modelling system developed to support *ex ante* assessment of city logistics policies/measures. In order to test its goodness, the proposed system was calibrated on the basis of a real test case (the city of Rome). Models were specified within the quantity/delivery/vehicle mixed modelling approach. Quantity was used since it enables the mechanisms underlying freight transport demand to be well captured. Delivery allows us to improve the definition of delivery tours, while vehicle is required by assignment model for the estimation of road link performances.

This modelling system allowed us to take into account the influence of: the economic characteristics of a traffic zone on attracted freight traffic, the localisation of freight centres (e.g. distribution centres, warehouses) on freight traffic generated for each zone, the characteristics of shops with related depots and the shipment size on the choice of service type (retailer on own account, wholesaler on own account, carrier) and vehicle type. This system of models also considers the pattern of delivery tours according to freight type, origin and destination zone accessibility, vehicle type, shipment size and capacity of the zone attraction.

The calibrated models can be considered the results of the first calibration phases developed to test the goodness of the general architecture of the proposed modelling system. Although these first results confirm the goodness of the approach used, further analysis is required to validate the modelling system. Other calibrations considering different structures (e.g. nested logit) and distributions of random residual (i.e. mixed logit and Probit) are in progress.

This research is like to proceed in the following main directions: development of probabilistic-behavioural models for simulating the attraction and acquisition considering other socio-economic variables, e.g. economic level of the study area (quantity model sub-system); development of probabilistic-behavioural models to investigate how other attributes could influence the definition of trip-chain order or the choice of delivery location; development of pick-up (delivery) choice location models for retailers; modelling of choice set generation within the delivery location model; analysis of transferability of these first results that is in progress for the city of Santander (northern Spain), where similar surveys have been recently carried out (Nuzzolo et al., 2012b).

Further improvements in this study may also include the development of a general modelling framework in order to simulate goods movements at urban scale combining urban passenger travel and commodity flows and taking into account the presence of large-scale retail trade. The extensions of results from the inner-city area to the whole city should be investigated. Finally, the long-term effects can also be considered through land-use interactions (e.g. LUTI-type modelling), mainly developing models of localisation of urban freight centres and large shopping centres.

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