European Commission

JRC SCIENCE AND POLICY REPORTS

TRANSPORT AND TRAFFIC MODELS FOR STUDYING ELECTRIC MOBILITY

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2014

Joint Research Centre

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Italy, European Commission, Joint Research Centre, 2014

Abstract

The objective of the current document is to help clarify whether or not transport models can be useful or even needed in order to analyse the introduction of electro-mobility in road transport, to study impacts and make predictions for e-mobility scenarios.
To this aim, the general conditions under which the use of transport models is recommended for e-mobility studies are outlined in the 'introduction'. In the successive section the 'phenomenon' to be modelled is described: first, individual travel behaviour is schematized and then, the impact of BEVs on individual travel choices is discussed. The mutual dependency of individual travel choices and traffic and the role of congestion conclude the section.
In the section 'transport simulation models', travel demand models are classified according to their approach and briefly described and discussed. Traffic assignment models, that allow restoring consistency between demand and supply models outputs are also introduced in the context of e-mobility. Based on the previous discussions the last section provides a quick summary of requirements and future directions for integrated modelling of e-mobility.

CONTENTS

LIST OF ACRONYMS USED:

- *AER*: All-Electric Range. It is the distance the vehicle is able to travel purely on electricity.
- *BEV*: Battery Electric Vehicle. A battery electric vehicle (BEV) is a type of electric vehicle (EV) that uses chemical energy stored in rechargeable battery packs. BEVs use electric motors and motor controllers instead of internal combustion engines (ICEs) for propulsion (Wikipedia).
- *ICEV*: Internal Combustion Engine Vehicle.
- *MBEV*: Medium range BEV.

Scope

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To this aim, the general conditions under which the use of transport models is recommended for e-mobility studies are outlined in the 'introduction'. In the successive section the 'phenomenon' to be modelled is described: first, individual travel behaviour is schematized and then, the impact of BEVs on individual travel choices is discussed. The mutual dependency of individual travel choices and traffic and the role of congestion conclude the section.

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Introduction

Many analyses of the transport-energy system can be carried out by means of data only. For instance, multi-day GPS data over a full year of many drivers can be used to predict the market potential of BEV [*1, 2, 3*]. From such data, quantities like the percentage of drivers whose daily journeys would not be affected by switching from ICEVs to BEVs (i.e. drivers with all the daily journeys shorter than the vehicle AER), can be calculated.

However, as far as variations in future scenarios can modify travel behaviour and mobility choices, to simply assume that behaviours do not change, can lead to biased results. Such bias is further amplified by the mutual interactions among the system components as well as by their internal interactions. For instance, changes in the power system, like new energy pricing policies or new plans for charging infrastructures, are expected to change travel behaviour for the users of BEVs, i.e. destinations, routes, departure times. This affects the spatial and temporal distribution of energy demand and consumption as well as that of traffic congestion, which can modify travel behaviours and energy consumption patterns in its turn. The system equilibrium, if any, can be rather different from that resulting from the simple assumption of invariable travel behaviour. For this reason, when changes to the transport or power systems are expected to produce variations in the travel behaviour, the use of models able to predict such variations is recommended. In fact, if current travel data can tell the market potential of BEV, for instance, they can be barely used to tell the impact on the power network of the introduction of a time-varying energy pricing scheme [*4*].

As model outputs are always affected by uncertainty the choice of whether or not to apply such models lies on the analyst, who has to evaluate the trade-off between the errors in the model-based predictions and the bias resulting from considering invariable behaviours or making other simplifying assumptions.

As it is clear from the example at the beginning of the section, the magnitude of these potential errors – resulting from the use of models and/or imputable to other approaches or rigid assumptions – depend on the analysis objective. However, it is important to consider the following conceptual difference. The bias resulting from rigid assumptions (e.g. invariable travel behaviours) is ***not predictable***, because of the complexity of the system and the multiple interactions of its components. It is also *not reducible*, as it is a structural deficiency of our analysis setting. On the contrary, the uncertainty entailed in the predictions of a model can be reduced by means of appropriate techniques e.g. calibration, sensitivity analysis, when sufficient information (data) are available for the system at hand. In fact, the higher the amount and the quality of available data, the lower the residual uncertainty in the model outputs after a proper modelling uncertainty management.

From travel behaviour to traffic: the influence of BEVs

Prior to introducing the models that aim to describe travel behaviour and in order to better understand their differences, it is useful to give a brief description of the 'travel phenomenon'. This is also crucial to understand how travel behaviour can be affected by the use of BEV and, therefore, how transport models can support e-mobility studies.

The behaviour of an individual traveller, in the case of passenger transportation, can be thought as the result of multiple choices. In general, these choices range from long-term decisions, such as residence and employment location and vehicle ownership, to shorter-term decisions such as trip frequency, timing, destination, mode and path.
Leaving apart long-term decisions that are out of the scope of this document, short term decisions can be schematized as in Figure 1.

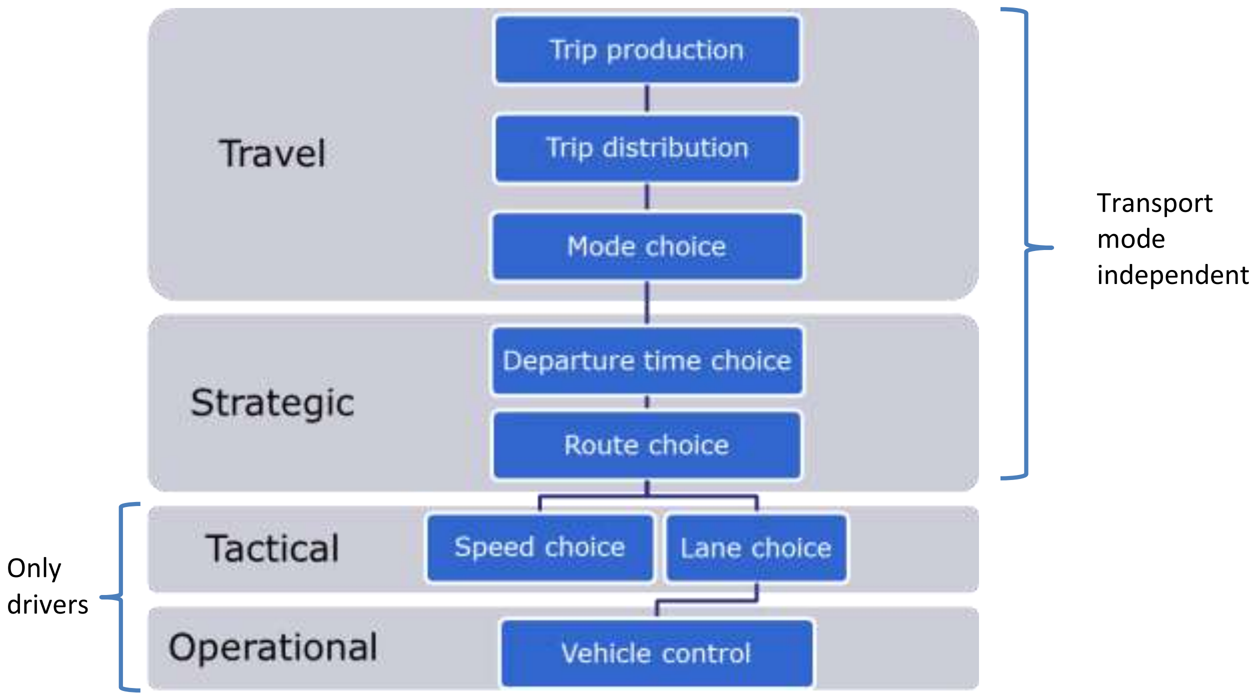

Figure 1 – Different decision layers correspond to different detail levels of the information required to make the corresponding choices

This simplistic schematization of the travel decisions reflects the assumptions behind the class of travel demand models known as "trip-based" models, as will be clearer later. Though simplistic from a modelling point of view, it is adopted here to provide an intuitive introduction to the problem. In the figure, the choices made by the traveller are grouped in different decision layers.

The two upper layers (i.e. travel and strategic) are usually modelled by travel demand models (see later), while the lower ones have been added in order to reflect specific choices pertaining to car drivers only.

The *travel decision layer* includes *i)* the choice of whether or not make one or more trips (‘*trip production or emission or frequency’* as the corresponding trip-based model is usually called), *ii)* the choice of a destination (*‘trip distribution’*) and *iii)* the choice of the transport mode (*‘mode choice’*).

The *strategic decision layer* includes those choices defining the trip ‘strategy’ such as the *departure time* and the *route to follow*. These choices usually require more detailed information about the actual performances of the transport network, in order to make effective choices.

The last two layers refer to the driver’s short term choices, such as that of the speed to attain or the lane to keep (*tactical*), and to the proper control of the vehicle (*operational*) in order to meet the choices at the tactical decision layer.

At this point it is useful to focus on e-mobility and try to figure out how e-mobility affects these travel/driver choices. In general, the two main aspects of e-mobility deemed to have impact on the transportation system are the AER and the recharging time [*5*]:

1. First, Medium range BEVs (MBEV) have an AER around 150 km [*6*].
2. Second, while ICEV can refuel in a matter of minutes, a typical EV may require 6-8 hours in order to recharge in a normal charger [*7*]. However, recently, fast chargers (or DC chargers) have been introduced into the market, which allow 80% of the battery capacity to be charged in 30 minutes [*8*]. Still these fast chargers seem to have a negative effect on battery life.

These two specific aspects affect drivers’ choices in the following way (see Figure 1):

1. AER affects *travel, strategic and tactical* decision layers (from a psychological point of view the impact on people of limited AER is usually called ‘*range anxiety’* [*3*]):
    a. *Travel decision layer.* The available range modifies active accessibility of places (i.e. impossibility of reaching destinations out of the available range) affecting the choices of destination and mode. For instance, given a

shopping centre out of the available AER, a person can either decide to change shopping destination or to shift to public transport or alternative modes, in order to reach the preferred shopping centre.

b. *Strategic decision layer*. Given a specific available range, the active accessibility of destinations can change depending on the time of day or, the day of week. In fact, the deterioration of network performances due to traffic congestion can make a destination unreachable (because out of AER) during a specific time window or a specific day. This in turn might affect the departure time choice and the route choice (i.e. congestion avoiding strategies).

c. *Tactical decision layer.* In order to reduce the energy consumption and increase the AER, the driver can reduce his or her speed, i.e. adopt *eco-driving*.

2. Availability and spatial distribution of (fast) recharging stations can affect *travel and strategic* decision layers:

   a. *Travel decision layer.* Passive accessibility of locations can change due to the presence of recharging stations. An unreachable destination (out of the individual destination choice-set, because out of the vehicle AER) can become reachable if a recharging facility is present in the route or nearby the destination.

   b. *Strategic decision layer.* Route choice and departure time choice can be affected by fast recharging. In fact, these choices can be supposed to be insensible to slow charging (as slow charging needs some hours, it can be assumed to take place at destinations, i.e. during medium to long duration activities).

So far we have discussed about travel behaviour and travel choices of individuals, as if they do not interact. Actually, the number of vehicles we can count at a road cross-section in a unit time interval i.e. the *traffic flow* – with the local speed, the only system observables until few years ago – result from the combination of multiple individual choices, as represented in Figure 2.

Figure 2. Traffic flows on a network as the result of multiple individual choices.

However, it is not only a matter of composing individual choices to obtain aggregate traffic. In fact, the choices of individuals are mutually dependent and influence each other. The reason of this dependence and the way in which such dependence happens is known as **'congestion'**. The fact that a transport system (or component) is a congested system means that its performances change with the number of users. For instance, travel times on a road depend on the number of cars present on that road[1].

Therefore, on the one hand, individual choices affect system performances e.g. travel times. On the other hand, system performances affect individual choices e.g. people usually choose the fastest routes. This circular dependency is represented in Figure 3 where the interaction of individual choices (horizontal arrows) causes congestion, while congestion affects the individual choices (vertical curved arrows).

Such circular dependency is generally solved by looking for an '**equilibrium'** solution[2]. At equilibrium, individual choices and network performances are mutually consistent, i.e. the

[1] For other transport systems, like low frequency railway services, congestion relevance is lower e.g. train travel times are not influenced by the number of people aboard, though people at stations can influence departure times.

[2] The so-called Wardrop's user equilibrium principle is generally adopted, equivalent to a Nash equilibrium

travel time values of routes as resulting from the number of users travelling on those routes, coincide with the travel time values on which the users based their choices.

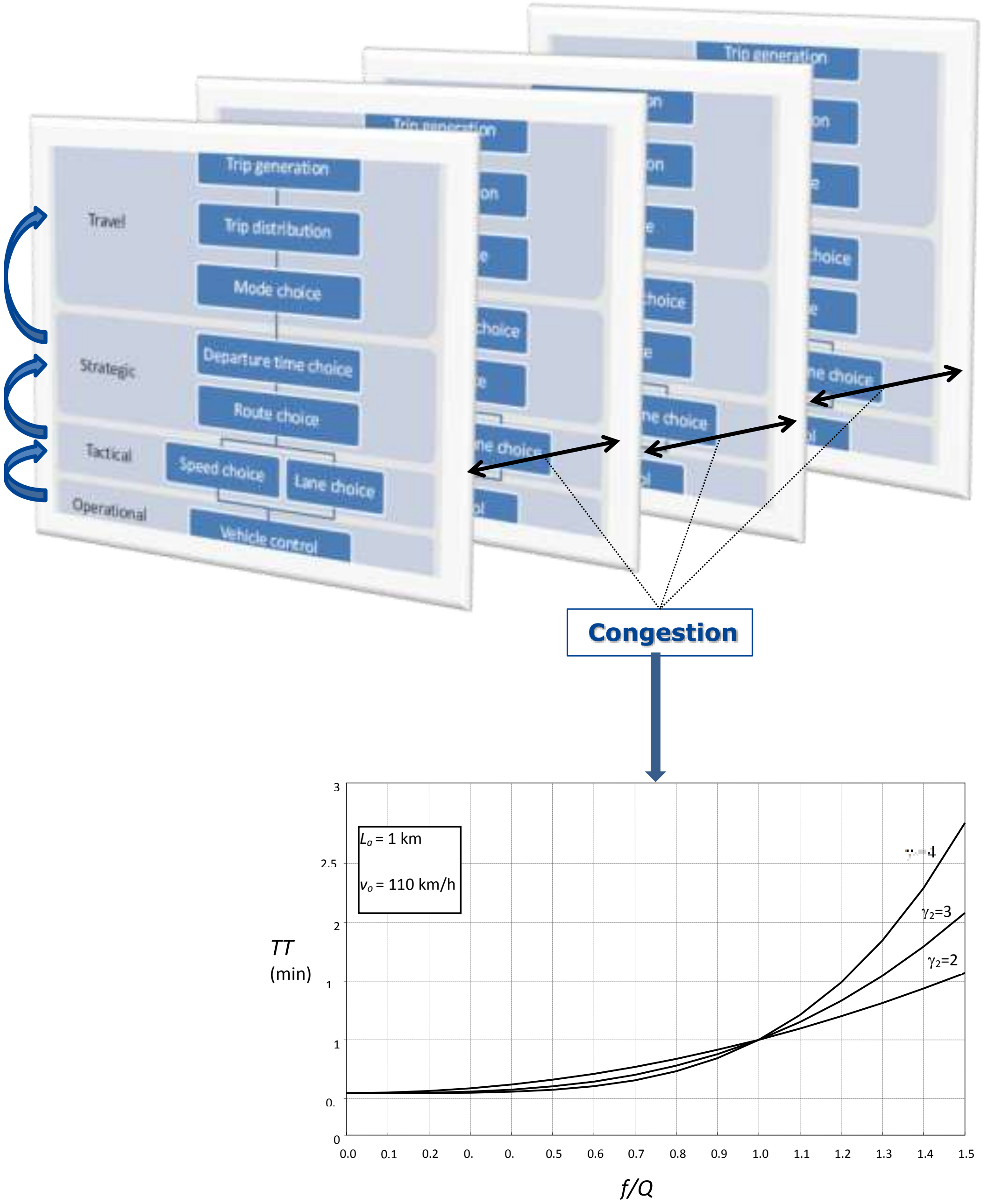

Figure 3. Circular dependency between individual choices and transport performances

Having outlined which are the travel choices more likely to be affected by e-mobility, and how these choices affect the transport systems, we can move to examine which transportation models can be useful to simulate the impacts on the transport system - and, consequently, on the power system - of the introduction of BEVs.

Transport simulation models

In transport modelling, the travel and the strategic decision layers in Figure 1 are modelled through the so-called ***travel demand models*** that, simulating travel choices, provide aggregate or disaggregate *demand flows* as output.

As network performances are an input to travel demand models (i.e. choices of travellers are affected by network performances), travel demand models need to interact with ***supply models.*** In turn, supply models provide the *network performances* as a function of *demand flows*.

The models referred as ***traffic assignment models***, solve this circular dependency by simulating the interaction of demand and supply on a transportation network, as intuitively described in the previous section and shown in figure 4 (source [*9*]).

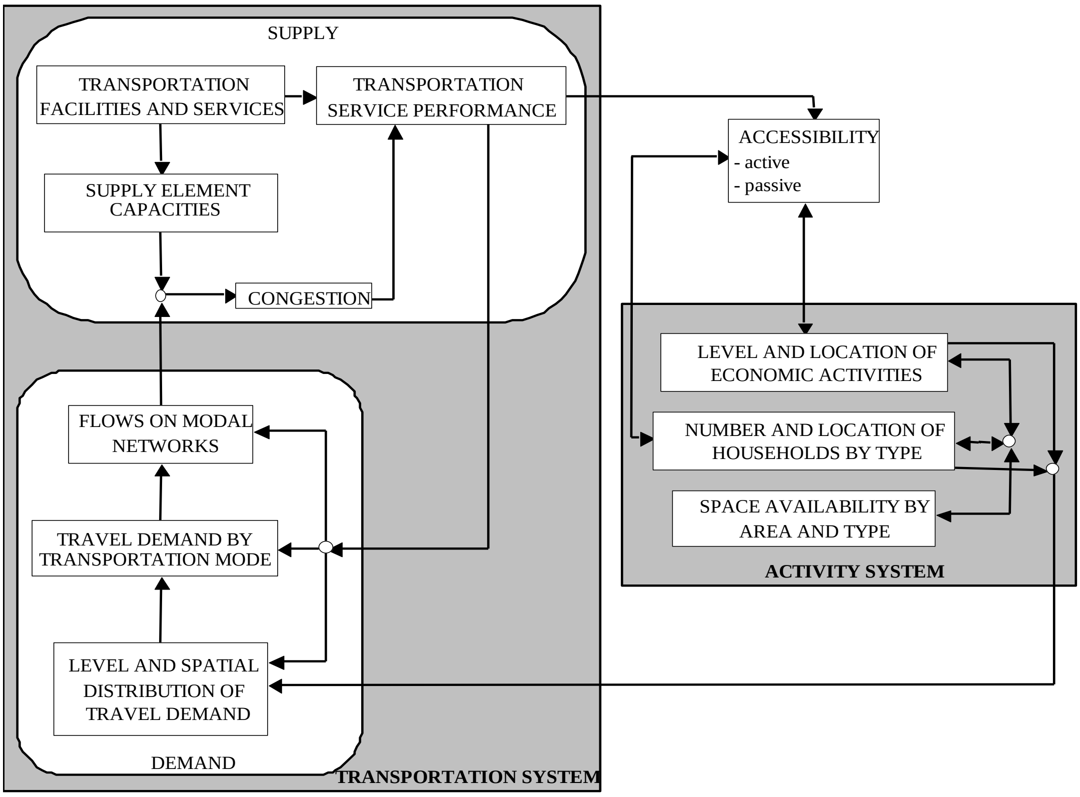

Figure 4. Relationships between the transportation system and the activity system (source [9]).

Travel demand models

Travel demand models typically result from the integration of a number of sub-models. They can be classified based on the approach to model travel demand, i.e. for predicting the outcome of the travel choice decisions and representing the mutual effects of the different decisions on each other [*9*].

Trip-based travel demand models implicitly assume that individual travel choices of an origin-destination trip are independent by the choices of other trips in the same journey. In reality though travel choices of trips within a journey are mutually dependent. For instance, the choice of using the car for the first trip of a daily journey (e.g. home-work trip) might be dictated by the need of using the car for the following trips (e.g. for shopping). The approximation of modelling choices among trips as independent is made to simplify the analysis, and is reasonable when most of the journeys in the modelling period consist of round trips (origin-destination-origin).

Trip chaining travel demand models, on the other hand, assume that the choices concerning the entire journey influence each other. In this case, the choice of an intermediate destination, if any, takes into account the preceding or following destinations on the trip chain, the choice of transportation modes takes into account the whole sequence of trips in the chain, and so on. Models of this type have been studied for several years and have been applied to real situations, though less frequently than trip-based demand models.

Eventually, ***activity-based travel demand models*** predict transportation demand as the outcome of the need to participate in different activities in different places and at different times. They therefore take into account the relationships among different journeys made by the same person during a day and, in the most general case, between journeys made by the various members of the same household. They are often implemented as agent-based models[3], in which the decisions, activities and trip-making of a large number of individual households and their members are explicitly represented. Models of this type are obviously more complex than those described previously and are aimed at understanding

[3] Often these models are also referred as micro-simulation models. However, they do not have to be confused with traffic micro-simulation models, though both refer to the simulation of individual agents and, for this reason, are inclined to be integrated, as discussed in the section “traffic assignment models”.

relationships between the demand for travel and the organization of the different activities of a person and his/her household.

Trip-based travel demand models

Trip-based travel demand models predict the average number of trips that have given characteristics and that are undertaken in a specific reference period (average trip flows). Trip characteristics that are often considered relevant include (see [9] for details):

i the user's class (category of socio-economic characteristics)

o,d the zones of trip origin and destination;

s the trip purpose, or more properly the pair of purposes;

h the time period, i.e. the time band in which trips are undertaken;

m the mode, or sequence of modes, used during the trip;

k the trip path, i.e. the series of links connecting centroids *o* and *d* over the network and representing the transportation service provided by mode(s) *m*.

In formal terms, trip-based models can be expressed as follows:

$$d\,[K_1, K_2, \ldots] = d(\boldsymbol{SE}, \boldsymbol{T}; \boldsymbol{\beta})$$

where the average travel demand flow between two zones having characteristics K_1, K_2,..., K_n is expressed as a function of a vector $\boldsymbol{SE}$ of socio-economic variables related to the activity system and/or the decision makers; and of a vector $\boldsymbol{T}$ of level-of-service attributes of the transportation supply system. Demand functions also involve a vector $\boldsymbol{\beta}$ of coefficients or parameters.

By making explicit the trip characteristics, the demand flow, $d^i_{od}\,[s, h, m, k]$ provided by a trip-based demand model becomes:

$$d^i_{od}\,[s, h, m, k] = d(\boldsymbol{SE}, \boldsymbol{T}) \qquad (1)$$

Although different travel choices are generally dependent on each other, for reasons of analytical and statistical convenience, in trip-based modelling the global demand function in (1) is decomposed into a product of sub-models, each of which relates to one or more choice dimensions.

The sequence most often used is the following [9]:

$$d^i_{od}[s,h,m,k] = d^i_{o.}[sh](\boldsymbol{SE},\boldsymbol{T}) \cdot p^i[d/osh](\boldsymbol{SE},\boldsymbol{T}) \cdot p^i[m/oshd](\boldsymbol{SE},\boldsymbol{T}) \cdot p^i[k/oshdm](\boldsymbol{SE},\boldsymbol{T}) \qquad (2)$$

where:

$d^i_{o.}[sh](\boldsymbol{SE}, \boldsymbol{T})$	is the trip production or frequency model, which gives the number of users in class *i* who, from origin zone *o*, undertake a trip for purpose *s* in time period *h*;
$p^i[d/osh](\boldsymbol{SE}, \boldsymbol{T})$	is the distribution model, which gives the fraction of users in class *i* who, undertaking a trip from origin zone *o* for purpose *s* in period *h*, travel to destination zone *d*;
$p^i[m/oshd](\boldsymbol{SE}, \boldsymbol{T})$	is the mode choice or mode split model, which gives the fraction of users in class *i* who, traveling between zones *o* and *d* for purpose *s* in period *h*, use mode *m*;
$p^i[k/oshdm](\boldsymbol{SE}, \boldsymbol{T})$	is the path choice model, which gives the fraction of users in class *i* who, traveling between zones *o* and *d* for purpose *s* in period *h* by mode *m*, use path *k*.

Superscript *i* designates a class of decision-makers having the same attributes, parameters and model functional form. The system of models described above predicts the average trip demand flow with its relevant characteristics by initially estimating the total number of trips (*trip productions*) from each zone *o* in the reference period $d_o[sh]$ and then splitting these trips between the possible destinations, modes and paths. For this reason, the model is known as a *partial share model* (or system of models). Note that the first two models predict the demand's spatial and temporal characteristics, and therefore provide the elements of the **origin-destination matrix**.

The sequence of sub-models in equation (2) reflects an assumption about the order in which decisions involving different choice dimensions are made, and therefore about how these decisions influence each other. The specification used in (2), corresponding to the model structure shown in Fig. 4, implies for example that destination choice depends only on trip production or frequency choice, while mode choice depends on destination and frequency choices. In other words, the decision-maker first chooses the trip destination from among all the available destination zones, and then the travel mode from among all the modes available for the chosen *od* pair.

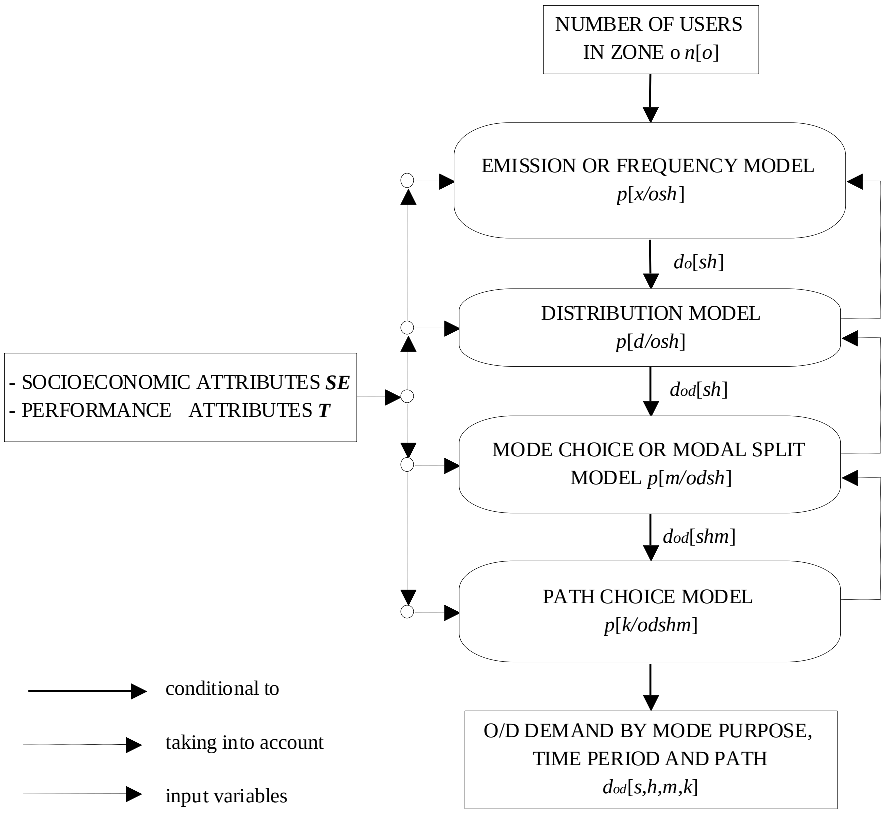

Figure 5. Four-step trip-based travel demand model system (note the equivalence with the two upper layers in Figure 1) (source [9]).

Different sub-model sequences are clearly possible; for example, some specifications proposed in the literature reverse the order of destination and mode choice in the sequence (2). Any sequence should be carefully reviewed in the calibration phase and compared with reasonable alternatives, in order to determine the best.

Importantly, the user explicitly chooses each trip's mode and path, but other travel dimensions such as trip frequency and destination might depend on higher-level user choices such as residence and work locations (e.g. for regularly-made trips like home-work and home-study). In these cases, the sequence (2) can be applied first for estimating trip frequency and destination using descriptive models, and then mode and path choice using behavioural models.

Upper-level choices (e.g. destination) are actually made taking into account the alternatives available at lower levels, such as the modes and paths available to reach the various possible destinations (see also Figure 5).

Equation (2), because of its structure, is known as the ***four-step model***. However, a greater or smaller number of levels can be used, and the fractions included in the models may differ from those shown. For example, it is possible to specify a six-level urban demand model that explicitly includes a trip production model $d^i_{o.}[s]$ to represent the average number of class *i* users who travel from zone *o* over the entire day; a choice model for the time period *h* in which to make a trip of purpose *s*, $p^i[h/osx]$ (***SE***, ***T***); and a model of parking location (d_p) and type (t_p) choice for auto trips (*a*) between origin *o* and final destination *d*, $p^i[d_p t_p/oshda]$(***SE***,***T***).

Several arguments have been advocated against trip-based models stemming from their simplified assumptions and structures [*10*]. As mentioned in the introduction to travel demand models, a fundamental criticism concerns the *assumption of independency* between the choices. First, such models do not capture any dependency between trips belonging to the same journey (i.e. trip chain) or between different journeys during the same day. Secondly, they model single persons-trips independently by the other household components, so that resulting choices neither capture any relationship nor preserve consistency among different members of the same household (for example, in case that one or more cars are shared by the household members a mutual constraint has to be considered in modelling the choices of household members). Eventually, the assumption of a rigid sequence of choices also is likely to introduce a bias in the results. These assumptions imply that trip-based models cannot capture the actual travel behaviour where a change in one aspect of a daily activity programme may cause changes or shifts in other aspects of the individual travel plan or in the plan of other household members. They can therefore only predict primary policy effects while complex behavioural adaptation patterns to external policies cannot be evaluated.

A second argument is related to the *strong aggregate nature* of trip-based models, both in space and time. For the sake of computational treatability, the study area is segmented in discrete 'homogeneous' zones. The results provided by these models are therefore origin-destination trip matrices (per mode and time interval) that basically give the number of trips from each origin zone to each destination zone in which the area is segmented.

Information on the actual detailed space distribution of origins and destinations is therefore lost. Also time is segmented and, in order to obtain results for a whole day, peak periods and off-peak periods are simulated independently. Independence not only stems from the assumption of travel choices independence, as mentioned before, but also from the way in which consistency between demand and supply is achieved for trip-based travel demand models. In fact, *static traffic assignment* is performed with such travel demand models. A static assignment assumes *stationary variables* within the simulated interval e.g. the peak period, and it does not describe the transport system dynamics such as the evolution in time of traffic over the network. As traffic dynamics are not described – i.e. no differential equations come into play – initial conditions are not required and the simulation of a period is independent by that of the previous one. The mobility over a whole day is therefore described by aggregating results of independent simulation for each period of the day where, independence, is both in the travel choices of individuals and in the traffic conditions between periods.

While the impact of these fundamental shortcomings may be relatively small in the context of investment decisions of large-scale infrastructure (the typical application domain of trip-based travel demand models), ***their use for the most of e-mobility studies is not effective***. In fact, in such a context, constraints on the system like the limited AER and the location and duration of recharging affect the full chain of trips in a day as well as the management of mobility needs within a household (e.g. car-sharing in car-deficient households). On the other hand, it requires simulating sequences of choices that have to be consistent among each other and with the time-varying traffic conditions over the network.

Trip-chaining travel demand models

It has been mentioned in the introduction to travel demand models that the assumption of travel choices independency is reasonable only when the journey is a "round trip" with a single destination and two symmetric trips. However, human activities have become increasingly complex, especially in urban areas. One reflection of this in the domain of transportation is an increasing number of journeys that connect multiple and disparate activities in different locations, i.e. journeys consisting of sequences of trips that influence each other in complex ways (Figure 6). For example, if a personal car is not used for the first trip in a journey, it will not be available for subsequent trips either. A number of demand models have been then proposed in the literature to address the sequence, or chain, of trips making up a journey. Some of these models represent the activities carried out (i.e. the different purposes of the journey) together with the trips that link them.

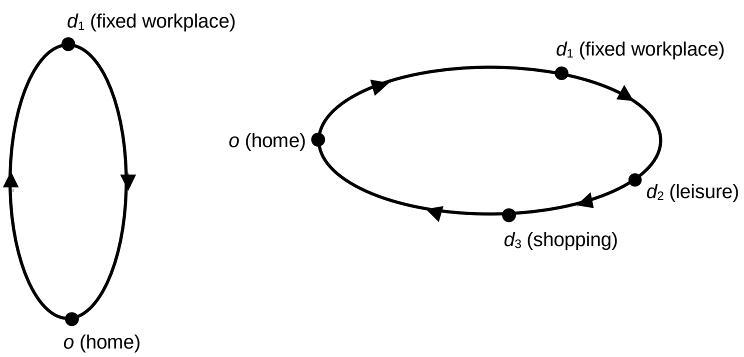

Figure 6. Examples of round-trip and chain journeys (source [9])

The mathematical models proposed to represent trip or activity chains do not have a standard structure as, for example, trip-based demand models do. This is due both to the relatively recent interest in these models (so there are fewer examples of them), and to the greater complexity of the phenomenon to be represented.

However, the most commonly used modelling structure, and the one closest to the structure described in the previous sections for single trips, is based on the concept of a *primary activity* (destination) for a particular journey. In other words, it is assumed that each journey is associated with a primary activity (or purpose), and that this activity is conducted in a particular place, known as the primary destination. Experimental studies suggest that the activity that the user perceives as primary for a particular journey is determined by relatively few criteria. These include:

- hierarchical level of purpose (in decreasing order, workplace or study, services and professional business, other purposes);
- duration of the activity (the primary activity is that which, within the highest hierarchical level, takes the most time);
- distance from zone of residence (the primary activity, given the same hierarchical level and duration, is that which is carried out in the place furthest from the residence).

Being able to represent relationships between the different trips that constitute an individual's travel chain, trip-chain models generalize considerably conventional trip-based models. However, ***they do not address the fundamental factors that determine the actual formation and choice of particular trip chains and round trips, thus limiting their use also for e-mobility studies***.

Activity-based travel demand models

To address all the limitations of previous approaches, it is necessary to consider explicitly the activities that individuals and households undertake, and that give rise to transportation demand. Models that derive travel patterns from a representation of these more basic activities are called *activity-based demand models*.

In activity-based models therefore travel is the direct outcome of the need of carrying out personal or household activities. Therefore, an individual's daily pattern of activities is modelled as a function of the role of the individual in the household and obeying to a number of constraints such as the availability of alternative travel modes or the availability of time. On the contrary of previous approaches, these models focus on 'activities' instead of 'trips' thus being closer to the actual decision-making process at the basis of mobility. The mobility described by these models arise from individuals schedules and it is not a sort of statistical description of spatial mobility patterns such as in trip production and trip distribution models. This approach is particularly suited to capture current urban mobility, where an increasingly larger share of multi-purpose, multi-stop trips is observed, calling for models able to capture the temporal and spatial interdependencies of the individual daily patterns.

The essence of the activity-based modelling framework is admirably captured by the following five arguments identified by [*11*]:

a. travel is derived from the demand for activity participation;
b. sequences or patterns of behaviour, and not individual trips are the relevant unit of analysis;
c. household and other social structures influence travel and activity behaviour;
d. spatial, temporal, transportation, and interpersonal interdependencies constrain activity and travel behaviour;
e. activity-based approaches reflect the scheduling of activities in time and space.

By predicting which activities are conducted, where, when, for how long, with whom, and the transport mode involved, activity-based models provide information about many transportation variables, such as vehicle-kms of travel, travel mode, and occupancy rates for auto modes, travel according to time of day, and time/location of starts, for instance. This turns out to be ***crucial for e-mobility studies where it is essential to research***

the way how these vehicles are used and their interaction with the road infrastructure, in order to optimise how, where, and when the vehicles may be recharged [*12*].

The substantial developing of activity-based models started in the 1990s to overcome limitations of previous approaches [*10*]. The 1990 Clean Air Act Amendments in the USA was a major drive for such a change of paradigm as it called for the inclusion of transportation control measures in transportation improvement programmes in heavily polluted non-attainment areas (see e.g. [*13*]). In particular, the evaluation of the impacts of so called 'soft measures' such as teleworking, congesting pricing and ridesharing incentives required a different type of travel demand modelling. Moreover, the clean air amendments demanded forecasts of mobile emission levels at a much higher level of spatial and temporal resolution. To achieve these goals the US Federal Travel Model Improvement Program funded the development of the TRANSIMS and AMOS. Since then plenty of activity-based models of travel demand have been developed following different approaches (detailed overview can be found in [*14*] and [*10*]).

One of these models, in particular, has been recently applied also for e-mobility studies. It combines the results emerging from the FEATHERS activity-based model with assumptions on electric vehicles market share to predict energy and power demand in time and space for the Flanders region [*15*]. As generated schedules by activity-based models determine how charging periods can float in time, they were also able to calculate smart grid management effects. Following the same approach, [*16*] it evaluated the total storage capacity per zone for the Flanders region and proposed some strategies for EV aggregator[4], allowing the aggregator to fulfil bids on the electricity markets. [*17*], using again FEATHERS explored to what extent charging electrical vehicles can be exploited to stabilize smart grids.

The FEATHERS' model, applied in the previous e-mobility studies, is an operational activity-based model built on the Albatross kernel [*18*]. According to [*10*] it can be considered as a 'rule-based' or, also, 'computational process models'. Its output consists of a travel schedule for a given day-of-week for each member of the synthetic population. For each predicted trip a series (origin, destination, start time, duration, and mode) is predicted that

[4] An aggregator is an agent between the system operator (SO) and the thousands of EVs owners, who participate in the electricity market with supply and demand energy bids.

allows calculating expected mode-specific traffic flows in time and space. FEATHERS input data consists of [*17*]:

- *the synthetic population for the study area. This contains socio-economic data (household composition, education level, income category, age category, etc.) describing each individual so that the distributions fit the census data.*
- *an area subdivision into traffic analysis zones (TAZ).*
- *land-use data for each TAZ. This consists of tens of attributes including number of people living in the TAZ for several age and employment categories, amount of people employed in the TAZ in several economic segments (industry, agriculture, education, distribution, hospitals, etc.).*
- *impedance matrices specifying the travel time and distance between TAZ for off-peak, morning-peak and evening-peak periods and for several transportation modes (i.e. car, slow, public transport).*
- *a set of decision trees trained using large scale (periodic) travel surveys. Those data essentially specify individual behaviour as a function of socio-economic data and partial schedule characteristics. They are used as conditional probability functions to sample agenda and activity attribute values for each individual.*

[…] The model makes use of 26 decision trees to first predict the basic travel agenda containing mandatory periodic activities and related trips (work, school) and, in a second stage, the flexible activities (shopping, social visits, etc.). The decision trees are used in a fixed order that models the decision making process. Each step determines new attributes for agenda components by stochastic sampling. The resulting schedules are consistent at the household level (resources available to the partners).

Apart from the specific modelling approach different level of complexity and consistency can be achieved by the models and the corresponding outputs, depending on the underlying assumptions. For example, referring again to the FEATHERS platform, a development trajectory has been outlined in [*19*] from the most basic configuration, referred as 'static', to a full microscopic model integrated with microscopic route-choice.

At the *static* level, the model provides the 'pre-day' travel agenda of the individuals under the assumptions of:

i) stationary environment; i.e. travel behaviour does not change with e.g. the day of the week or the weather;

ii) no within-day re-scheduling or learning processes; in reality, within-day changes to the schedules are motivated by e.g. time pressure, non-stationary environment or information provision and can cause change of destination, transport mode, and other facets of activity-travel patterns. The current state of the agent and of the network being generally used to update the schedule;

iii) no consistency with the network flow: the impedances of the transportation system (e.g. travel times) used to calculate the individual schedules are different from those resulting from the execution of such schedules. In other words, there is no consistency of the generated schedules with the traffic observed on the network.

At the *semi-static* level the first assumption of environment stationarity is removed. The following step, fully operational at the moment of this report, is a *dynamic* activity-based model which allow for within-day activity re-scheduling and learning processes. This is based on the concept of 'schedule execution' that introduces a feedback between the state of the transportation network and the scheduling process. The consistency with the flow over the network, in fact, is obtained by iterative assignment of the scheduled trips to the network. The calculated schedules are aggregated by time period and by mode, in origin destination (OD) matrices that are assigned to the network in a static manner. The updated network performances, i.e. path travel times, are used to recalculate the schedules that are assigned again to the network to obtain updated path travel times. The process is iterated until convergence (if any).

Despite the introduction of a feedback process with the network state to ensure consistency of the planned schedules with the network flows, the aggregation of schedules in OD matrices – the typical output of trip-based models – and the use of static assignment algorithms, is undoubtedly a step backward in the activity-based modelling framework. In fact, by aggregating the schedules in time-uncorrelated OD matrices and by using non-microscopic traffic assignment algorithms, the agent-based concept is contravened. The interaction of the (re-)scheduling process with the network performances is obtained only through aggregate impedance matrices provided by such static traffic assignment. These simplifying assumptions introduce a bias in the calculations, especially concerning the evolution of traffic over the network and its impacts on the re-scheduling process. This might affect, in particular, e-mobility studies where the consistency of travel diaries with the actual traffic flow conditions on the network is crucial, given the impact of congestion on travel behaviour of BEVs drivers (see e.g. the impact on travel behaviour of limited AER and recharging needs).

This issue can be resolved by incorporating microscopic route choice behaviour in the dynamic activity-based model (see next section). In this case, based on the agent-based scheduling process each individual chooses the optimal route (or the multi-modal path), affecting network performances. The dynamic feedback from the network not only induces rerouting behaviours but, due to the schedule execution mechanism affects the agent-based re-scheduling process.

This step, referred in [*19*] as 'full microscopic activity-based model with microscopic route choice', is the subject of ongoing investigations in the research field of activity-based modelling, as discussed in the following section.

Demand-supply interaction models

Travel demand models provide mobility flows over the network. The level of detail and aggregation ranges from static OD matrices, providing the number of trips by mode (and by trip purpose) between traffic zones in specific intervals (like e.g. peak and off-peak periods) to individual travel diaries containing detailed information on the origin and destination locations, departure times and modes of each agent. As told before, these two different levels of detail are provided, respectively, by traditional trip-based models and by activity-based models. Whatever the approach followed, in order to keep consistency between the demand forecasted and the traffic over the network, traffic assignment models are required.

For static trip-based models, long-established techniques exist to solve the circular dependency between demand and supply, generally based on the concept of equilibrium. The limitations of such a static traffic assignment have been already discussed in the section of trip-based models.

The modelling challenge is clearly much more complex in an activity-based framework being inherently disaggregate and dynamic. In this case, in fact, as individual daily travel schedules are available as output of demand models, disaggregate and dynamic traffic assignment models would be best suited for the purpose. Nonetheless, until recently, the detailed output of activity-based models is aggregated into OD matrices and provided to static (multi-modal) assignment models, which therefore lose the most of the information produced by the disaggregate travel demand models.

For this reason, recently, the possibility of integrating operational activity-based models within dynamic traffic assignment frameworks was explored. [*20*] describe the integration of DaySim, an activity-based travel demand forecast model developed for the Sacramento, California, with TRANSIMS, a disaggregated dynamic network assignment tool. In [*21*] a similar exercise is carried out using the Toronto, Canada, activity-based model. Both the previous studies show that the results produced by such agent-based approaches are more realistic from a temporal point of view. Further, [*22*] explored the potential integration of an existing activity-based travel demand model (TASHA) with the agent-based tool kit for emission modelling.

In the studies [*21*] and [*22*], however, the starting points for the integration were still the origin–destination matrices produced by aggregating the individual schedules of activity-based models. In [*23*], instead, the Tel Aviv, Israel, activity-based model and parts of the functionality of the MATSim agent-based framework [*24*] have been used in an attempt to integrate the disaggregate demand representation from the activity-based model and the disaggregate supply representation of the agent-based framework. In fact, MATSim is primarily an agent-based traffic simulation model. However, it already includes a re-scheduling functionality of individual activities based on an evolutionary algorithm.

Thanks to this re-scheduling functionality, the MATSim model has been applied also independently by any activity-based model i.e. without relying on the individual travel plans provided by these models. In fact, to run MATSim an initial demand based on a synthetic population has to be created, which is successively adjusted by means of the before mentioned rescheduling functionality. For this purpose census data and travel surveys can be used instead. For instance, several applications of MATSim in Switzerland relied on the very detailed data from the Swiss census to generate the synthetic population and on the Swiss National Travel Survey to create the initial demand (i.e. the travel plans).

Based on these features, [*4*] proposed a framework that already integrates the three domains mainly affected by electric mobility (see Figure 7). In fact, vehicle fleet evolution and vehicle energy demand simulations are combined with MATSim, thus determining the daily behaviour of electric vehicles and providing individual battery energy levels at the different locations of the vehicles during the day. Further, the implementation of a charging control algorithm allowed the impact of electro-mobility on the electricity network to be evaluated, as well as the adaptation of transport behaviours. In the simple laboratory test case presented, synthetic travel plans were used as basic travel demand inputs.

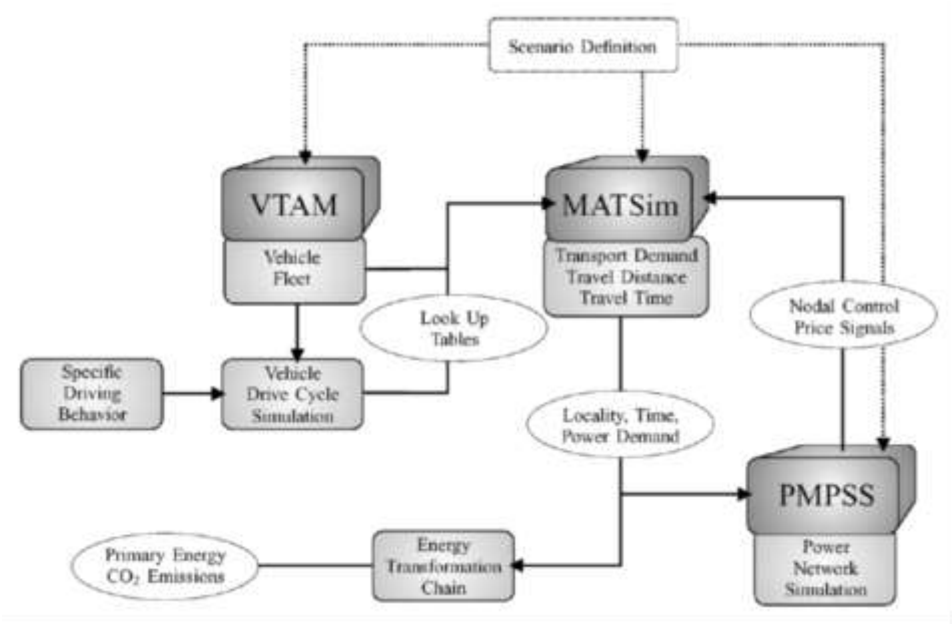

Fig. 7. The integrated method comprising the vehicle technology assessment model (VTAM), the multi-agent transportation simulation (MATSim), and the PEV management and power system simulation (PMPSS). Source [*4*].

Despite the possibilities already offered by tools like MATSim, the integration of activity-based models with agent-based traffic micro-simulation tools is one of the most relevant future development of activity-based models [*10*] and many model developers are already devoting substantial efforts in this direction (as discussed, for example, in the presentation of the development trajectory of the FEATHERS model). In the most recent field literature, indeed, it is deemed that only the integration of such disaggregated frameworks would allow to fully exploiting the benefits of both the approaches. If the advantages of such integration for activity-based models should be clear at this point, it is worth mentioning that also dynamic traffic (micro-) simulation would clearly benefit from that. In fact, the main problem in using dynamic traffic simulation models is the availability of time-varying input demand. 'Incidentally', this is just the output of activity-based models.

The benefit from such integration is particularly relevant in all the situations where detailed dynamic representation of the scheduling process and of its interaction with the network performances is needed. This is also the case of e-mobility.

Conclusions

This document has outlined and discussed existing and future approaches in transport and traffic modelling in view of e-mobility investigations. Existing work in the field of e-mobility have been also discussed synthetically.

As argued along the document, ***a modelling framework including activity-based travel demand models and agent-based dynamic traffic simulation models seems the best suited*** for investigating the introduction of e-mobility and its complex interactions with both the transport and the electricity networks.

In synthesis, this consideration stems, from the three following points:

- As the impact of electric vehicles on the distribution grid and, consequently, the evolution of the State Of Charge (SOC) of the battery of each vehicle during the day are sought, departure/arrival times, stopping times and locations are needed. Therefore, the sequence of trips scheduled by BEV drivers i.e. their daily travel plan is a prerequisite. This calls for activity-based travel demand models.
- In order to simulate the behaviour of individual BEVs over the network, discrete and detailed representation of traffic is needed i.e. microscopic (or mesoscopic) supply models;
- In order to obtain meaningful results in terms of distances and routes travelled, stopping times, energy consumptions, etc. the execution of individual travel plans has to be carried out consistently with the actual traffic over the network. This calls for the integration of activity-based models in agent-based dynamic traffic simulation tools.

Given the complexity of such modelling framework the major challenge is model validation. The availability of unprecedented data both for amount and quality, however, is making possible this really hard task (see e.g. the travel data made available through the smartphones or from equipped vehicles). Future trend in researching this field – as many others – will be therefore developing methods to build valid and credible models from redundant data, instead of accepting simplified modelling assumptions.

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European Commission
Joint Research Centre – Institute of Energy and Transport
Italy, 2014

Title: **TRANSPORT AND TRAFFIC MODELS FOR STUDYING ELECTRIC MOBILITY**

Author(s): Vincenzo Punzo, Panagiota Dilara (editor)

2014 – 38 pp. – 21.0 x 29.7 cm

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