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ORIGINAL PAPER

An activity-based approach for complex travel behaviour modelling

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Abstract
Purpose In this paper an activity-based modelling framework is presented. It enhances many of the characteristics of existing approaches and enables a more accurate travel demand modelling.
Methods The model approach proposed explicitly takes into account the households' role, as well as time and space constraints. Issues related to activity participation and activity planning are explicitly addressed with respect to the horizon of a whole week. The proposed framework allows to reproduce activity lists and activity patterns in an explicit and consistent way. As a consequence, time and mode characteristics of travel demand are more accurately computed. The approach has been designed in order to capture interactions among households members and to explicitly represent trip-chains and relationships between trips within activity patterns. In this paper a comprehensive formalisation of the modelling framework is presented and part of it is estimated on the basis of ad-hoc collected data.
Application The modelling framework has been then applied to the Naples' metropolitan area (southern Italy), a catchment area with about three million inhabitants.
Results and Conclusions The proposed framework has shown a satisfying flexibility, as well as a good ability in reproducing real data. It seems to be a good compromise between accuracy and operative issues, which improves the range of reproducible mobility phenomena and the accuracy of this reproduction and at the same time it moves some step forward the practical applicability of activity-based approaches.

Keywords Activity-based · Demand model · Travel behaviours · Nested logit · Transport model · RP survey

1 Introduction

As known, travel demand derives from the need to carry out activities in multiple locations. In the last decades, the increased economic and social welfare has drastically changed the shape of our style-of-life and induced an increasing complexity in our activity patterns and travel behaviours. As a consequence an increased congestion can be observed also in off-peak periods and often across the whole day. The main implication of this increased complexity is the need of modelling the whole day and using, at this aim, more complex and rigorous travel demand modelling approaches.

The *trip-based* approach is certainly the most simple and popular. It approximates mobility phenomena by considering one-way trips. In other terms, all trips carried out by individuals in the whole day are modelled independently from their reciprocal relationships. An early example of a comprehensive trip-based approach was developed by the MTC (Metropolitan Transportation Commission) for the San Francisco Bay Area [1]. Other relevant examples can be found in [2] and in [3]. In [4] Horowitz presented a trip

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frequency, destination and mode choice modelling framework able to incorporate (still within a trip-based framework) some inter-trip dependencies.

The *trip chaining* approach is able to represent relationships between the different trips that constitute an individual travel chain, and thus considerably generalize conventional trip-based models. Trip-chain models have been studied for several years; however, they have been rarely implemented in real contexts and seldom in complex urban areas. Early examples can be found in late 1970s (see for instance [5]). Relevant experiments have been made in 1980s in Netherlands [6, 7]. Relatively more recent trip-chain modelling frameworks have been developed for Stockholm [8] and Salerno [9]. However, the trip-chain approach does not address the fundamental factors that determine the actual configuration of particular trip chains and round trips. To address such questions, it is necessary to explicitly consider the activities that individuals and households undertake, and that give rise to transportation demand.

The *activity-based* approach just derives travel patterns from a representation of these more basic activities by taking into account the interaction among individuals participating to the same set of activities as well as all temporal and physical constraints among single trips. Jones in [10] has defined some characteristics that an activity-based model should have:

1. travel demand should be treated as a derived demand;
2. activity sequences should be considered, rather than trips or trip-chains;
3. households should be considered as decision-making units;
4. spatial and temporal constraints should be explicitly taken into account;
5. activity scheduling over time and space should be considered.

In past years significant efforts have been devoted to refine the activity-based theory. However, few consistent specifications have been presented and most of them are not suitable from an operational standpoint and/or are incomplete with respect to the representation of all the Jones' implications. In [11] some aspects related to activity duration (*time-budgeting*) and *activity scheduling* have been addressed through coupled discrete/continuous choice models. In [12] day-to-day variations in travel patterns have been analysed and in [13] activities and travel choices within a weekly activity pattern have been modelled. In [14] an activity-based-like approach has been restricted to trip generation, while in [15] the aim of the analysis has been restricted to deal with consistency issues in mode-choices within sequences of trips. In [16] enhanced methods for modelling activity duration have been introduced while in [17] a model specification has been proposed addressing most of the Jones' topics. Other relevant contributions to the development of the activity-based approach can be found in [18–24].

The attempt of this paper is to move a further step toward an advanced and comprehensive formulation of the activity-based approach, allowing for a better simulation tool for the estimation of demand matrices. The paper is organized in four sections. Section 2 shows an example clarifying the main limits of *non activity-based* approaches. In Section 3 a comprehensive theoretical activity based framework trying to overcome all these limits is proposed. In Section 4 part of the proposed modelling framework is estimated on the basis of ad hoc collected data and then applied to a real case study. Section 5 reports some conclusive remarks.

2 Limits of non activity-based approaches

This section shows an example aimed at clarifying the main limits and errors of *non activity-based* approaches in reproducing complex transport behaviours.

Consider a household composed by a couple of young employees with two children. Assume they own one car and have to carry out the following activities in a given work-day:

– working (*W*); both household members work; one for 8 h a day (8:00 to 16:00) and the other for 4 h a day (10:00 to 14:00);
– shopping at supermarket (*S*);
– pick up and delivering of children at (the same) school (P/D);

The activity list is completed by adding the *staying at home* activity (*H*). Assume the planning of daily activities for member 1 of the household (8 h working-time) consists in driving children school, going work and after work taking children back, going to the supermarket and finally coming back home. In the meanwhile, members 2 (4 h working-time) goes working by bus and after work comes back home. The resulting activity lists, activity patterns and the related trip-chains are summarised in Fig. 1.

For sake of simplicity, trip durations are not explicitly depicted in the previous figure; these are assumed to be somehow included within the activity durations. Transport modes for any trip-chain are indicated in the figure.

Now assume that, for some reasons, from 16:00 to 17:00 congestion increases and member 1 is no longer able to take back children on time in his/her way back from work. This activity will therefore be carried out by member 2 by using the car. Being more comfortable also going by car to the supermarket, the new plan for daily activities changes toward the one depicted in Fig. 2.

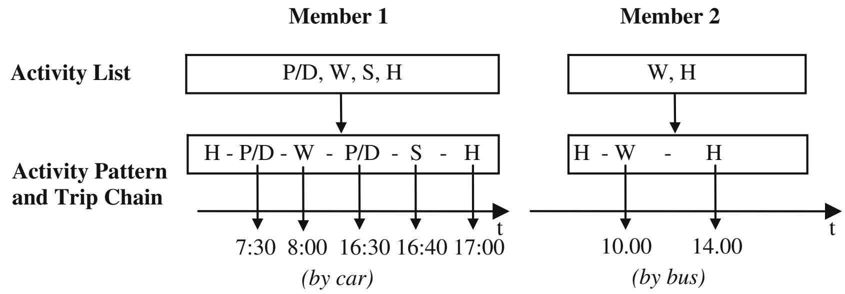

Fig. 1 Activity lists, activity patterns and trip-chains of the reference day

This example is useful in order to show how a congestion increase in a time slice of the day could cause change in the daily individual activity lists of a household and, consequently, in the activity patterns and trip chains of each individual. The result can be a significantly different number of trips (a counterintuitive increase, in this example), carried out in different periods of the day and with different modes (in the example with a counterintuitive increased use of the car).

It is worth noting that such a complex behaviour can be managed only through a fully deployed activity-pattern approach which endogenously deals with activity lists and activity patterns.

A (even sophisticated) trip-chain approach could reproduce, at most, how the above-mentioned increase of congestion can influence the trip chain organization of each individual (trip chains vs. round trips), as wtime-period and mode choices of secondary activities (P/D, S). It is worth noting that the final result could have been in our example a *tout-court* reduction of car use due to the increase of congestion, which is not the same result obtained by using the activity-based approach. Moreover, the reallocation of activities as well as of the car availability from one member of the household to the other cannot be reproduced by a trip-chain approach, with a consequent unsatisfactory modelling of the actual mobility of the whole household.

A trip based approach is even more limited since it could reproduce, at most, frequency and car use reduction for trips in the congestion period (for P/D and S activities), without considering at all how this congestion could influence the mobility pattern in different time-periods of the day.

In the next section an activity-based approach is formalised with the aim of addressing all issues highlighted by the previous example.

3 A theoretical reference framework

In this section a possible theoretical formulation for the specification of a system of models in activity-based-style will be presented. The overall structure of the proposed framework is shared by several models and is shown in Fig. 3.

This particular architecture aims to explicitly model all travel phenomena related to activity pattern and travel choices: from household weekly activities to individual single trips. It is composed by five sub-models:

1. *Weekly Household Activity Model (WHAM)*, which reproduces the number and types of activities carried out by households within a week;
2. *Daily Household Activity Model (DHAM)*, which reproduces the distribution of all household activities over days of the week;
3. *Daily Individual Activity List Model (DIALM)*, which distributes daily activities among the household components;
4. *Daily Individual Activity Pattern Model (DIAPM)*, which combines the individual daily activities leading to actual activity patterns and related trip-chain sequences;
5. *Trip chain Model*, which reproduces the organization of all trips provided within an activity pattern.

Figure 3 shows that each level is related to the previous and subsequent. The three upper levels refer to longer term

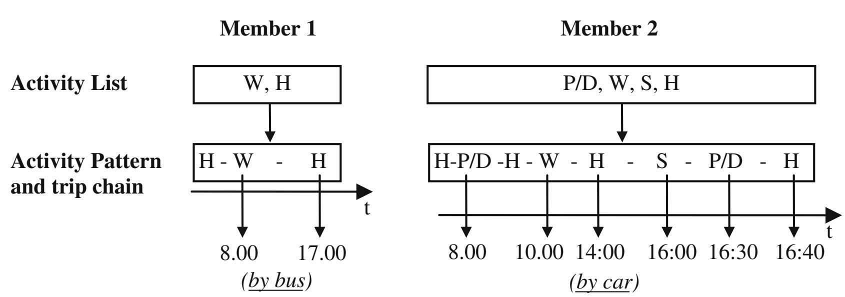

Fig. 2 Activity lists, activity patterns and trip-chains of the reference day after congestion increase

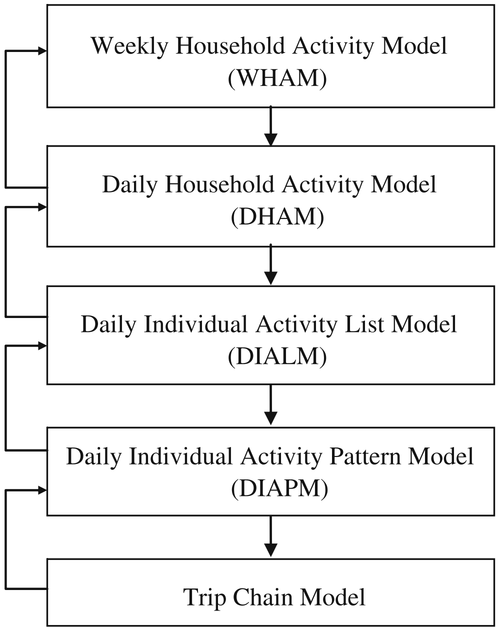

Fig. 3 Model Architecture

decisions, they reproduce the activity organization among household members in a fixed period of time. The latter two levels represent shorter term travel decisions. All the models of the overall framework will be formalised in this section, while in Section 4 the DIAPM and the Trip-chain models will be specified and estimated through ad-hoc collected data.

3.1 Weekly household activity model

The model aims to reproduce the whole set of activities carried out by a household within a week. *G*iven a list of possible activities (work, study, shopping, sport, etc.), the generic alternative w^i is given by the set of activities carried out by a household of type i within a week. Formally we may write:

$$w^i = (x^i_{w;1}, x^i_{w;2}, \ldots, x^i_{w;a}, \ldots, x^i_{w;n_a}) \qquad \forall i \in \{1, 2, \ldots, n_h\} \quad \forall w^i \in \{1, 2, \ldots, C^i\} \tag{1}$$

where:

- $x^i_{w;a}$ is the number of times that an activity of type a is performed by household i within a week in alternative w
- n_a is the number of possible activities
- n_h is the number of different household types
- C^i is the choice set i.e. the set of all possible weekly sets of activities for household i.

Just as an example, alternative w^i could be composed by: $x^i_{w,1} = 12$ work activities, $x^i_{w,2} = 8$ study activities and so on (assuming, for instance, that 1 stands for *Work* and 2 for *Study*).

Relevant attributes are the household's characteristics and may include the number and age of employed adults, the number and age of non-adults, the dwelling-place, income, number of driving licences, number of cars, etc. as well as a logsum variable related to the lower choice dimensions.

3.2 Daily household activity model

In this case the model aims to reproduce how the set of weekly activities identified by the previous model is split into daily activity sets. The generic alternative $d^i_{g/w}$, is given by any set of daily activities consistent with the weekly set of activities w^i. Formally we may write:

$$d^i_{g/w} = (x^i_{g/w;1}, x^i_{g/w;2}, \ldots, x^i_{g/w;a}, \ldots, x^i_{g/w;n_a}) \qquad \forall g \in \{1, 2, \ldots, n_g = 7\} \tag{2}$$

where:

- n_g (=7) is the number of days in a week
- $x^i_{g/w;a}$ is the number of times that an activity of type a is carried out during day$g$ by the household of type i given the weekly household set of activities w;

and the following constraints have to be satisfied:

$$\sum_{g=1}^{n_g} x^i_{g/w,a} = x^i_{w,a} \quad \forall a \in \{1, 2, \ldots, n_a\}, \quad \forall w^i \in C^i, \forall i \in \{1, 2, \ldots, n_h\} \tag{3}$$

For example if, as in the previous example, $x^i_{w,1} = 12$ work activities, $x^i_{w,2} = 8$ study activities, the following conditions have to be satisfied:

$$\sum_{g=1}^{7} x^i_{g/w,1} = 12, \quad \sum_{g=1}^{7} x^i_{g/w,2} = 8 \quad 1 = \text{Work}, 2 = \text{School}$$

Constraints (3) implicitly define the choice set $C^i_{g/w}$ of this choice dimension. However, it is useful in practical implementation to reduce the combinatorial complexity of the problem by dropping out unlike alternatives Relevant attributes are in principle similar to those of the previous models.

Note that the model can be also formalized in an aggregate way by defining the average weekday (holiday) $\overline{g}_{wd}(\overline{g}_{hd})$. In this case the generic alternative becomes:

$$d^i_{\overline{g}/w} = (x^i_{\overline{g}/w;1}, x^i_{\overline{g}/w;2}, \ldots, x^i_{\overline{g}/w;a}, \ldots, x^i_{\overline{g}/w;n_a}) \tag{2b}$$

and constraints (3) become:

$$5 \cdot x^i_{\overline{g}wd/w,a} + 2 \cdot x^i_{\overline{g}hd/w,a} = x^i_{w,a} \quad \forall a \in \{1, 2, \ldots, n_a\}, \quad \forall w^i \in C^i, \forall i \in \{1, 2, \ldots, n_h\} \tag{3b}$$

where *5* and *2* are the number of weekday and holiday in a week respectively.

3.3 Daily individual activity list model

This sub-model reproduces the distribution of daily activities among the components of a household. This leads to daily individual activity lists which are the starting points for reproducing the daily travel choices of each individual. In this case the generic alternative $k^i_{r/g,w}$ is given by the daily activity list of each component r of household i, i.e. types and numbers of activities he/she carries out during a day g given the daily set of household activities $d_{g/w}$:

$$k^i_{r/g,d_{g/w}} = (x^i_{r/g,d_{g/w};1}, \ldots, x^i_{r/g,d_{g/w};a}, \ldots, x^i_{r/g,d_{g/w};n_a}) \quad \forall r \in \{1,2\ldots,n^i_r\} \tag{4}$$

where:

$x^i_{r/g,dg/w;a}$ is the number of times that an activity of type a is carried out by component r of household i in day g, given the daily set of household activities $d_{g/w}$

n^i_r is the number of components of the type i household

and the following constraints have to be satisfied:

$$\sum_{r=1}^{n^i_r} x^i_{r/g,d_{g/w};a} = x^i_{g/w;a} \forall a \in \{1,2,\ldots,n_a\}, \quad \forall g \in \{1,2,\ldots,n_g = 7\}, \quad \forall w^i \in C^i, \forall i \in \{1,2,\ldots,n_h\} \tag{5}$$

Once again, constraints (5) implicitly define the choice set of this sub-model $\left(C^i_{r/g,w}\right)$ but in order to reduce the combinatorial complexity of the problem, this can be reduced by dropping out unlikely activity lists.

Relevant attributes are also in this case similar to those of the previous models but concern the specific individual and obviously include gender and occupational status.

Also in this case the model can be formalized in an aggregate way by considering the average day g. In this case the generic alternative becomes:

$$k^i_{r/\overline{g},d_{\overline{g}/w}} = (x^i_{r/\overline{g},d_{\overline{g}/w};1}, \ldots, x^i_{r/\overline{g},d_{\overline{g}/w};a}, \ldots, x^i_{r/\overline{g},d_{\overline{g}/w};n_a}) \quad \forall r \in \{1,2\ldots,n^i_r\} \tag{4b}$$

and constraints (5) become:

$$\sum_{r=1}^{n^i_r} x^i_{r/\overline{g},d_{\overline{g}/w};a} = x^i_{\overline{g}/w;a} \quad \forall a \in \{1,2,\ldots,n_a\}, \forall w^i \in C^i, \quad \forall i \in \{1,2,\ldots,n_h\} \tag{5b}$$

3.4 Activity pattern and trip chain models

This model reproduces how different activity patterns can be generated from a given daily individual activity list. Figure 4 exemplifies some possible activity patterns (right) which can be generated from a given daily individual activity list (left). The generic alternative $\pi^i_{r/k,g,d_{g/w}}$ represents the generic activity pattern π of component r of household i given the daily individual activity list k of the day g, the daily set of household activities d and the weeky set of household activities w.

It is worth noting that the daily individual activity list provides the number of times each activity is carried out within the day (one in Fig. 4), except for *home* which can be repeated several times. The number of times (minus one) activity *home* is repeated in a given activity pattern implicitly determines the number of trip-chains related to that activity pattern. For instance, three chains are associated to the second activity pattern in Fig. 4 (H-P/D-O-H-W-H-L-H) since activity *home* is replicated four times.

Also in this case the number of possible activity patterns which can be associated to each activity list can be reduced by considering only those which are chosen with a significant frequency in the sample.

Relevant attributes are also in this case socio-economic characteristics of the individual. The *logsum* variable related to the subsequent trip chain model includes the generalized costs of the different chains. Therefore the choice of the activity pattern is influenced by the network congestion at different times of the day.

Also in this case the model can be formalized in an aggregate way by considering the average day $\overline{g}$. Given an activity pattern (i.e. a given succession of trip chains), the role of the trip chain model is to reproduce when and how these trip chains are carried out within the day, introducing not only consistency within the generic trip chain but also among the different chains of the day, mainly in terms of activity duration and departure time. More details about these internal and external consistencies will be given in the following sections.

4 Specification, calibration and application

The proposed general formulation was partially specified (with respect to the *DIAPM* and the trip-chain model), calibrated and applied for travel demand modelling in the Naples metropolitan area (southern Italy), a catchment area with about three million inhabitants. The application should be considered as illustrative and not comprehensive: to reduce complexity, the model was applied to a single category: workers.

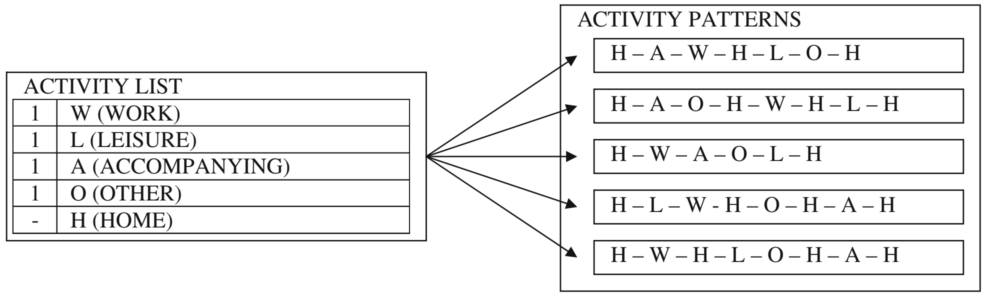

Fig. 4 Activity pattern production from a given activity list

Although all the proposed architecture could consistently use the discrete choice approach, the first three sub-models (*WHAM*, *DHAM* and *DIALM*) have been estimated exogenously according to a descriptive approach, following the results of a survey conducted on the Naples metropolitan area; this means that the results of the first three models are given and fixed.

According to the survey results, the activity patterns that have been verified as feasible (i.e., that are actually observed in the sample) consist either in home-based trip-chains or double tours. The incidence of more complex patterns was found to be negligible for workers in the Naples area.

A disaggregate estimation of activity pattern (*DIAPM*) and time-of-day choice models was performed, while an aggregate estimation (*parameter updating*) of destination and mode choice models was carried out starting from the results of a disaggregate calibration available for Naples demand models ([25]). The validation tests used are the ρ^2 and the *t-student* for the disaggregate calibration and the *Mean Absolute Percentage Deviation (MAPD)* for the aggregate one.

4.1 The survey

A fundamental aspect for the specification, calibration (parameter estimation) and implementation of a system of activity-based models is a properly designed database which can describe the observed pattern of urban travel mobility. The model system was specified and calibrated from a complex survey (extended overtime) carried out in the metropolitan area of Naples. A complex methodology was followed to collect extensive information, since travel and activity choices information must be gathered for all individuals of a household and for all the days of a week. The aim of the survey was to find out the household's and individual's "diary" throughout an entire week, in order both to analyse the phenomenon and generate a database for model specification and estimation. The sample consists of roughly 100 households, comprising 300 individuals, in the Naples urban area, who were asked about all their activities during a given week.

Table 1 Sample characteristics

Number of individuals per household	Number of households sampled	% incidence
1	9	9.5%
2	23	24.2%
3	20	21.1%
4	26	27.4%
5	14	14.7%
6	3	3.2%
total	95	100.0%

Some of the most significant results are reported briefly in the following tables. In particular, in Table 1, the percentages of households with different number of components are shown. As it can be seen, most of the households include 2, 3 or 4 components (24%, 21% and 27% of the households sampled respectively).

In Table 2, the average number of weekly activities per household typology are reported, distinguishing between in-house and out-door activities. As it can be seen, the total number of activities carried out on average by a single component of the household is quite independent by the number of components of the household: for example it is 29 for single households and about 28 for two, three and four-components households.

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Concerning the in-house activities it can be observed that *personal care* and Housework activities are more frequently carried out by single component households (4 weekly activities which represent the 36% of the total weekly activities). By contrast, 6 components households carry out these kind of activities 14 times in a week on average (i.e. 2.3 per person) which represent the 21% of the total weekly activities. An opposite trend can be observed for *leisure* activities which represent the 9% of

Table 2 Average number of weekly activities per household and number of components

		Number of individuals per household						Total
		1	2	3	4	5	6	
In-house activities	Work	0 (0%)	1 (4%)	1 (2%)	2 (4%)	1 (2%)	0 (0%)	5 (2%)
	Study	0 (0%)	4 (16%)	6 (14%)	9 (16%)	11 (21%)	8 (12%)	38 (15%)
	Personal care and housework	4 (36%)	6 (24%)	12 (29%)	17 (31%)	15 (29%)	14 (21%)	68 (27%)
	Leisure	1 (9%)	4 (16%)	11 (26%)	14 (25%)	13 (25%)	30 (45%)	73 (29%)
	Meal preparation	3 (27%)	4 (16%)	5 (12%)	6 (11%)	6 (12%)	4 (6%)	28 (11%)
	Other	3 (27%)	6 (24%)	7 (17%)	7 (13%)	6 (12%)	11 (16%)	40 (16%)
	Tot. in-house activities	11 (100%)	25 (100%)	42 (100%)	55 (100%)	52 (100%)	67 (100%)	252 (100%)
Out-door activities	Work	6 (33%)	6 (20%)	6 (14%)	11 (20%)	10 (18%)	18 (23%)	57 (21%)
	Study	3 (17%)	6 (20%)	7 (17%)	11 (20%)	11 (20%)	18 (23%)	56 (20%)
	Shopping	1 (6%)	2 (7%)	4 (10%)	4 (7%)	3 (5%)	2 (3%)	16 (6%)
	Food purchase	1 (6%)	3 (10%)	5 (12%)	5 (9%)	5 (9%)	5 (6%)	24 (9%)
	Sport	1 (6%)	1 (3%)	1 (2%)	2 (4%)	3 (5%)	3 (4%)	11 (4%)
	Leisure	2 (11%)	4 (13%)	8 (19%)	10 (18%)	12 (22%)	14 (18%)	50 (18%)
	Pick up and Delivery	0 (0%)	3 (10%)	2 (5%)	3 (5%)	2 (4%)	7 (9%)	17 (6%)
	Restaurant	2 (11%)	1 (3%)	2 (5%)	2 (4%)	1 (2%)	1 (1%)	9 (3%)
	Other	2 (11%)	4 (13%)	7 (17%)	8 (14%)	8 (15%)	9 (12%)	38 (14%)
	Tot. out-door activities	18 (100%)	30 (100%)	42 (100%)	56 (100%)	55 (100%)	77 (100%)	278 (100%)
total		29	55	84	111	107	144	530

the total weekly activities for single component household, the 16% for 2 components households, the 25% for 3, 4, and 5 components households and the 45% for 6 components households.

Concerning the out-door activities it can be observed that single component households carry out, on average, a higher percentage of *work* activities (33% versus about 20% for the other typology of households). Also in this case, *leisure* activities are carried out more frequently by households with higher number of components (11% and 13% for one and two components households respectively and about 20% for the others households typology).

Finally, Table 3 shows the activity patterns which are more frequently chosen by the workers in the sample.

Table 3 Worker activity patterns

Id.	Activity-patterns	%	Activity	
1	H-W-H	28.5%	H	Home
2	H-W-H-W-H	14.9%	W	Work
3	H-W-H-L-H	4.7%	L	Leisure
4	H-W-H-P/D-H	3.3%	P/D	Pick up and Delivery
5	H-W-H-O-H	2.7%	O	Other
	Total	54.2%		

As shown in the table, the most selected activity pattern in the sample is a H-W-H simple tour with work purpose (28.5%). Also the double tour with work purpose H-W-H-W-H has a high percentage, (14.9%). These results show that most of the workers perform only work-based trips. Moreover, the first five activity patterns represent more than the half of the sample and each of the other activity patterns (not reported in the table) are chosen by less than the 2% of the sample.

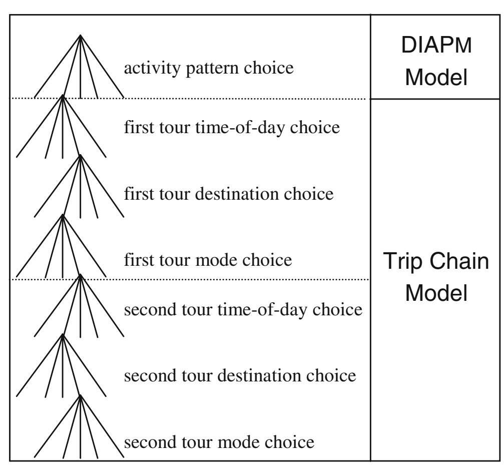

Fig. 5 Modelling architecture

4.2 Model specification and calibration

The choice dimensions considered for the application are (see Fig. 5):

- activity pattern choice (*DIAPM*);
- tour choices (*trip-chain Model*), consisting in:
  - (a) first tour:
    - (i) time-of-day choice;
    - (ii) destination choice
    - (iii) mode choice
  - (b) second tour
    - (i) time-of-day choice;
    - (ii) destination choice;
    - (iii) mode choice.

As stated above, in order to simplify the application, the survey results have been used to reduce the model choice sets. In particular, the choice set of the activity pattern model is that reported in Table 1.

The alternatives considered for the time-of-day choice of the trip-chain model (first and second tour) are shown in Table 4. Both for the first tour and for the second, a timeframe has been considered in which the individual could undertake his/her tour and activity. As regards the morning departure time for the first tour, a single timeframe (7:00–9:30) has been considered, according to what observed in the sample.

For the destination choice models (both for the first and second tours) the Naples urban area has been divided into 16 macro-zones representing the major districts, while for the mode choice models three alternatives have been taken into account: car, public transport (bus, metro, funicular, rail and pedestrian) and motorbike. The whole modelling system exhibits a Nested-Logit structure. Accordingly with the formalization used in Section 3, the following sub-models are considered:

(DIAPM)

- *activity pattern choice model*, reproduces the choice of the activity pattern π (with $\pi \in \{1,2,3,4,5\}$ see Table 3) for each origin zone o (with $o \in \{1,2,\ldots,16\}$); for the level of aggregation considered in the application the notation introduced in Section 3.4 was simplified;

Table 4 Time-of-day alternatives (first and second tour)

id	First tour		Second tour	
	Start	Finish	Start	Finish
1	7:00–9:30	12:30–15:00	15:00–17:30	15:00–17:30
2	7:00–9:30	15:00–17:30	15:00–17:30	17:30–20:00
3	7:00–9:30	17:30–20:00	17:30–20:00	17:30–20:00

(Trip-Chain Model)

- *first tour time-of-day choice model*, reproduces the choice of the time-of-day I_1 for the first tour (with $I_1 \in \{1,2,3\}$ see Table 4);
- *destination choice model for the first tour*, reproduces the choice of the first destination d_1 (with $d_1 \in \{1,2,\ldots,16\}$);
- *mode choice model for the first tour*, reproduces the choice of the mode m_1 for the first tour (with $m_1 \in$ {*car, public transport, motorbike*});
- *second tour time-of-day choice model*, $\forall \pi \neq 1$ reproduces the choice of the time-of-day I_2 for the second tour. The choice set of this choice dimension is considered a function of the time constraints of the first tour (if the first tour has not ended, the second cannot start): $I_2 \equiv 3$ if $I_1=3$; $I_2 \in \{1,2,3\}$ otherwise (see Table 4);
- *destination choice model for the second tour*, $\forall \pi \neq 1$ reproduces the choice of the second destination d_2. Because the time-of-day 1 and 3 (Table 4) for the second tour have a limited time window (150 min), the choice set of this choice dimension d_2 was constrained in the following way:

  $d_2 \in \{1,2,\ldots,16\}$ if $I_2=2$ otherwise
  $d_2 \in \{1,2,\ldots,16\}$: $Y_{o,d2,I2,\pi,I1,d1,m1} \leq 0.097$ otherwise;

where $Y_{o,d2,I2,\pi,I1,d1,m1}$ is the mode choice logsum variable of the second tour (see Tables 5 and 6), related to the o-d_2 pair, the time-of-day for the second tour I_2, the activity pattern π, the time-of-day I_1, the destination d_1 and the mode m_1. The value 0.097 was estimated jointly with the other model parameters. This estimated value corresponds to an average car/motorbike travel time of about 30 min and an average public transport travel time of about 40 min. In this way the destination choice set was considered a function of transport accessibility;

- *mode choice model for the second tour*, $\forall \pi \neq 1$ reproduces the choice of mode m_2 (with $m_2 \in$ {car, public transport, motorbike}) for the second tour.

For the specification of the system of models we considered socio-economic, level-of-service and dummy variables. In Table 5 model attributes, model parameters and validation tests are reported. In Table 6 the attributes used are described.

With respect to the activity pattern choice model, the attributes used seek to highlight different observed behaviour between males and females, since females are more likely to make second tour with other than work purpose or to come back home for lunch (H-W-H-L-H, H-W-H-P/D-H, H-W-H-O-H), while males either do the simple work-tour (H-W-H), which is the most widely chosen activity pattern, or the double work-tour (H-W-H-W-H).

Table 5 *DIAP* and *trip-chain* model: attributes, parameters and validation tests

Model		Alternative	Attribute	β_i	t_student	ρ^2/MAPD
DIAP	Activity patterns	1	H-W-H	3.241	4.135	0.289 (ρ^2)
			$Y_{o,\pi}$	1.422	1.512	
		2	$male_o$	1.677	4.855	
			$Y_{o,\pi}$	1.422	1.512	
		3, 4, 5	$female_o$	0.675	1.906	
			$Y_{o,\pi}$	1.422	1.512	
Trip-chain Model	First tour time-of-day	1	$female_o$	1.374	3.744	0.197 (ρ^2)
			NoWork2	1.337	3.435	
			$Y_{o,\pi,I1}$	1.452	2.713	
		2	$Y_{o,\pi,I1}$	1.452	2.713	
		3	π1	1.303	3.852	
			$work\_own_o$	2.818	2.986	
			$Y_{o,\pi,I1}$	1.452	2.713	
	First tour destination	d_1	Emp_{d1}	0.982	–	19% (*MAPD*)
			$Y_{o,d1,\pi,I1}$	0.587		
	First tour mode	*car*	car	0.713	–	12% (*MAPD*)
			$T_{o,d1,I1}$ (minutes)	−0.032		
			centre	−2.296		
			$Y_{o,d1,m1,\pi,I1}$	0.221		
		Public transport	fare (€)	−0.002	–	
			$Tb_{o,d1,I1}$ (minutes)	−0.037		
			$Tw_{o,d1,I1}$ (minutes)	−0.021		
			$Tp_{o,d1}$ (minutes)	−0.013		
			$Ntrn_{o,d1,I1}$	−0.307		
			$Y_{o,d1,m1,\pi,I1}$	0.221		
		motorbike	motorbike	−1.381	–	
			$Tm_{o,d1}$ (minutes)	−0.007		
			age_o	0.631		
			ExtraUrb	−2.314		
			$Y_{o,d1,m1,\pi,I1}$	0.221		
	Second tour time-of-day	1	$Y_{o,I2,\pi,I1,d1,m1}$	0.077	0.667	0.342 (ρ^2)
		2	$manager_o$	1.031	2.155	
			$Y_{o,I2,\pi,I1,d1,m1}$	0.077	0.667	
		3	π_NoWork	1.776	3.365	
			$Y_{o,I2,\pi,I1,d1,m1}$	0.077	0.667	
	Second tour destination	d_2	Emp_{d2}	0.401	–	25% (*MAPD*)
			Szone	0.651		
			$Y_{o,d2,I2,\pi,I1,d1,m1}$	0.604		
	Second tour mode	car	car	0.713	–	22% (*MAPD*)
			$T_{o,d2,I2}$ (minutes)	−0.032		
			centre	−2.296		
			Smode	1.651		
		Public transport	fare (€)	−0.002	–	
			$Tb_{o,d2,I2}$ (minutes)	−0.037		
			$Tw_{o,d2,I2}$ (minutes)	−0.021		
			$Tp_{o,d2}$ (minutes)	−0.013		
			$Ntrn_{o,d2,I2}$	−0.307		
		motorbike	motorbike	−1.381	–	
			$Tm_{o,d2}$ (minutes)	−0.007		
			age_o	0.631		
			ExtraUrb	−2.314		

Table 6 *DIAP* and *Trip-chain* model: attribute description

H-W-H is an alternative specific attribute related to the activity pattern 1: Home – Work – Home;
$Y_{o,\pi}$ is the logsum variable corresponding to the first tour time-of-day choice model, related to origin zone o and activity pattern π
$male_o$ is a dummy variable of value 1 if the worker is male, 0 otherwise; this attribute reproduces the preference of male workers of choosing activity pattern 2: Home – Work – Home – Work – Home
$female_o$ is a dummy variable of value 1 if the worker is female, 0 otherwise; this attribute reproduces the preference of women of choosing activity patterns with more than one activity and starting their activities early in the morning.
NoWork2 is a dummy variable of value 1 if the activity pattern π consists of two tours without a work activity in the second tour ($\pi \in \{3,4,5\}$), 0 otherwise
$Y_{o,\pi,I1}$ is the logsum variable corresponding to the first tour destination choice model, related to origin zone o, activity pattern π and time-of-day I_1
$\pi 1$ is a dummy variable of value 1 if activity pattern $\pi = 1$ (Home – Work – Home), 0 otherwise; this attribute reproduces the preference of choosing time-of-day 3 (start: 7:00–9:30; finish: 17:30–20:00) for *H-W-H* workers
$work\_own_o$ is the work on one's own percentage in origin zone o; this attribute reproduces the preference of this class of workers to work till late in the afternoon (and thus finish the tour between 17:30 and 20:00)
Emp_{d1} is the logarithm of the number of employees at destination d_1; this attribute is representative of zone d_1 attractiveness
$Y_{o,d1,\pi,I1}$ is the logsum variable corresponding to the first tour mode choice model, related to origin zone o, destination d_1, activity pattern π and time-of-day I_1
car is an alternative specific attribute
$T_{o,d1,I1}$ is the car travel time (in minutes) from origin zone o to the first destination d_1 (and return) during time-of-day I_1
Centre is a dummy variable of value 1 if destination d_1 is inside the city centre, 0 otherwise; this attribute reproduces the disutility of choosing the car mode for reaching the city centre (caused for example by parking difficulties)
$Y_{o,d1,m1\pi,I1}$ is the logsum variable corresponding to the second tour time-of-day choice model, related to origin zone o, destination d_1, mode m_1, activity pattern π and time-of-day I_1
fare is the public transport fare (in €)
$Tb_{o,d1,I1}$ is the public transport on-vehicle time (in minutes) from origin zone o to the first destination d_1 (and return) during time-of-day I_1
$Tw_{o,d1,I1}$ is the stops waiting time (in minutes) from origin zone o to the first destination d_1 (and return) during time-of-day I_1
$Tp_{o,d1}$ is the pedestrian walking time (in minutes) from origin zone o to the first stop, between intermediate stops and from the last stop to destination d_1 (and return)
$Ntrn_{o,d1,I1}$ is the number of transfers from origin zone o to the first destination d_1 (and return) during time-of-day I_1
motorbike is an alternative specific attribute
$Tm_{o,d1}$ is the motorbike travel time (in minutes) from origin zone o to the first destination d_1 (and return)
age_o is the employee percentage in origin zone o with age $\in$ [18, 29]; this attribute allows us to reproduce the preference of young workers to use the motorbike mode.
ExtraUrb is a dummy variable of value 1 if destination d_1 lies outside the Naples metropolitan area, 0 otherwise; this attribute reproduces the disutility of choosing the motorbike mode for extra-urban trips
$Y_{o,I2,\pi,I1,d1,m1}$ is the logsum variable corresponding to the second tour destination choice model, related to the origin zone o, the time-of-day I_2, the activity pattern π, the time-of-day I_1, the destination d_1 and the mode m_1
$manager_o$ is the manager percentage in origin zone o; this attribute reproduces the preference of this class of workers of doing work activities in the afternoon (starting between 15:30 and 17:30 and finishing between 17:30 and 20:00)
π_NoWork is a dummy variable of value 1 if activity pattern π does not comprise a work activity in the second tour, 0 otherwise; this attribute reproduces the preference of doing no work activities in the second tour between 17:30 and 20:00
Emp_{d2} is the logarithm of the number of employees at destination d_2
Szone is a dummy variable of value 1 if $d_1 = d_2$, 0 otherwise; this attribute reproduces the preference of doing the activity of the second tour within the same zone chosen for the first tour
$Y_{o,d2,I2,\pi,I1,d1,m1}$ is the logsum variable corresponding to the second tour mode choice model, related to origin zone o, destination d_2, time-of-day I_2, activity pattern π, time-of-day I_1, destination d_1 and mode m_1
Smode is a dummy variable of value 1 if $m_1 = m_2 = car$, 0 otherwise; this attribute reproduces the preference of doing the second tour by car if this mode was chosen for the first tour

The attributes used for the first tour time-of-day choice model allow the observed data to be reproduced satisfyingly; part-time workers (especially female) choosing double tours, with non-work second tours (H-W-H-L-H, H-W-H-P/D-H, H-W-H-O-H), prefer the first timeframe (7:00–9:30/12:30–15:00) for the first tour, while workers who choose the single tour (H-W-H) prefer or are forced to choose the last timeframe (7:00–9:30/17:30–20:00) for the second tour.

With respect to the second tour time-of-day choice model the calibration results, consistently with the observed

Table 7 Modal share (first and second tour)

	Urban destination				Extra-urban destination			
	Car	Public transp.	Motorbike	tot	Car	Public transp.	Motorbike	Tot
tour 1	36.9%	41.8%	21.3%	100%	69.9%	27.1%	3.0%	100%
tour 2	67.4%	23.4%	9.2%	100%	87.4%	11.9%	0.8%	100%

data, show that the workers who choose to carry out a second tour with non-work activities (H-W-H-L-H, H-W-H-P/D-H, H-W-H-O-H) prefer the third timeframe (17:30–20:00/17:30–20:00), probably more suitable for carrying out such activities.

Estimation of destination choice model (for the first and second tour), as well as mode choice model, requires the computation of the level-of-service variables (travel times and transportation costs) for all the mode alternatives. Costs and travel times are defined in traditional ways, although the models require values of these attributes by time-of-day. As shown in Tables 5 and 6, the attribute *Szone* (same zone of first destination) used in the second tour destination model assumes a double meaning: it highlights either the probability of choosing the same destination for the first and second tour of the day, because the zone in which an individual works is generally well known by him/her, or the existing link among the trip-chains of a day.

With respect to the mode choice model (for the first and second tour), the attribute *centre* was used to reproduce the cost and travel time disbenefit to reach a zone in the city centre. Furthermore, workers tend not to use motorbikes to reach the zones outside the metropolitan area and to cover long distances. Hence the attribute *ExtraUrb* was introduced. Motorbikes are usually preferred by young people (18–29 years old). For the second tour of the day, the attribute *Smode* was used to reproduce the link among different trip-chains since individuals who prefer the car mode for systematic trips (first tour) generally prefer to use it “tout court”.

The estimation results, consistently with the observed data, show a very different modal share both between urban and extra-urban tours and between first and second tours (see Table 7). With respect to the first tours, public transport is the mode most frequently used for urban trips (about 42% of the total), while cars are used by about 37% of users and motorbikes by more than 21% of users. As regards extra-urban trips, the modal share is completely different; public transport declines to 27% (probably due to less frequent services with less extra-urban coverage), while the car is the preferred mode with about 70% of the total; motorbikes are less widely used for this trip type, amounting to 3% of the total.

With respect to the second tours, we observed that for urban trips more than 67% of users travel by car while only 23% choose public transport and more than 9% use motorbikes. For extra-urban trips we observed a similar trend, with car trips more than 87%, public transport trips about 12% and motorbike trips about 1%.

It is worth noting that mode choices for second tours are not constrained by mode choices made for the first tours, provided that tours are home-based and the car is considered to be available at home at some extent which is equal for the first and the second tours.

The great difference between the urban car percentage for the first tours and the equivalent for the second tours (about 30% difference) is probably caused by the TDM policies adopted in the Naples city centre, in which parking pricing by the hour discourages the use of the car mode for systematic trips and longer staying, which are generally associated to the first tours.

After the estimation phase, the whole model system has been implemented and applied to the Naples’ metropolitan area. The application results for the City of Naples (just urban trips) are shown in Table 8 in terms of total trips per time-of-day and per mode, not explicitly distinguishing the effects of first and second tours. However, the going-to-work trips of the first tour actually determinate the total number of trips of the first timeframe; similarly, only (part of) the caming-back trips of the first tour contribute to the trips in the second timeframe. In all other timeframes the contributions of different tours are mixed and therefore the modal shares are some intemediate values between those characteristic of tour 1 and 2 reported in Table 7.

In more detail, the morning peak-hour, 07:00–09:30, is characterized by about 200,000 work trips inside the city of

Table 8 Naples worker travel demand by time-of-day and mode

Timeframe		Car	Public transport	Motorbike	Total
7:00	9:30	70,215 (36%)	83,697 (42%)	44,120 (22%)	198,032 (100%)
12:30	15:00	38,458 (36%)	45,882 (42%)	24,162 (22%)	108,502 (100%)
15:00	17:30	55,311 (41%)	53,693 (39%)	27,480 (20%)	136,484 (100%)
17:30	20:00	92,381 (53%)	56,258 (32%)	24,544 (14%)	173,183 (100%)

Naples. In this timeframe the most frequently used mode is public transport, accounting for 84,000 trips (42% of the total); cars are chosen by more than 70,000 workers (35%); and the motorbike mode is used by more than 44,000 workers (22%).

In the off-peak timeframe, 12:30–15:00, the modal shares are the same as the morning peak-hours, as previously anticipated, with a worker demand level of about 110,000.

Between 15:00 and 17:30 more than 135,000 workers travel within the city of Naples. In this timeframe cars and public transport have the same modal share with about 55,000 workers per mode (about 40% of the total), while motorbikes are used by more than 27,000 workers (20%).

The 15:00–17:30 timeframe is the afternoon peak-hour; the Naples demand exceeds more than 170,000 workers; the most widely used mode is the car, with more than 92,000 trips (53% of the total); public transport is chosen by more than 56,000 workers (32% of the total), while motorbikes are used by about 25,000 workers (14%).

5 Conclusions

In this paper an activity-based modelling framework has been presented which tries to take into account the interaction among individuals participating to the same set of activities, as well as all temporal and physical constraints among single trips. The proposed framework allows to reproduce activity lists and activity patterns in an explicit and consistent way. As a consequence, time and mode characteristics of travel demand are more accurately computed.

In the paper a comprehensive formalisation of the modelling framework is presented and part of it is estimated on the basis of ad-hoc collected data. The modelling framework has been then applied to the Naples' metropolitan area.

The proposed framework has shown a satisfying flexibility, as well as a good ability in reproducing real data. It seems to be a good compromise between accuracy and operative issues, which improves the range of reproducible mobility phenomena and the accuracy of this reproduction and at the same time it moves some step forward the practical applicability of activity-based approaches.

Of course, the proposed approach presents an higher computational complexity with respect to more consolidated trip or tour-based models, but the way it can be employed for transportation policy analyses and/or appraisals is not different from traditional demand modeling approaches. It can be employed in order to obtain more realistic Origin/Destination modal matrices, as well as more realistic elasticity of these matrices to changes of network levels of service. Assignment of these matrices to networks also allows for more realistic assessment of network and congestion effects of transportation policies.

Future research will mainly attempt to extend the model specification and estimation to the first three choice dimensions, related to the weekly household activity list formation and distribution among the days of the week and the individuals of the household. The proposed framework should also be applied to contexts different from that used for the estimation and the obtained results should be compared with those obtainable from other activity and non activity-based approaches, so as to highlight the introduced improvements. The hope of this paper is that of providing anyway an interesting contribution to the literature of this complex field by showing a possible comprehensive theoretical formulation of the problem and its applicability to a real context.

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