



Modelling electric vehicles use: a survey on the methods



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ABSTRACT

In the literature electric vehicle use is modelled using of a variety of approaches in power systems, energy and environmental analyses as well as in travel demand analysis. This paper provides a systematic review of these diverse approaches using a twofold classification of electric vehicle use representation, based on the time scale and on substantive differences in the modelling techniques. For time of day analysis of demand we identify activity-based modelling (ABM) as the most attractive because it provides a framework amenable for integrated cross-sector analyses, required for the emerging integration of the transport and electricity network. However, we find that the current examples of implementation of AMB simulation tools for EV-grid interaction analyses have substantial limitations. Amongst the most critical there is the lack of realism how charging behaviour is represented.

1. Introduction

Electric vehicles (EV) uptake has been promoted around the globe for the benefits EVs are expected to bring in terms of energy security, global and local environment, and economical growth. Energy security is potentially improved as battery electric vehicles (BEV) and plug-in hybrid vehicles (PHEV) reduce the oil consumption of countries traditionally relying heavily on foreign imports. Impacts on global climate change from the transport sector can be reduced if the road transports electrification occurs in parallel with the decarbonisation of power generation. Local air pollution, especially in urban areas, can be reduced as higher fraction of driven miles is carried by zero tailpipe emissions vehicles such as BEVs. Economic growth can be stimulated by the development of an EV production supply chain as well as by deployment of the charging infrastructure and the development of business to operate it.

Along with the expected benefits, large scale EV deployment poses both a challenge and an opportunity for the operation of power grids. On one hand electric grids capacity can be strained by an unmanaged EV load, especially at the distribution level where the capacity bottlenecks are most easily reached. On the other, if charging demand flexibility can be harnessed by implementing smart charging strategies, not only can costly grid capacity upgrades be minimised, but the operation of grid systems can be enhanced making use of a potentially very large responsive storage constituted by the batteries of grid-connected EVs.

EV deployment impacts, being on the energy security, the environ-

ment, the economy or on grid system operations have been identified, studied and quantified mainly by means of mathematical models. Such models are necessary essentially for two reasons. Firstly, real world data about EV use is scarce due to the low adoption levels to date. Secondly, and most importantly, even when data is available, models need to be developed to assess impacts in conditions that do not necessarily coincide with those described by the available data, including the testing of new technological and policy scenarios. In fact, real world EV use data, collected in most cases during demonstration projects or trials, have been analysed mainly descriptively in few studies [1–3]. These descriptive analyses help gain qualitative insight into EV use and charging behaviour, but they essentially draw a picture of the status quo. As a matter of fact, such static pictures are of limited use in the rapidly evolving context of transport electrification which requires tools that are sufficiently flexible to inform decisions in a rapidly changing context. Such flexibility is enabled only by models.

Reviews of the studies into integration of EV into grid systems have been carried out to identify system architectures, to summarise the practical challenges for their implementation, to characterise the types of impacts expected from EV-grid integration, as well as to highlight the modelling methodologies applied [4,5]. The review of the methods, however, misses an in depth analysis on how EV use and charging demand is modelled or represented in various studies, despite the obvious effect this necessarily have in the study outcomes. This gap is filled by the present paper.

Here we review the approaches adopted to model electric vehicle use and changing patterns across a variety of impacts studies published

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in transport, energy and power sector journals. Across the sectors the modelling approaches are widely diverse. This diversity makes it difficult to compare the analyses' results from different studies. Because the focus of impact studies is not demand itself, but the impacts of EV deployment, there is a lack of critical analysis of the approaches used to model the demand of EV use, which is in fact the essential input of impact analyses. The diverse approaches for EV use demand modelling are organised in the present paper by means of a classification framework that enables to identify the weakness and strengths in each approach with respect to the scope of the impact studies.

The next section outlines our classification framework. Sections 3 and 4 provide the analysis of the literature and Section 5 provides our conclusions from this analysis.

2. Literature analysis approach

The papers analysed for this survey are broadly classified along two dimensions: time scale at which the EV usage patterns are represented and along substantive methodological differences in EV usage patterns modelling.

The classification along the time dimension distinguishes between models of car ownership and annual vehicle use models of daily vehicles' patterns. In car ownership and annual vehicle use models, vehicle holdings are typically modelled at the household level; vehicle use is typically modelled as vehicle annual mileage (VAM). Therefore these models are disaggregate with respect to observation unit of the vehicle usage level, but the frequency of observation is of the order of the year. In models of daily vehicle patterns the usage metrics are trips, the daily mileage, or daily activity-travel schedules (i.e. trip chains interspersed by drivers' non-travel activities). For ease of reference refer to the class of models of daily vehicle patterns with the label *Short-period models* (SPM). This label is intended to highlight that vehicle usage is modelled typically as it evolves over a single day or few days and not in as a single summary metric covering a *longer periods* of time (e.g. a year). Incidentally, the label *short-period* should not be confused with *short-term*, a label more often used in demand modelling/forecasting. While the latter refer to predictions of future demand, in a not far future with respect to a typical time scale of the quantity analysed, the label short-period used here refers purely to the time resolution of vehicle usage metric, with no reference to how far in the future the vehicle use is modelled. Indeed most EV studies based on either VAM models or SPMs, could be considered *long-term* as they assume large EV deployment scenarios rather far from the current levels of EV market penetration, thus often several years far from the present.

A systematisation of the literature also along a methodological dimension of EV patterns models is necessary essentially because in SPMs a wide variation of approaches has been adopted. The appropriateness of a methodological approach for the analyses of the impacts mentioned in the introduction are discussed in details throughout the critical review of the literature presented in Sections 3 and 4, but the main characteristics affecting method appropriateness are summarised in Fig. 1 and are related to the time resolution and the output disaggregation level required. In particular, the output disaggregation level achievable varies across SPMs, (Fig. 2).

Figure 2 provides an overview of the classification of the EV use modelling approaches adopted in this paper. Vehicle ownership and annual mileage models (VOAMM) constitute a single class. For SPMs methods we identified classes and subclasses:

- Summary travel statistics models (STSM)
- Models based on entire activity travel schedules: (Direct use of observed activity travel schedules, DUOATS; and proper activity based models, ABM).
- Markov chain models (MCM) of vehicle state.

The structure of Sections 3 and 4 of this paper reflects Fig. 2: these two sections discuss the strengths and weaknesses for each model class relative to the typical application contexts of EV use models. The paper will conclude by summarising the main research gaps and suggest avenues for further work. The highlights of our analysis of the literature are presented in Table 1 below. The table compares advantages, disadvantages and application areas for each of the modelling solutions discussed in details throughout the paper.

3. Vehicle ownership and annual mileage models

VOAMMs have traditionally been developed and improved by transport demand researchers for variety of planning purposes of interest to a diverse stakeholder community [6,7]. Stakeholders and purposes include:

- Car manufacturers: to measure consumer valuation of car attributes;
- Energy companies, oil companies specifically: to forecast the use of their product, therefore are interested in forecasting both car ownership and use;
- Financial institutions and international organisations: to guide investment decision making assistance;
- Governments: to forecast impacts of changes in taxation levels, but also to forecast tax revenues;
- Governmental and non-governmental organisations from national to local level: to forecast transport demand (in which case these models are integrated with traditional four-step models for transport demand), energy demand and emission levels, and to simulate policy impacts on the demand.

EV ownership and mileage demand models have some obvious applications. For example utilities are interested in, forecasting EV ownership to estimate the future size of the EV stock on the road to estimate the potential additional demand for electricity for investment planning purposes. Governments striving to foster EVs' uptake make use of these models to testing the effectiveness of incentives (e.g. direct subsidies on the capital costs, tax rebates or exemptions, deployment of public charging infrastructure). Vehicle manufactures are interested in analysing market potentials of EVs to devise their production strategies. However, if properly applied, EV ownership and mileage demand models can provide less obvious insights. For example, investments in public charging infrastructure deployment can be viewed on the one hand as a strategy to incentivise EV adoption. On the other hand, the infrastructure location is not irrelevant for the effectiveness of these investments. These two aspects can be jointly analysed with appropriate vehicle ownership models, provided that the model can account for spatial heterogeneity in car buying households. For instance spatial heterogeneity in the availability of private parking spaces (driveways and garages) and in income may have important effects, regarding how to direct investments incentivising EV uptake. In some areas, reducing the charging infrastructure barrier may be more effective than providing incentives on capital costs, whereas in other areas, where private driveways or garages are more common, capital incentives rather than investment in charging infrastructures may be more effective. A further example of less direct application of disaggregate EV adoptions model is long term spatial analysis of electricity demand, which is of interest for electric infrastructure planning.

The nature of the applications described above suggests that a considerable level of model disaggregation is desirable along several dimensions: vehicle characteristics, household characteristics, and in space to analyse local effects. In EV market studies both aggregate and disaggregate modelling methodologies have been used, which include agent based modelling, diffusion rate and time series models, discrete choice models [8]. The first and the last disaggregate methods and thus offer the possibility, at least in theory, to achieve disaggregation along the highest number of dimensions. Agent based models are mainly

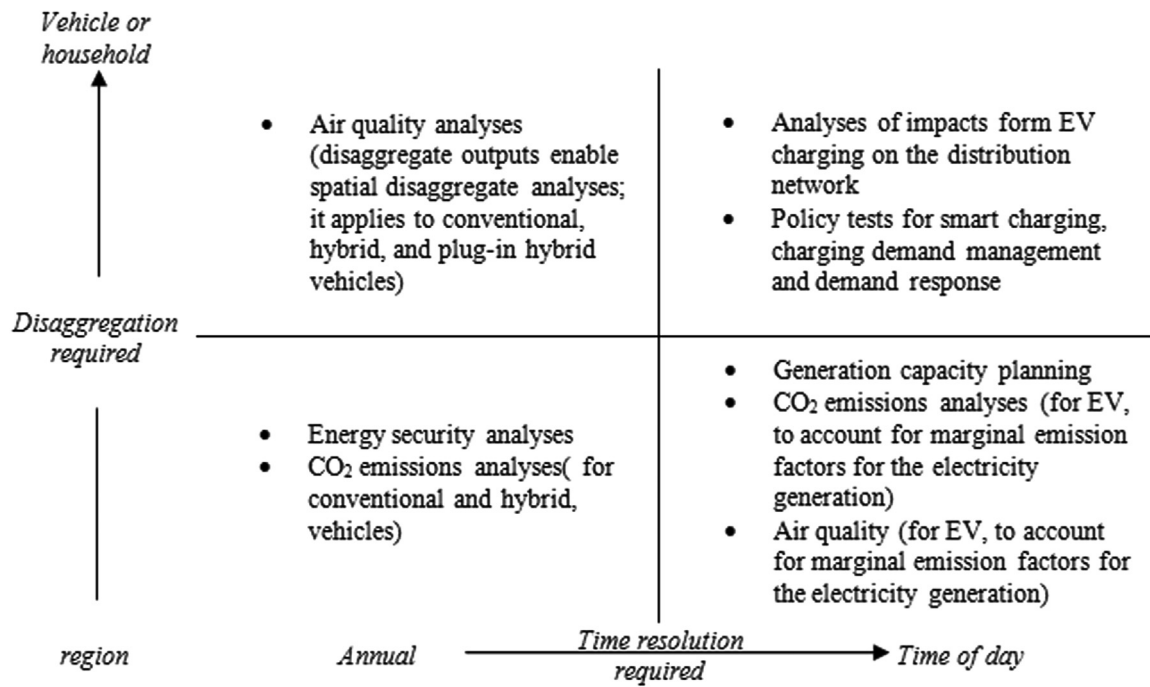


Fig. 1. Spatial aggregation levels and time resolution in EV use models required by the analysis purpose.

based on theoretical formulation of consumers behaviour or when their parameter are estimated empirically, consumer behaviour is often modelled making use of discrete choice models. In the next subsection, we will focus on reviewing application of discrete choice models for EV adoption, because due to their disaggregated nature they are better suited for the application context described. The subsection following the next will review studies where such models have been integrated with vehicle use models to forecast jointly vehicle ownership and annual use.

3.1. Discrete choice models in vehicle adoption models

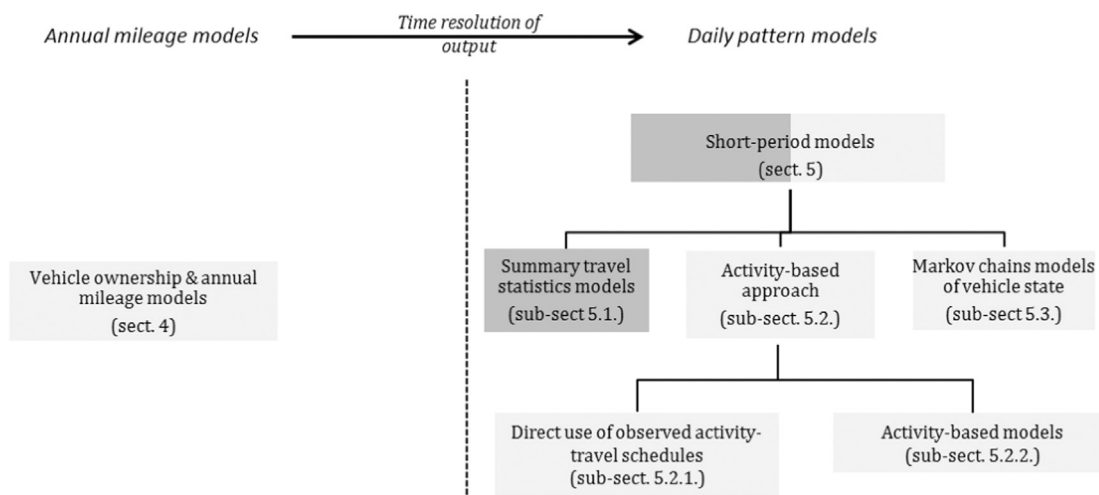
In discrete choice models individual chooses between a complete set of exclusive alternatives (e.g. the vehicle type to own or the number of vehicles to own), from each of which the individual consumer or the household would derive some utility, if the alternative is chosen.

According to classical microeconomic theory, the individual will choose the alternative that maximizes his utility. The utility of each alternative depends on the characteristics of the alternatives and the values that each individual places on these characteristics. Because the analyst cannot observe the utility directly, he cannot specify a model providing the choice outcome with invariable success. Thus the concept of Random Utility becomes necessary [9]. This means that the utilities are actually random variables; therefore the analyst can only identify the choice probability for each alternative, but not the choice outcome.

The general structure for the utility an individual n places into the alternative i belonging to the choice set J_n can be written as:

$$U_{ni} = V_{ni} + \epsilon_{ni} \quad \forall i \in J_n$$

where V_{ni} is the observable (or systematic) component of the utility, that the analyst can describe as a function of the alternative's attributes and the decision maker's characteristics, while ϵ_{ni} is the random error



Level of output aggregation is colour coded. Dark grey: models provide aggregate outputs. Light grey: models provide outputs with a high level of disaggregation.

Fig. 2. Classification of EV use modelling approaches.

Table 1
Synopsis of advantages, disadvantages and applicability of EV use modelling approaches.

Modelling approach	Advantages	Disadvantages	Applicability
VOAMM	<ul style="list-style-type: none"> Disaggregate outputs (can be aggregated if necessary) 	<ul style="list-style-type: none"> Vehicle usage is in terms of annual mileage whereas time of day time scales are required for most e-mobility analyses 	<ul style="list-style-type: none"> Vehicle ownership sub model vehicle penetration (first step in any EV deployment impact analysis) Long term air quality analyses
STSM	<ul style="list-style-type: none"> Disaggregate outputs (can be aggregated if necessary) 	<ul style="list-style-type: none"> High data requirements for model estimation Time scale of EV usage compatible with most e-mobility analyses Do not represent daily travel patterns consistently Travel patterns are fixed, i.e. they lack responsiveness is policy tests (policy analyses are carried out via scenarios) 	<ul style="list-style-type: none"> Long term energy demand may make use of All EV impact analyses requiring time of day time scales (see right quadrants in Fig. 1), except policy tests for smart charging/charging demand management/demand response
DUOATS	<ul style="list-style-type: none"> Disaggregate outputs (can be aggregated if necessary) Represent daily travel patterns consistently 	<ul style="list-style-type: none"> Travel patterns are fixed, i.e. they lack responsiveness is policy tests (policy analyses are carried out via scenarios) 	<ul style="list-style-type: none"> All EV impact analyses requiring time of day time scales (see right quadrants in Fig. 1), except policy tests for smart charging/charging demand management/demand response
ABM	<ul style="list-style-type: none"> Disaggregate outputs (can be aggregated if necessary) Represent daily travel patterns consistently Responsiveness to policies (if charging behaviour is modelled explicitly) 	<ul style="list-style-type: none"> Higher complexity than STSM or DOATS High data requirements for model estimation 	<ul style="list-style-type: none"> All EV impact analyses requiring time of day time scales (see right quadrants in Fig. 1), including policy tests for smart charging/charging demand management/demand response if charging behaviour is explicitly modelled
MCM	<ul style="list-style-type: none"> Fully disaggregate year long EV patterns Consistent vehicle patterns 	<ul style="list-style-type: none"> Lack of behavioural realism make questionable the policy sensitivity 	<ul style="list-style-type: none"> All EV impact analyses requiring time of day time scales (see right quadrants in Fig. 1), except policy tests for smart charging/charging demand management/demand response

component. The distinct sources of randomness that are typically found are: unobserved attributes, unobserved taste variations, measurement errors and imperfect information, instrumental variables, i.e. variables that are related to actual attributes that are though unobserved [10].

The choice probability for alternative i is thus:

$$P(i|J_n) = Pr[V_{ni} + \epsilon_{ni} > V_{nj} + \epsilon_{nj}, \forall j \neq i \in J_n] = \int_{\gamma} I(\epsilon_{nj} - \epsilon_{ni} < V_{ni} - V_{nj} \forall j \neq i) g(\gamma_{ni}) d\gamma_{ni}$$

where I is an indicator function equal to 1 when its argument is true; $\gamma_{ni} = \{\epsilon_{n1} - \epsilon_{ni}, \epsilon_{n2} - \epsilon_{ni}, \dots, \epsilon_{n(i-1)} - \epsilon_{ni}, \epsilon_{n(i+1)} - \epsilon_{ni}, \dots, \epsilon_{nJ_n} - \epsilon_{ni}\}^T$ is a $J_n - 1$ dimensional vector of the difference in errors for alternatives j and alternative $i \forall j \neq i \in J_n$; $g(\cdot)$ is the density of the error differences (which can be derived from the density of $\{\epsilon_{n1}, \dots, \epsilon_{nJ_n}\}^T$); and γ the support of $g(\cdot)$. Once choice probabilities for individuals are known, then several aggregation techniques are available to estimate aggregate demand [9,11].

Traditionally in car ownership models discrete choice models have been used to model: number of cars owned by a household [12,13]; vehicle transactions type (addition versus replacement of vehicle to holding); and vehicle type choice (class, power-train, brand etc...). Clearly the latter dimension is the most relevant for EV adoption models.

Alternative fuel vehicle adoption studies using discrete choice modelling show an evolution of the modelling technique along three main lines: (1) in the explanatory power of the systematic utility; (2) in the characterisation of the error structure to capture more realistic substitution patterns; and (3) in the overall modelling framework, to explicitly capture latent construct that qualitative studies have demonstrated play a major role in vehicle adoption behaviour (such as attitudes and symbolic values; or multidimensional attributes not apt to direct measurement).

3.1.1. Systematic utility specification

Around thirty years of discrete choice modelling studies carried out mainly using stated choice experiment data have identified several significant vehicle attributes affecting car buyers purchase decision

when electric vehicles are amongst the alternatives in their choice sets. These include: purchase price, operating costs, driving range, recharging times, recharging/refuelling network density, power and emissions [14]. Heterogeneity in taste for such attributes have been partially explained by drivers' socio-demographics especially gender and education level [14].

3.1.2. Error structure specification

The workhorse of discrete choice modelling has been Multinomial logit model (MNL). This model is characterised by closed-form choice probabilities and is derived by assuming that the error terms in the expression of the utility for an alternative are iid Gumbel distributed. The expression for the choice probabilities is [15]:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J_n} e^{V_{nj}}}$$

The MNL model thanks to its simple form has been widely used in vehicle adoption studies [16–21]. However the advantage of closed-forms choice probabilities comes at the cost of realistic substitution patterns amongst the alternatives, which are constrained by the so called *independence from irrelevant alternative* property of the MNL. This property consists in the fact that the ratio between the MNL probabilities of two distinct alternatives i and k in one's choice J_n set does not depend on any other alternative available in J_n , nor on the attributes of the other alternatives. As a result, MNL models predict that the introduction of a new alternative, the elimination of an existing one, or changes in the attributes of one of the alternative lead to a change in the probability of the other alternatives such that the ratios of probabilities remain the same. This has a serious implication in the substitution patterns amongst alternatives in vehicle type choices when EVs are part of the choice set. An example of the effect of using an MNL for forecasting the uptake of EVs is provided by Brownstone and Train [22]. Suppose that a small size EV becomes available in the choice of individuals from a population whose choice set was originally characterised by conventional vehicles only. The IIA property fixes the ratio between, for example, the share of small gasoline cars and large gasoline cars, therefore the share of the newly introduced small EV must draw proportionally from both the share of small and large

gasoline cars, so that the ratio above remains constant. Intuition, however, would suggest that the unobserved utilities of small gasoline cars and the small EV would be more correlated than the utility of the EV and large gasoline cars: this would realistically lead to a higher substitution rate between the small EV and small gasoline cars than between the small EV and large gasoline cars. IIA makes the MNL unfit to represent this phenomenon. More flexible substitution patterns can be achieved by the use of error term specifications other than MNL that relax the IIA property.

The Generalised Extreme Value (GEV) framework, (of which the MNL is a special case) provides the means to model various substitution patterns. Apart from MNL the most common GEV model, especially in transport research, is the Nested Logit (NL) model. The NL has been used to model alternative fuels vehicle choices [23,24], allowing to capture correlations within “nests” of vehicles types sharing unobserved common attributes. GEV models with more complex correlation structure have been also proposed in EV adoption studies. In particular, Hess, et al. [25] hypothesised a heightened substitution rate between cars either having the same body class or using the same type of fuel. To account for this in the correlation structure of the unobserved utility, they adopt a cross nested logit (CNL) model [26].

Because any type of random utility discrete DCM error specification can be approximated by the Mixed multinomial logit model (MMNL) [27], such DCM specification has been widely applied to model flexible substitution patterns and in electric/alternative fuel vehicles demand modelling [21,22,28–30]. In the MMNL, the error term is specified as the sum of a zero mean type I extreme value term IID and another term with a zero mean whose distribution over individuals and over the alternatives depends in general on observed data, and the underlying parameters of the distribution. Therefore, unlike the MNL, the MMNL does not have closed-form choice probabilities and require the solution of multiple integrals over the mixing distributions numerically, which however is currently not a problem due today's computational capabilities. These have also allowed the use also of the multinomial probit model [22,31]. In this model, flexible substitution patterns are obtained by specifying the full error terms as multivariate normally distributed, with a covariance matrix specified to reflect the hypothesised correlation structure.

3.1.3. Hybrid choice model framework

It has been acknowledged that there is a wide range of evidence that alternative fuel vehicle adoption decisions are also determined by symbolic values and attitudes such as social status concerns, environmental attitudes, innovativeness and other meanings that individuals choosing a certain vehicle communicates to themselves and others [32–34]. These are latent quantities, i.e. unobserved. In addition, there are also car attributes that, due to their multidimensionality, are not measurable objectively (e.g. safety and comfort). Psychometric indicators are one way of revealing these underlying latent attitudes. However, their direct use as explanatory variables in the systematic utility of an alternative in a choice model is not advisable for several reasons, such as [35]:

- Attitudinal statements may not translate into a causal relationship with choice;
- Future attitudinal indicator values cannot be predicted for future populations, thus cannot be used as exploratory variable in forecasting choices;
- Attitudinal statements may be characterised by measurement errors, leading to inconsistent estimates;
- The likely correlation between the error term and the indicators might cause endogeneity bias.

Similarly, using a single proxy variable to account for complex multidimensional attributes such safety would lead to biased parameter estimates [14].

The Hybrid Choice Models (HCM) modelling framework extends random utility DCM to enable to make use of latent constructs information to be accounted for in choice models [36–39]. In the alternative fuel vehicle choices literature HCMs have been mainly used for the following purposes: to identify a latent class of potential vehicle adopters more inclined towards EVs [40]; to account for environmental preferences in vehicle adoption behaviour [40–43]; and to model the effect of safety in vehicle choice [44].

The rich behavioural insights captured by HCMs come at the cost of increased data requirement (e.g. collection of psychometric information together with more traditional vehicle type choice data). Moreover, it remains unclear whether the heavier data requirements and model complexity are paid off by the real benefits in practical applications of these models in real-world problems [45].

3.2. Modelling annual vehicle use

The vehicle use component in long period models is as mentioned in the introduction to this section typically characterised in terms of the annual mileage metric. Vehicle annual mileage is typically modelled jointly with the discrete vehicle adoption component.

The reason why mileage and vehicle adoption tend to be modelled jointly is that it is recognised a household's choice of how many cars to own and of which types to is interrelated with the how much the household drives. In turn, preference for vehicles attributes and mileage driven will depend inter alia also on households' characteristics.

An influential approach to modelling joint car ownership and use rigorously based on microeconomic theory was proposed by Kenneth Train [6]. While it consists of separate sub-models for the choice of number of cars owned by a household, for class and vintage of each cars and the annual mileage travelled by each of them, it is in effect a joint model of vehicle adoption and use. Indeed, the modelling structure is derived from the theory of choice in which individual households makes those choices jointly. Only for practical reasons the vehicle adoption and use are estimated separately (sequentially), though could be potentially estimated jointly. The interdependence of vehicle adoption and use is recognised and preserved in the derivation of the demand function for annual mileage. The demand continuous function for the annual mileage driven is obtained from the conditional indirect utility function, using Roy's identity, given that the discrete choice of a specific vehicle.

Building on Train's approach, Brownstone, et al. [46] developed an integrated modelling system to forecast demand for new and used vehicles, annual vehicle mileage and EVs charging demand. The vehicle use sub-model is based on structural equation modelling [47]. The endogenous variables are vehicle annual mileage and main driver's age, gender and employment status whereas; vehicle and household characteristics are exogenous. This formulation recognises the influence of the effect of the main drivers' characteristics on vehicle use which was ignored in Train's discrete continuous formulation. However, as the authors acknowledge, it neglects the endogeneity of vehicle type choice and vehicle use. The endogenous estimation of the main drivers characteristics is appealing for the model application in forecasting, when multiple vehicles are owned by a household. Indeed, exogenous forecasts of households' characteristics and their vehicle holdings as inputs to the vehicle use models are easier to obtain than principal drivers characteristics. Endogenous estimation of the latter enables skipping this step, while still accounting for their effect on the prediction of vehicle use.

A recent formulation of discrete-continuous models takes into account that in household vehicles holdings, different vehicles are driven with different annual mileages depending on their characteristics, and that a the choice of a holding is affected by how the various vehicles are driven. Such model is the so called multiple discrete-continuous extreme value model (MDCEV) [48,49]. The MDCEV

formulation accounts for the multiple discreteness of in the choice of acquiring a vehicle holding as well as the fact that the “annual driving miles budget” of a household is not distributed evenly distributed amongst vehicles in the holding.

Further discrete-continuous models evolutions account for the dynamic nature of vehicle transactions in an integrated fashion using dynamic a discrete-continuous choice model. This embeds discrete-continuous choice of vehicle ownership and use into a dynamic programming framework [50]. This methodology allows vehicle transaction type over time, fuel type of the vehicle, ownership status over time and annual vehicle use to be modelling jointly. Because vehicle fuel type choice is modelled, the model has potential applications in analysing the demand for alternative fuel vehicles, including EVs.

3.3. Applicability and limitations of VOAMMs

The adoption of VOAMMs for electric vehicle use modelling is suited when yearly time scales are of interest. That is for the type of analyses that feature in the left quadrant of Fig. 1: (e.g. annual energy consumption, or yearly air quality impact of electric vehicle deployment). The vehicle demand modelling subsystem is also important in any analysis of electric vehicles deployment to generate penetration scenarios that are sensitive to various policies potentially implemented to foster EV uptake and their evolution as well as other exogenous context variables (e.g. to capture the effect on EV penetration of plummeting oil prices).

The annual mileage metric indeed strongly limits the applicability of the forecasted EV usage from VOAMMs. VOAMMs are not suited for the direct study of charging patterns in time and space and the impact of charging demand peaks on power grids or accurately estimate the emission associated with EV charging, given the scales of the time-dependence of relevant electric load dynamics and marginal emission factors of the electricity generation mix of a grid systems.

Therefore, the use of VOAMMs in electric mobility analysis should be mainly focused on forecasting the EV stock on the road and their spatial distribution. Apart for the application mentioned, the annual mileage should be considered a useful endogenous quantity to improve EV ownership prediction. Using forecasts of annual use for short period analyses would require a further downscaling step, for which the short period models described below are necessary, to avoid arbitrary assumptions with regard daily use and charging patterns.

4. Short-period models

While transport modellers have traditionally mainly focused on modelling EV adoption and annual use, power system, energy and environmental analysts tended to be more interested in treating EV use and charging at a finer grained time resolution (typically of the order of the hour or fraction of the hour). However, the approaches for short period EV use patterns modelling by transport planners and demand modellers and those of power systems/energy and environment analyst are currently converging with the adoption of activity-based approach originally developed for transport policy analyses. Nevertheless, the largest body of analyses carried out making use of short period models is still within the power systems and energy/environmental domains. The purposes of studies undertaken can be summarised as follow:

- To verify that electricity generation capacity can provide for the additional load caused by EV;
- To evaluate the costs of the electricity generation for EV charging, (as marginal costs are time dependent);
- To assess whether EV associated load will generate congestion at bottlenecks in the distribution network;
- To appraise the effectiveness of demand side management or demand response strategies in shaping EV charging load profiles, so that costly investment for grid upgrades can be minimised and

grid power system operations can be enhanced, by for example contributing to ensure supply reliability when an increased share of wind power (or other variable renewable energy sources) is added to a grid system.

- To estimate with more precision than with models based on annual usage the extent of liquid fuel displacement in favour of electricity by PHEV, by taking into account the actual recharging opportunities during the course of the day;
- To obtain more precise estimates of greenhouse gases (GHGs) and pollutant emissions, taking into account the time dependence of the (marginal) emission factor.

It should be pointed out, however, that, as short period models of EV use can be used as planning tools to optimise the location public parking spaces with charging facilities, also the transport and city planners can benefit from them. Moreover, if such tool are developed within simulation framework that allow also more traditional analyses of travel demand, as it is the case for activity based models, integrated cross-sector analyses of multilayered networks (e.g. energy and transport networks) become possible.

Apart from a few notable exceptions [51–56], in SPMs, charging behaviour is not explicitly modelled, but fixed by scenario. These scenarios are typically based on actual policy variables, such as charging infrastructure availability and characteristics of the charging facilities (installed charging power) and predetermined charging behaviours, or charging strategies, to simulate a boundary conditions demand response to electricity tariff structures. Typical charging behaviour scenarios found in the literature include:

- Uncontrolled charging - also referred to as “uncoordinated charging”. This implies that the charging operation starts as soon as vehicles reach locations with charging opportunities (defined by charging infrastructure scenarios) and is carried out until the vehicle is fully charged or leaves to reach the next destination. While in disaggregate models, and activity based approaches specifically, charging terminates with vehicle departure, even if the battery is not full, aggregate models often assume that vehicles are always charged fully.
- Delayed charging (or night charging) – vehicles are assumed to delay charging for a number of hours, so that charging starts in the evening, to ensure electricity costs are minimised. This scenario is intended to simulate the demand response effect to lower night-time prices of electricity, on assumption that the price difference is high enough to induce the large majority of EV users to charge during low price hours.
- Off-peak charging – vehicles are assumed to charge only in off-peak hours. This scenario requires direct control by the system operator. The underlying behavioural assumption is that users accept this type of direct control. Clearly this type of control could also be implemented in a decentralised way by on-board ICT systems, receiving signals from the system controller, although these could potentially be overruled by the user. With this alternative implementation method the validity of the scenario rests on the extent users allow only off-peak charging. In fact, the off-peak charging scenario may be thought of as simulating the ideal effect of electricity tariffs designed to discourage charging in peak hours.

Apart from the charging behaviour scenarios described above, other types of charging strategies can be implemented in EV-grid models in order to coordinate charging of EVs so that the impacts of EVs on the environment or on the grid are minimised. These types of optimisation strategies, which require either centralised direct control or decentralised control through pricing signals, are collectively denominated as “smart charging” or “coordinated charging”. Typically these smart charging strategies are implemented in an agent based fashion assuming that EV are cost minimising agents, who choose the minimum cost

charging schedule that enable the execution of their journeys between charging opportunities.

The use of fixed charging behaviour scenarios instead of explicit models is a strong limitation, because it implies pre-determined outcomes of a demand management policy. Pre-determined outcomes mean that the effectiveness level of a policy has to be assumed a priori, whereas explicit models of charging behaviour, possibly accounting for drivers' heterogeneity, could test how effective a policy is.

The lack of explicit charging behaviour models is mainly due to the lack of available data on charging. Although, as has been mentioned, some results from EV trials have started to be published, the original datasets are not easily available on account of proprietary or participant privacy issues. This is indeed a barrier for the development and empirical estimation of policy sensitive charging models, i.e. in which the response of drivers is the results of underlying behavioural models calibrated on charging behaviour data. A typical example would be that of models based on consumer theory in which charging strategies are the result of empirically elicited driver preferences.

In the rest of this section a selection of the full sample of studies [53,56–86] adopting short period analyses considered for this review are discussed according to the classification in Fig. 2. Table 2, below instead gives an overview of the modelling approach and study scopes adopted by each paper in the full sample. To the benefit of the readers we also provide in the appendix a table (Table A1) that summarises each study in the full sample in more detail, including: modelling approach, scopes, charging behaviour and infrastructure assumptions, geographic area which the study considers and main findings.

4.1. Summary travel statistics models

A common approach adopted in modelling EV use patterns is based on indicative information about (conventional) vehicle use extracted from national, regional or metropolitan travel surveys. Travel patterns' summary statistics or empirical distributions obtained from travel surveys are used to generate deterministic or stochastic vehicle use patterns. These are mostly utilised in combination with charging behaviour scenarios to generate charging profiles.

To study smart demand management of the distribution network, Zakariazadeh et al. use 7 archetypal driving patterns generated based on summary driving patterns statistics a survey in a “real town”, each of the archetype has specific times during which EVs has parked at home and at work as well as trip durations [77,78]. This approach to model EV use does capture the main structures of travel patterns but strongly limits capturing the effects of travel patterns variability.

Mullan et al. [80] use a reference daily distance of 40 miles, the average vehicle distance travelled in Western Australia, and assume that all EVs in a simulation are charged for 4 h at 1.5 kW, in order to refill the battery of the energy consumed for driving such a distance. They use charging behaviour scenarios to determine the charging period (e.g. 16:00–23:00 “evening only” or 23:00–7:30 “night only”) and assign random delays to introduce variability in the charging start times. Other studies in order to represent the variability in both the daily vehicle mileage and the charging availability start times, use empirical distributions of daily distance and vehicle trip timings [79,81–86].

Table 2

Full sample of the reviewed studies in the short period models class by EV use modelling technique and scope.

Modelling technique	Study scopes								Study
	EEl & P ^a	CIP ^a	EGl & P ^a	V2G ^a	SC & DM ^a	EconI ^a	DNI & P ^a	Meth ^a	
ABM					X			X	[53]
ABM								X	[57]
ABM	X								[58]
ABM	X								[59]
ABM					X			X	[60]
ABM	X					X			[61]
ABM				X		X		X	[56]
DUOATS	X	X							[62]
DUOATS	X								[63]
DUOATS		X							[64]
DUOATS			X	X	X	X			[65]
DUOATS	X	X							[54]
DUOATS	X								[66]
DUOATS	X								[67]
DUOATS	X					X			[68] ^b
DUOATS	X		X			X			[69]
DUOATS	X		X		X	X			[70]
DUOATS	X								[71]
DUOATS	X								[72]
DUOATS	X	X							[73]
FSM		X				X	X		[74]
MCM						X	X		[75,76]
STSM				X		X	X		[77]
STSM						X	X		[78]
STSM						X	X		[79]
STSM			X			X			[80]
STSM			X						[81]
STSM			X	X		X			[82]
STSM					X		X		[83]
STSM		X			X				[84]
STSM									[85]
STSM									[86]

^a EGI & P=Electric generation impacts and planning; DNI & P=Distribution network impact and planning; SC & DM=smart charging and demand management; EEI & P=energy and environmental impacts and policy (here by energy impacts are intended mainly in terms of oil-based fuels consumption reductions and environmental impacts in terms of GHG and pollutant emissions into the atmosphere); EconI=economic impacts (mainly to consumers or on the power system); CIP=charging infrastructure planning; Meth=methodological.

^b In this paper time of day analyses are not carried out, although may be possible.

4.1.1. Applicability and limitations of STSM

STSM models, being essentially trip based, lack a consistent travel schedule structure and therefore miss the spatial and temporal details required for impact analyses at the distribution network level. Instead, they may appear suitable for analyses which require less accuracy along the spatial and temporal dimensions, e.g. for generating capacity planning purposes. An inherent weakness of this approach is that the exogenous vehicle usage patterns generation typical of STSM models implies that effects on travel patterns of charging demand management are inevitably neglected. Moreover if the travel patterns variability is reduced by the use of summary statistics only (or using archetypal driving patterns), and their randomness is not recaptured by randomly drawing from the travel patterns distributions, the inherent load flexibility of aggregate demand is lost.

4.2. Activity based approaches (ABA)

In activity-based approaches consistent daily activity-travel schedules are considered. The activity-based analysis framework appears particularly suitable to model EV daily use and charging patterns because it analyses travel “as daily or multi-day patterns of behaviour, related to and derived from differences in lifestyles and activity participation among the population” [87]. This type of analysis is particularly appealing as it is rooted in the time of day timescales, obviously absent in vehicle use modelling based on the annual distance driven metric. An activity-based model with a charging behaviour component, allowing users preferences for different charging strategies to be modelled, would allow the effect of charging demand management policies both on charging and travel patterns to be simulated without relying on predefined charging behaviour scenarios.

Before introducing examples of studies where proper activity based models (ABM) have been used for analysing EV patterns, we review below (in Section 4.3) analyses that, instead of making use of activity-travel schedules generated by ABM, utilise observed conventional vehicle travel patterns to model EV use. This is one of the most commonly used approaches in impact analyses. Utilisation of observed conventional vehicle diaries is still considered here as part of the activity-based approach, since structurally consistent activity-travel schedules are used for EV pattern modelling.

4.2.1. Direct use of observed activity-travel schedules

Use patterns of conventional (i.e. non-electric) cars have been used to simulate EV use patterns. This is done in several ways: using travel diaries from existing travel surveys collected by various agencies; collecting car diaries in ad hoc surveys; or using GPS data.

Darabi and Ferdowsi [64] extract from the US 2001 National Household Travel Survey (NHTS) the arrival time last trip of the day and daily vehicle mileage for each vehicle in survey. The use mileage information to calculate the remaining state of charge in a PHEV type characterised by a given energy consumption (based on the vehicle size class) and a given all-electric-range. Each PHEVs is assumed fully recharged after the last trip, the charging availability would start at the arrival time from the last trip. Charging scenarios entailing shifting variation in charging powers and delaying charging are used to show how charging demand peaks can be moved in times, if time shift and charging powers could be “enforced”. In order instead to simulate the effect of time of use pricing, they design a charging scenario in which 20% of drivers are responsive to the price signal and shift to off-peak hour charging.

Kang and Recker [66] generate PHEV usage patterns by replicating car diaries extracted from the Travel Diaries of the 2000–2001 California Statewide Household Travel Survey. The charging patterns are generated using infrastructure and charging behaviour scenarios. It is not clear whether the car diaries generated are vehicle based or person-based, and, in the latter case, whether vehicle use by multiple drivers was accounted for. In fact, neglecting use of one vehicle by

multiple drivers would lead to an underestimate of the daily energy needs of the vehicle and to an overestimate of the time the vehicle is available for charging (indeed, neglecting use by multiple drivers is equivalent to assuming that each driver uses a different vehicle). It should be pointed out that, for analyses aiming at assessing the impact of EV charging on the grid at the distribution level, which require not only fine temporal resolution but also fine spatial resolutions, especially in urban contexts, analyses using vehicle-based diaries ensure more accuracy in energy use and time of charging estimates.

In order to assess potential energy impacts in California from “user-designed” PHEVs, Axsen and Kurani [62] model PHEV use and charging profiles making use of one day car diaries from a previously administered US nation-wide survey designed to assess, inter alia, consumer priorities in PHEV designs [88,89] and the effective availability of EV recharging opportunities in car-owning households [88,90]. For the latter task, the travel diary collection instrument embedded questions about the availability of electrical outlets and their distance from the car at the parking locations visited during the survey day. One day diaries, charging opportunities data and characteristics of user-designed PHEVs were also used to generate charging profiles that integrated with an energy dispatch model so as to estimate the greenhouse gas emissions. The charging profiles in Axsen and Kurani’s work are generated using charging behaviour scenarios, in line with most of the short period models applications.

Similar types of analyses are carried out by Kelly et al. [67]. Kelly and colleagues extract one-day vehicle diaries from the US 2009 National Household Travel Survey diaries, and generate aggregate time of week PHEV charging load profiles, making use of charging infrastructure and charging behaviour scenarios.

Khan and Kockelman [68] use multiday GPS tracked vehicle patterns, to carry out another type of analysis, consisting in the assessment of how EVs (BEVs and PHEVs) can satisfy households’ vehicle use needs. From a sample of 255 Seattle households they find that a BEV with a 100 miles range could meet 50% of the needs of single vehicle households and 80% of the needs of multivehicle households, charging once a day and relying on another vehicle or mode just four days in a year. Khan and Kockelman, instead of using current driving data to model EV patterns, assess the potential of EVs to replicate current driving data. Their results show that single vehicle households in Seattle need to change their travel patterns in BEV scenarios, if only one charging opportunity is available. Clearly this may not apply to PHEVs. Incidentally, one of the reasons why many analyses using observed conventional vehicle patterns for EV modelling only involve PHEVs is that the argument for unchanged travel patterns in BEV deployment scenarios is not so convincing, at least in some parts of North America. Nevertheless, even in parts of the world where current driving patterns are more compatible with typical BEV ranges or even in the case of PHEV deployment, the assumption of unchanged travel patterns is arguably challenged by future charging service modes, tariff structures and infrastructure availability, and of course on the driver’s preferences in terms of range availability, and cost.

4.2.2. Applicability and limitations of DOUATS

The underlying assumption is that the introduction of EVs does not significantly change travel patterns, even in large deployment scenarios. This assumption is of course acceptable if the object of the analysis is PHEVs, which do not have range limitations. Concerning BEVs, the assumption is justified by the high feasibility of journeys and tours under various charging infrastructures and charging behaviour scenarios. Nevertheless, as time of day road pricing can affect car patterns [91], the complex tariff structures of electricity for EV charging demand management, and their spatial and temporal variability (e.g. different prices at home, work charging facilities or at other locations), are likely, in principle, to induce price sensitive drivers to adapt their travel patterns to minimise their travel costs.

The inherent rigidity of the DUOATS approach stemming from the

use of fixed EV travel schedules and pre-determined charging behaviour scenarios, makes the approach insensitive to policies potentially affecting EV travel and charging behaviour. Nevertheless this approach has been applied across the full applicability spectrum of SPM, including studies charging demand management and response. This translates into results more reflective of the analyst expectations of the effect of a policy under scrutiny rather than a of the potentially heterogeneous response of EV drivers to such policy.

4.2.3. Activity based models

The activity based modelling of travel demand, comprising a set of heterogeneous behavioural theories and conceptual frameworks (microeconomic theory of consumer behaviour, remaining the dominant choice), implementation methods (econometric models or heuristics approaches) and empirical applications, in essence tries to reconcile travel behaviour modelling and analysis with the common shared perspective that travel behaviour represents just a facet of a complex pattern of behaviours that the analyst observes, individuals seek participation in activities. Traditional transport trip-based modelling has lacked a strong foundation in this more holistic philosophy, since in the most often used trip based framework, the Four Step Model (FSM), activities affect mainly trip generation and their influence decreases as the sequence of modelling steps proceed [92]. The effort to improve travel demand modelling by adopting ABM frameworks has not been driven purely by the intellectual trend towards solving the dialectics between this philosophy and modelling practice to reach the transcending unity that would appease theoreticians. In fact, the theoretical deficiencies¹ present in the trip-based approach prevent its use in policy analyses beyond “certain well-defined situations” [93], which in practice consist of their original objective of urban highway investment analysis [94]. More precisely, the most prominent policy types requiring enquiring tools that would overcome FSM’s limitations were: “global and highly flexible policies”, such as fare changes in public transport and policies that would lead to “substantial [and heterogeneous] travel response”, like road pricing [94].

Practitioners have indeed introduced improvements to the FSM framework to make it more flexible in reflecting more realistic behavioural responses. These improvements, however, had the aim to obtain more reasonable result at the aggregate level, rather than actually improve behavioural modelling at the individual level. In contrast, at the heart of the development of activity based models there is the representation of the individual decision process as disaggregate.

In order to analyse the effect on travel and EV charging patterns of policies intended to manage the EV power demand profile and of travel demand management policies on EV load, ABMs appear particularly suitable for several reasons including the following:

- They capture inter-dependence of activity and mobility patterns and therefore on the relation between travel patterns and the durations of vehicle dwell time at locations where activity are carried out and where vehicle may potentially be recharged.

¹ Mc Nally and Rindt summarise six main theoretical limitations of trip-based models as: “(1) ignorance of travel as a demand derived from activity participation decisions; (2) a focus on individual trips, ignoring the spatial and temporal interrelationship between all trips and activities comprising an individual’s activity pattern; (3) misrepresentation of overall behaviour as an outcome of a true choice process, rather than as defined by a range of complex constraints which delimit (or even define) choice; (4) inadequate specification of the interrelationships between travel and activity participation and scheduling, including activity linkages and interpersonal constraints; (5) misspecification of individual choice sets, resulting from the inability to establish distinct choice alternatives available to the decision maker in a constrained environment; and (6) the construction of models based strictly on the concept of utility maximization, neglecting substantial evidence relative to alternate decision strategies involving household dynamics, information levels, choice complexity, discontinuous specifications, and habit formation”.

- They are suited to model the response to road pricing policies, so they have the potential of modelling the response to charging electricity tariffs.
- Their bottom up structure, allows flexibility in aggregation, and consequently in analysis goals.

Despite the apparent advantages of ABMs for the type of policy analyses of interest in the realm of EV deployment, to the authors’ knowledge, only a few ABM implementations are documented in the literature. The first prominent example is the MATSim–PMSS integration developed in Switzerland at ETH [53,55].

4.2.3.1. The MATsim–PMPSS simulation tool as exemplar case. The ETH researchers integrated an EV and power system simulation tool PMPSS with MATSim, a tool for agent-based activity-based transport modelling [95]. In MATSim a population of vehicle owners (agents) is generated from census data (or through a population synthesiser if only the marginal distributions of vehicle owner characteristics are available). Based on specific EV penetration scenarios, each agent is assigned a BEV, a PHEV or another vehicle. Each agent is also assigned a plan of a trip and activities, (the initial demand). In an iteration of MATSim each plan is executed and scored with a utility value (based on the activities in the plan, their durations, delayed arrivals, earlier departures, and early arrivals at locations with opening times) and re-planned, i.e. by adapting time choice; route choice; mode choice; and destination choice. The goal of each agent is to maximise the utility and this is achieved via a co-evolutionary algorithm in which the plans are varied via crossovers and mutations, and by eliminating adaptations with lower utility. In the integrated MATSim–PMPSS, the cost for charging an EV is also taken into account in the utility. This depends on the price of the electricity at the time when the vehicle is charged and on the amount of energy required (depending on the total time on charge, given a fixed charging power). An additional “charging module is added to the original MATSim configuration, that:

- Assigns charging times to EVs, based on specific charging scenarios to the cars;
- Assigns the cost of the electricity charged that is used in the evaluation of the plan utility.

The MATSim simulation iterates until a relaxed state has been reached. At this point the charging times, locations and state of charge of the agents are sent to the PMPSS which determines if the load from charging infringes physical network conditions. Depending on the type of analysis being carried out, the PMPSS may feedback a real-time electricity price signal containing network congestion information to the MATSim scheduler, so that the cost of congestion is also included in the scheduling process. In this case, an outer optimisation loop takes place, (see Fig. 3).

Note that the EV agents are also modelled in the PMPSS system. Here, a (deterministic) game theoretical approach is used to model the charging behaviour of several connected EVs, both in congested and non-congested networks. The game theoretic approach is applied here to enable modelling competition between EV agents over potentially scarce energy or network capacity at a certain node of an electric grid. For the details of the PMPSS model we refer specifically to [51,52,55]. Here, we just describe how the utility of EV agents is defined. EV agents derive benefit from their individual state of charge (SOC) and they feature an individual value for energy acquisition. At a time interval, while charging, the benefit from charging of an agent is modelled as a quadratic function of the SOC

$$b = \alpha SOC - \beta SOC^2 \quad \alpha, \beta > 0$$

This form of the benefit is chosen so that a satiation effect for the

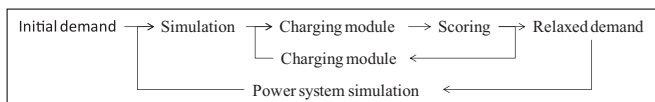


Fig. 3. MATSim-PMPSS optimisation loop Waraich et al. [53].

agent is represented by a decreasing marginal benefit: the higher the energy already available in the battery the lower the additional benefit attained by further increasing the SOC. The coefficient α sets the maximal marginal benefit and the coefficient β defines the slope of the marginal benefit. In the model implementation α is chosen to an equivalent to the current price of petrol, per unit of SOC (i.e. the price of a unit of petrol at the current price per liter that would generate the same energy as a unit of SOC). Choosing alpha in this way prevents PHEV to charge when driving with petrol is cheaper. The parameter β defines the “bidding behaviour” of the agent, i.e. the price is ready to pay to achieve a certain SOC. This parameter also needs to be chosen. In the implementation presented in [55] it is suggested to tune beta based on the if the minimum forecasted price of the electricity for the next day is low compared to the current equivalent price of gasoline β will be high and the benefit of charging now will decrease faster for higher SOC values (because the lowest is the forecasted price of electricity next day the more convenient would be to charge then). Clearly this approach to tune α and β is perfectly reasonable when PHEVs are involved, given that they can run on both gasoline and electricity, but the relevance and behavioural realisms of this scaling in case of BEVs is not evident.

The total utility u_T for an EV agent while charging, at each time interval T of the charging operation, is given by the benefit scaled by a private value θ_T minus the price p_T of electricity times the q_T quantity of energy acquired during the time interval.

$$u_T = \theta_T [\alpha SOC_T + q_T - \beta (SOC_T + q_T)^2] - p_T q_T$$

To maximise his utility an agent will charge as long as the marginal benefit, scaled by θ_T , is above the price of electricity. The private value is defined as a function of various parameters as well as the current state of charge. In particular, it decreases as the difference between the desired state of charge at departure and the current state of charge decreases and increases as the current time approaches the departure time.

The tuning parameters of the private value are somewhat arbitrarily defined to obtain curves that increase more or less steeply as the departure times approaches, given the state of charge and desired state of charge. Moreover, the desired state of charge is decided based on the energy required to drive the vehicle to the next location with a charging opportunity, whereas other factors, including range anxiety, seem to be neglected. Thus, the model of charging behaviour although plausible in the case of PHEVs where problems of range limitations do not exist, may be less suitable for describing BEV user behaviour. In any case, this charging behaviour model, while developed to be theoretically coherent with the game-theoretical framework, appears to lack proper empirical backing,² both in the calibration of the parameters (apart from the mentioned use of market liquid fuel prices to determine the upper bound of an acceptable electricity price for electric mobility, for the agents) and in the validation of the model structure.

4.2.3.2. Other ABMs applications in EV used modelling. A Belgian study [60] uses the FEATHERS activity based model to generate 24-h activity-travel schedules from which car schedules are extracted. Vehicle categories, represented by an equivalent internal combustion engine cylinder volume (small, medium and large) are assigned to each car user, reflecting the market share in Flanders. Each equivalent internal combustion engine vehicle category is mapped into a battery

capacity and energy consumption category, used to define the characteristics of BEVs or PHEVs. According to pre-set market penetration scenarios, EVs or conventional vehicles are assigned to schedules. Whether the assigned EV is a PHEV or a BEV is determined by market share scenarios and schedule BEV-feasibility. Charging scenarios are used to model charging behaviour, so that the power load from EV charging can be generated. In this work the methodology applied is very similar to that described in the previous subsection in which real travel diaries are used to model EV patterns. Here, instead of real travel diaries, ABM generated activity travel schedules are used. The way the ABM is used is not sensitive to electricity pricing because schedules are generated independently from charging behaviour scenarios. In fact, the analysis carried out in this work carries the same weakness of the analyses based on observed travel patterns; it lacks policy sensitivity when it comes to evaluating the potential effects of charging demand strategies on travel patterns.

A similar ABM implementation is also adopted by Hodge et al. [59], where the energy demand profile in Alexandria, Virginia from PHEV charging under various charging behaviour scenarios, are obtained based on vehicle schedules generated by the TRANSIMS model [96].

Nourinejad et al. [56] study vehicle to grid-operations using activity-based equilibrium scheduling. This study accounts for the interaction between EV use decisions and activity travel scheduling decisions adopting and extending Lam and Yin's [97] time-based utility theory model which models the utility an activity as time dependent and express the scheduling problem as a continuous equilibrium problem.

While this subsection has focused on the use of ABMs in EV pattern analysis, it is worth noting that, despite the much more widespread application in travel demand practice of the FSM approach, compared to ABMs, the literature on EV impact analysis using FSM for EV pattern generation is almost non-existent. The reason for this is that transport academics have almost completely given up publishing on this approach, given the limitations mentioned above for the type of policy analyses that are now required that go far beyond large infrastructure planning. In fact only one example was found by the author of the application of FSM: for the estimation of additional domestic load on the grid by EV deployment [74]. Huang and colleagues use hourly origin-destination matrices to deduce the number of (electric) vehicles arriving at home in each traffic analysis zone of Indianapolis, together with the total trip length and distance distributions so as to model the quantity of charge required. Amongst the drawbacks of this method, there is the fact that actual trip chaining is neglected. This has possibly negligible effects on aggregate home charging demand (for a given charging behaviour scenario). At the disaggregate level, however, where it is necessary to model nodal congestion on the distribution network, the effect of a lack of behavioural realism may have more profound effects.

4.2.4. Applicability and limitations of ABMs

ABM can be potentially applied for all the analyses requiring short-period models, (i.e. those upper left and lower left quadrants in Fig. 1). However, only by explicitly modelling charging behaviour (i.e. avoiding charging behaviour scenarios) jointly with activity-travel behaviour enables realistic representations of the interdependencies the road transport network and in the electric grid and the respective relevant phenomena congestions and demand management mechanisms. This has been achieved with the MATSim-PMPSS model system, which however has its limitations, specifically in the representation of the charging behaviour of EV agents. Essentially, as highlighted in the discussion of the representation of the utility attained by EV agent from the charging operation, we argue that the model is theoretically appealing, but lack empirical estimation (validation) of its tuning parameters, which ultimately define agents' preferences.

² Based on revealed or stated preference data.

Table A1
Summary of studies using short period models of EV use and charging – the colour coding represents the modelling technique adopted.

Study	Modelling technique	Study scope ¹	EV ²	Charging infrastr. scenarios	Charging behaviour scenarios	Region of analysis	Main findings
[53]	ABM	SC&DM; Meth;	PHEV	[-]	Uncontrolled; Price sensitive charging behaviour model	[-]	It is demonstrated that the model is policy sensitive to various price based charging demand management policies.
[57]	ABM	SC&DM; Meth;	BEV	[-]	Minimum cost allowing the completion of travel schedule	Flanders	Proves algorithm that generates EV charging schedules, taking into account maximum power constraints at each charging location and the individual EV energy requirements.
[58]	ABM	EEl&P;	PHEV	Home	Uncontrolled	Synthetic data	(+/-) If charging occurs only at home, then it is most likely in the afternoon and PHEVs represent around one third of the total load at peak and a 5th of the daily domestic electricity consumption.
[59]	ABM	EEl&P;	PHEV	[-]	Uncontrolled; Off-peak; As late as possible for a full charge next day	Alexandria, VA	(+) Small increases by introduction of PHEV in both total electricity demand and peak power; (+) Gasoline usage greatly influenced by charging scenarios; (+/-) CO2 and NOx emissions would decrease, but SO2 emissions increase due to the use of coal-based generation.
[60]	ABM	SC&DM;	EV	Home & Work	Off-peak; Minimum cost for maximum recharge	Flanders	Activity-based microsimulation can be used for smart grid design: energy demand and power peaks are obtained as function of charging scenarios.
[61]	ABM	EEl&P; Econl;	EV	Home & Work	Uncontrolled; Uncontrolled after last trip; Off-peak; Minimum cost for maximum recharge	Flanders	(-) Use of PHEVs leads to higher electricity consumption than BEVs; (+) Current off-peak period is long enough to distribute charging to avoid peaks in demand, while allowing savings for users.
[56]	ABM	V2G; Econl; Meth.	EV	Home, Work and "Eating zone"	Utility based charging behaviour model	[-]	(+) Results show that V2G reduces providers' cost and increase drivers' social welfare; (+)
[62]	DUOATS	EEl&P; CIP;	PHEV	[-]	Charging behaviour model based on bounded rationality	[-]	(+) Public charging favours small battery PHEVs since these allow day recharging to make up for battery capacity; (+) Public charging considerably reduces liquid fuel consumption.
[63]	DUOATS	EEl&P; CIP;	PHEV	Wherever socket is available; Wherever socket is available & Work	Uncontrolled; Off-peak	United States	(+) With consumer-designed PHEV most gasoline reduction is caused by charge sustaining fuel economy, not by gasoline displacement with electricity in charge depleting mode; (+) Uncontrolled charging where sockets are actually available generates more dispersed charging at early hours; (-) Increasing non-home charging opportunities may displace more gasoline but, in some areas, induce an increased peak load; (-) Off-peak charging reduces gasoline displacement by electricity.
[64]	DUOATS	EEl&P;	PHEV	Wherever socket is available; Wherever socket is available & Work	Uncontrolled; Off-peak	United States	(+) Consumer-designed PHEVs can reduce "source-to-wheel" GHG emissions compared to conventional vehicles; (+) PHEVs can also reduce GHG emissions relative to AE-20 or AE-40 designs when electricity is generated by sources with emissions above 600 gCO2/kWh.
[65]	DUOATS	CIP;	PHEV	[-]	Uncontrolled; Delayed; Off-peak	United States	(+/-) The all-electric range has a direct effect on charging profiles.
[54]	DUOATS	EGl&P; V2G; SC&DM; Econl;	PHEV	[-]	Off-peak charging by direct control; or decentralised intelligent vehicle response to real-time price signals (uncontrolled charging not analysed)	United States (6 region)	(+) Limited negative impacts on generation requirements if utilities can partially control timing of charging; (+) Dispatch able load by PHEVs could increase minimum system load, increase the utilization of baseload units, and decrease plant cycling (i.e. reduced cost for O&M); (+) PHEVs are suited for short-term ancillary services, moderate penetration of PHEVs could replace a substantial fraction of the capacity for "super peak" and peak reserve margin.
[66]	DUOATS	EEl&P;	PHEV	Home; Public/private parking places	Uncontrolled end of day; Uncontrolled; Off-peak	California	(+) Public parking facilities enable more daytime charging, allowing 60–70% of mileage to displace from fuel to electricity, and 80–90% for PHEV60; (+/-) Not certain that off-peak charging favours energy efficiency.
[67]	DUOATS	EEl&P;	PHEV	Home only; Home and work	Uncontrolled; Off-peak; Last minute; Minimum dwell time	United States	(+) A compact vehicle with a 10.4 kWh useable battery capacity has a utility factor between 63% and 78%; (+/-) As travel patterns vary with demographics so do the charging profiles.
[68] ²	DUOATS	EEl&P; Econl;	EV	[-]	Once a day charging	Seattle	(+) BEVs feasible for significant share of households in Seattle area (single or multivehicle); (+) Average single vehicle household saves 500\$ with PHEV instead of ICEV
[69]	DUOATS	EEl&P; EGl&P; Econl;	PHEV	Home only; Home and work	Uncontrolled; Delayed	13 North American Electric Reliability Corporation sub-regions	(+) Total electric energy requirement for the entire EV fleet modest compared to total production for non-transportation use; (+/-) Cost impact higher depending on regional capacity (where capacity is tight in current state, higher the costs in PHEV scenarios); (+/-) Impact of CO2 emissions is variable on a regional basis, depending on marginal generation (charging strategies have different effects based on marginal generation).
[70]	DUOATS	EEl&P; EGl&P; SC&DM; Econl;	PHEV	Home only; Everywhere (for the "continuous charging scenario")	Uncontrolled; Delayed; Off-Peak	Xcel Energy Colorado Service Territory	(-) Increased pressure on peaking generators in uncontrolled charging; (+) Additional capacity would be required, for large penetrations if minimal charging schedules optimisation in place; (+/-) Most near-term PHEV charging likely to be derived from gas units; cost of natural gas drives the cost of PHEV charging; mixed impacts in terms of emissions, except for net carbon dioxide reduction.
[71]	DUOATS	EEl&P;	PHEV	Home; Home & Work; Home, Work & Shopping centres	Uncontrolled; Delayed	United States	(-) Since driving patterns and power supply systems vary across NERC regions, so too, does the EV charging load (author compares CA to NY); (+) PHEVs with all-electric range 10-40 miles could cut gasoline consumption by more than 50%; (+) Marginal carbon dioxide emissions can be reduced by more than 50% @ current average US mix.
[72]	DUOATS	EEl&P;	EV	Home; Home, Work & Shopping centres	Uncontrolled	United States	(-) Uncontrolled charging induces an increase in power system peak load.
[73]	DUOATS	EEl&P; CIP;	PHEV	Home; Home & Work; Anywhere	Uncontrolled; Delayed; Minimum power for full SOC	South Coast Air Basin of California	(+) Decrease in fuel use by 45%/70% can be achieved with PHEV-16/40 in place of BEV, by home charging only. More relevant to the reduction of cold start pollutants (reductions increase if charging also occurs in other places than home). (+) Peak demand increases could be mitigated by avoiding uncontrolled charging.
[74]	FSM	CIP; Econl; DNI&P;	BEV	Home; public	Charge whenever at home & public charging when SOC below a limit; charging only at home and price is at lowest level, provided that minimum SOC is always kept (if SOC goes below charging can occur either home or at public stations)	Indianapolis	(-) Vehicle usage varies greatly from zone to zone, thus impacts on the distribution grid may be different (more significant in higher EV penetration zones)

¹EGI & P=Electric generation impacts and planning; DNI & P=Distribution network impact and planning; SC & DM=smart charging and demand management; EEI & P=energy and environmental impacts and policy (here by energy impacts are intended mainly in terms of oil-based fuels consumption reductions and environmental impacts in terms of GHG and pollutant emissions into the atmosphere); EconI=economic impacts (mainly to consumers or on the power system); CIP=charging infrastructure planning; Meth=methodological.

²In this paper time of day analyses are not carried out, although may be possible.

³BEV=battery electric vehicles; PHEV=plug-in hybrid electric vehicles; EV=plug-in electric vehicles (both BEV and PHEV).

4.3. Markov chain models

An alternative approach to generate consistent vehicle patterns is that pursued by Soares, et al. [75]. They develop a vehicle state Markov chain model chain, in which a one year EV pattern is generated by a discrete time state Markov Chain to define the state of each EV agent in each 30 min interval over one year. The states in which a vehicle can be are: driving, parked in a residential area, parked in a commercial area and parked in an industrial area. Initial state and transition probabilities are obtained from statistical information regarding traffic patterns in the region of analysis (the Porto area in Portugal for the specific case).

4.3.1. Applicability and limitations of MCMs

The theoretical applicability domain of the type of modelling approach described above would be those of short period analyses (again, upper left and lower left quadrants in Fig. 1). The further advantage of such a model is that can generate fully disaggregate year long EV patterns whereas, to do so AMBs would enable generating aggregated representative EV patterns over a year.

Notwithstanding the advantage of Markov Chains approaches such as in generating consistent vehicle patterns over longer time periods than activity based models, their lack of the theoretical link between activity demand and travel demand is problematic. Indeed, tradeoffs between activity participation and travel and charging requirements are not explicitly represented, therefore it appears more conceptually difficult to model the response of EV users to the variation of factors potentially indirectly affecting their charging patterns, by affecting activity participation.

5. Conclusions

This paper has reviewed the techniques that have been used to model the demand for EV acquisition, use and charging. A number of observations can be made regarding the state of the field and associated future research requirements.

In transportation research the bulk of studies in EV use demand modelling has focused on long term decisions such as vehicle acquisition and annual vehicle use, which are most relevant to strategic aspects of energy security, environmental impact and power infrastructure requirements. In comparison, less work has been undertaken into modelling the detailed spatial and temporal patterns of EV use and charging behaviour, which are vital for the analyses of integrated transport and power systems at the tactical and operational level. As a result, short time period models tend to rely on aggressive simplifying assumptions, such as the downscaling of annual use to time periods of the order of hours or less, the use of pre-determined charging behaviour scenarios or charging strategies and the use of fixed travel patterns (typically based on those observed in conventional cars). These simplifications render such approaches *de facto* policy-insensitive with respect to a number of key issues; for example, they are not sensitive to electricity tariff structures and therefore are inappropriate to test the effectiveness of alternative pricing policies.

We believe that there is an urgent need for new modelling frameworks to be developed that can provide a theoretically coherent, integrated and policy sensitive treatment of behaviour at these two timescales, taking into account for example of both long-term strategic consumer decisions (e.g. car ownership related decisions) with short term EV use and charging decisions. The framework of activity based modelling provides an attractive starting point for this work.

Within this general ABM approach, we believe further that an important area for future work is the modelling of charging behaviour. The models of charging behaviour available to date are largely theoretical in nature and lack well-confirmed empirical estimation of their parameters or strong validation. They moreover tend to neglect some important aspects of charging behaviour, such as range anxiety or the denial of spontaneous use, that may play an important role when EV drivers must respond to complex electricity tariffs designed to foster demand response are introduced. Modelling these demand-side processes is complex and will require innovation both in terms of theory and data. The limitations of existing data are particularly significant and although some of these limitations may be partially overcome by making use of stated preference data from hypothetical choice experiments, there remains a need for significantly improved datasets on real world charging behaviour both in the contexts of EV trials and demonstrations and, critically, in periods of normal operation. The development of commercial charging services may complicate access of these data and is an issue that the research community must urgently address.

A final area where we believe further research is urgently required is in the design of price and non-price incentives for behavioural change (in acquisition, use and charging behaviour) including but not limited to dynamic pricing, product bundling (e.g., vehicle and charging infrastructure access) and regulatory interventions. Current demand modelling methods provide a starting point but the design of incentives that can effectively and predictably expose demand side flexibility (in space and time) poses distinct challenges that have so far received little attention but which we believe will become increasingly important in the future.

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Appendix A. Summary of the full sample of short period models reviewed

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