Transportation Research Part C 80 (2017) 239–256

Contents lists available at ScienceDirect

Transportation Research Part C

journal homepage: www.elsevier.com/locate/trc

Simulation of electric vehicle driver behaviour in road transport and electric power networks ☆

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ARTICLE INFO

Article history:
Received 25 July 2016
Received in revised form 6 May 2017
Accepted 8 May 2017
Available online 13 May 2017

Keywords:
Electric vehicle
Multi-agent simulation
Routing and charging behaviour
Road transport network
Electricity grid

ABSTRACT

The integration of electric vehicles (EVs) will affect both electricity and transport systems and research is needed on finding possible ways to make a smooth transition to the electrification of the road transport. To fully understand the EV integration consequences, the behaviour of the EV drivers and its impact on these two systems should be studied. This paper describes an integrated simulation-based approach, modelling the EV and its interactions in both road transport and electric power systems. The main components of both systems have been considered, and the EV driver behaviour was modelled using a multi-agent simulation platform. Considering a fleet of 1000 EV agents, two behavioural profiles were studied (Unaware/Aware) to model EV driver behaviour. The two behavioural profiles represent the EV driver in different stages of EV adoption starting with Unaware EV drivers when the public acceptance of EVs is limited, and developing to Aware EV drivers as the electrification of road transport is promoted in an overall context. The EV agents were modelled to follow a realistic activity-based trip pattern, and the impact of EV driver behaviour was simulated on a road transport and electricity grid. It was found that the EV agents' behaviour has direct and indirect impact on both the road transport network and the electricity grid, affecting the traffic of the roads, the stress of the distribution network and the utilization of the charging infrastructure.
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1. Introduction

Environmental and energy security reasons are setting Electric Vehicles (EVs) as a major part in the future road transport networks (Element Energy, 2013). Integration of EVs will affect the road transport networks due to their particular characteristics, such as the frequency and the time needed for recharging the EV battery. Apart from being a major part in road transport networks, EVs are expected to influence significantly the electric power networks (Momber et al., 2013). Considering a typical battery capacity of 30 kW, the energy needs for recharging an EV is nearly double the average daily needs of a house. EV charging will affect significantly the load profiles unless smart grid control techniques are applied. Several studies indicate that uncontrolled charging of EVs will increase the peak demand of the power system, resulting in feeder voltage excursion and overload of the transformers and cables, especially in already stressed networks (Putrus et al., 2009; Clement-Nyns et al., 2010; Pieltain Fernandez et al., 2011; Papadopoulos et al., 2012). The integration of EVs will affect both electricity and transport systems, and consequently, research is needed on finding possible ways to make a smooth

☆ This article belongs to the Virtual Special Issue on "Technologies and Control for Sustainable Transportation".

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http://dx.doi.org/10.1016/j.trc.2017.05.004
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transition to the electrification of the road transport. To fully understand the EV integration consequences, the behaviour of the EV drivers and its impact on these two systems must be modelled.

Because of the limitations in the current battery technology, the EVs offer relatively low driving range. With no major changes in the following years, the EVs will need regular recharging periods depending on the average daily trip distances. Depending on the urban design, EVs are expected to recharge mainly at night, when the EV owners return home from their work (Putrus et al., 2009; Papadopoulos et al., 2012). However, this will not exclude recharging events during the day. Charging in public or street locations requires at least a parking space per charging point. Due to the finite number of parking spaces in a city, especially in the city centre, the number of EVs that are charging at the same time is limited. This will affect the road transport networks particularly the daily travel patterns and the congestion parameters (Rodrigue et al., 2009). Authorities should take into consideration this behavioural change and utilize proper mechanisms and parking schemes for the EV deployment.

The complexity of the dependencies between road transport and the electric power system is therefore likely to increase with higher EV market penetration. Coordination is essential to preserve a stable network operation and avoid unnecessary investments in infrastructure. Due to limits in power capacity within an electricity network, it might not be possible to serve all EVs that want to recharge their batteries. In order to protect the electric power network, and maintain a robust operation, the condition of the various components needs to be monitored. Future scenarios utilize advanced EV charging management mechanisms that use the available storage in the EV batteries and the flexibility of the charging demand to provide ancillary services to the grid operators (Karfopoulos et al., 2012; Lin et al., 2014; Marmaras et al., 2014; Karfopoulos and Hatziargyriou, 2016).

This paper proposes an integrated simulation-based approach, introducing the EV as an intelligent unit existing in both road transport and electric power systems. The main components of both systems have been represented in a single environment, and the EV driver behaviour was modelled using a multi-agent simulation platform. The proposed simulation-based approach serves as an enabling technology in order to understand the EV driver behaviour and its impact on both the road transport and electric power system. Section 2 presents a short literature review on modelling EVs in transport and electric power networks. Section 3 presents the architecture of the EV agent and the governing equations of its environment. Sections 4 and 5 present the battery characteristics and the behavioural profiles of the EV agent. An example case study is presented in Section 6, and conclusions are drown in Section 7.

2. Related work

The route choice behaviour of the drivers and the characteristics of the road transport network are strongly correlated. The route choice behaviour of drivers is affected by various factors like traffic information, weather and route attributes. According to Arentze et al. (2012), the road accessibility characteristics have a substantial impact on route preferences. Raveau et al. (2011) defined an angular cost variable to reflect the directness of the chosen route, and used it to improve the explanation of route choices. On the other hand, the route choice behaviour of the drivers affects the road transport network (Bhat, 1997; Yao and Morikawa, 2005). Multi-agent models are often used to model the behaviour of drivers on road networks (Balmer et al., 2004; Doniec et al., 2008; Bazzan and Klügl, 2013). Traffic simulation tools like SUMO, OMNet++ and Veins are generally used by researchers in order to quantify the impact of the route choice behaviour.

EV drivers however, need to consider additional factors when deciding their route. Factors like energy consumption, charging station availability, charging duration are introduced in the route choice decision. Nicholas et al. (2013) investigated the charging behaviour of EV drivers by simulating EVs travelling and charging at public chargers. The results show that more than 5% of the trips would require recharging at a public charger for different driving range and charging assumptions. The location of the charging stations is directly related to the impact of driving behaviour in urban road transport networks. In Ghamami et al. (2016) a general corridor model is used to propose the optimal location of EV charging stations, while the authors of Li et al. (2016) propose a multi-period optimization model to expand the charging network. Similar studies for an urban environment can be found in He et al. (2015, 2016) and Cavadas et al. (2015). A spatial-temporal demand coverage location approach is used in Tu et al. (2016) to address the location problem of electric taxi charging stations. The shortest-path and trip planning problem is investigated in Strehler et al. (2017), where the authors designed an approximation scheme to compute the energy efficient shortest route for EV drivers. Some traffic simulator platforms offer EV support and give to the user the ability to run traffic simulations with all or partially electrified vehicle fleets. Such a simulation can be found in Coninx and Holvoet (2014), where EVs are simulated in highway networks with on-line charging. Another example is found in Bae and Kwasinski (2012), where a spatial-temporal model is build based on a poison-arrival-location-model (PALM) for EVs charging at public chargers on the highway. These models however ignore the impact of EV charging on the electricity grid.

The charging behaviour of the EV drivers not only at public but also at the home chargers affects the electricity grid. The charging fashion in particular has been the certain of interest, as it defines the magnitude of this impact (Clement-Nyns et al., 2010; Pieltain Fernandez et al., 2011). In Schücking et al. (2017), the authors evaluate different charging strategies through performance indicators, and show that three characteristics are essential to develop a sustainable charging strategy: the maximum charging power, the duration of a full recharge, and the shape of the charging curve. All three characteristics impact directly the electricity grid. To take this impact into account, integrated models have been developed, which combine

a traffic simulator with power flow studies or another electricity grid simulation model. In He et al. (2013), the authors developed an equilibrium modelling framework that captures the interactions among availability of public charging opportunities, prices of electricity, and destination and route choices of plug-in hybrid electric vehicles (PHEVs) at regional transportation and power transmission networks coupled by PHEVs. van Dam and Lukszo (2006) developed a generic ontology to model different infrastructure domains in a multi-agent system, and showed that a generic/integrated approach is able to facilitate re-use, sharing and interoperability of agent-based models. MATSim was used in Galus et al. (2012), as part of an integrated approach to model EVs in transport and electric power systems. A vehicle technology assessment model was also used to simulate the EV's energy consumption and driving cycle, while a power system simulator was used to calculate the impact of EV charging on the electricity grid. However, the EV driver's behavioural profile and the EV battery is not modelled in detail. In addition, the EV charging procedure is assumed to be controlled by a third-party energy management platform (PEV manager) which could be the case only in future scenarios but not in the early stages of EV adoption.

A few probabilistic approaches are found, which generate a number of driving and charging demand profiles for the EVs (Soares et al., 2012; Olivella-Rosell et al., 2015). These probabilistic models however can only be used as an input to another simulation tool in order to capture the impact of EV behaviour on both transport and electric power networks. In addition, the existing studies assume one behavioural profile for the EV drivers, ignoring the development of the EV integration and the increase of the decision support infrastructure (such as communication and IT systems that increase the availability of data). In this paper, an integrated approach is presented to model EVs in a complex road transport and electricity network. Two behavioural profiles were considered for the EV drivers in order to describe the driving and charging behavioural change for different stages of EV adoption. The impact of each behavioural profile on the road transport and electricity network is demonstrated through a case study.

3. The EV agent's architecture

An *EV agent* was created using SeSAm (Klügl et al., 2006), simulating the behaviour of a rational EV driver. The EV agent interacts with the other agents, makes calculations and takes decisions regarding potential future actions. It lives in a complex environment consisting of a Road Transport network, an Electricity Grid and other EV agents. Its decisions and behaviour adapt to the behaviour of the other EV agents it can observe, and are affected from the status of the other simulated objects in the system. The EV agent's architecture is presented in Fig. 1.

The EV agent combines the driver and the vehicle in one entity. It operates according to the EV driver's decisions and strategy but is constrained by the vehicle's intrinsic characteristics like battery capacity. Its moving and charging actions entangle the EV agent with the Road Transport Network Environment and the Electricity Grid Environment respectively. The simulation of many EV agents and their environment resulted in studying and understanding their interactions in a realistic EV context. The following sections describe the modelling framework.

3.1. The road transport network environment

The considered road transport network represents a geographical region with a few communities. It is the geographical area where all the EV agents live, move and interact with each other. Each community was modelled as a *district* resource entity, considered as one node of a road transport network. Apart from the nodes, the considered road transport network contains links (which connect the nodes) to represent the roads connecting one community (district) to another. Each link was modelled as an *avenue* resource entity. The road hierarchy, the inter-node road network and traffic delay in nodes are neglected. The topology is presented in Fig. 2.

A district (D_X) is an area with both residential and commercial buildings, and thus it can be used either as a home district (where an EV agent's home is) or as a work/shopping district (where an EV agent does various activities) from the EV agents. It was assumed that the home district is different from the work/shopping district of an EV agent. The avenue entities (A_X)

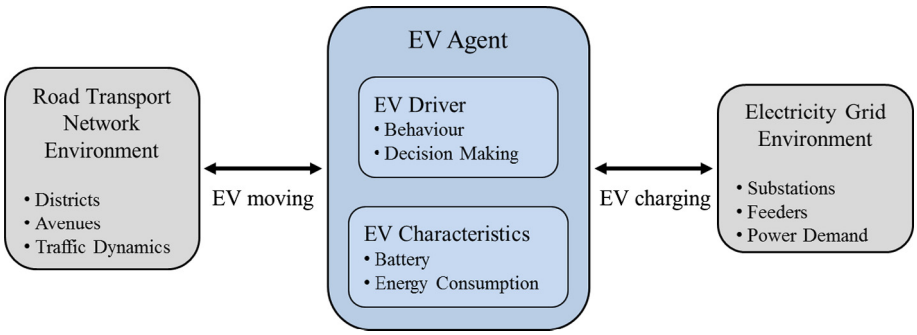

Fig. 1. Architecture of the modelled EV agent.

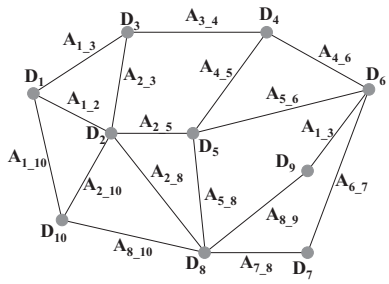

Fig. 2. The considered road transport network.

represent the roads of the transport network, therefore they have traffic. The traffic on the roads was modelled following a macroscopic approach on a per-minute granularity. Three variables were used to describe the traffic on an avenue:

i. Density (k)
ii. Flow Rate (q)
iii. Mean Speed (u)

Density k reflects the number of EV agents per kilometre of an avenue and is expressed in vehicles per kilometre (veh/km). At a specific time t, the density k of an avenue with length ΔX is calculated from Eq. (1).

$$k(t) = \frac{n(t)}{\Delta X}, \tag{1}$$

where $n(t)$ is the number of EV agents at time t on that avenue.

The flow rate represents the number of EV agents that passes through a certain section per time unit and is expressed in vehicles per hour (veh/h). The maximum possible flow rate of an avenue is the *avenue capacity*. For a time interval ΔT, the flow rate of each avenue is calculated from Eq. (2).

$$q(t) = \frac{m}{\Delta T}, \tag{2}$$

where m represents the number of EV agents that passes the specific location during ΔT .

The mean speed $u(t)$ is defined as the quotient of flow rate and density and expresses the average travelling speed of all the EV agents on an avenue. It was assumed that all EV agents travel at a constant speed along an avenue, equal to $u(t')$, where t' is the time when the EV agent enters the avenue.

The three variables are linked through the *fundamental relation of traffic flow theory* as shown in Eq. (3) (Maerivoet and De Moor, 2005).

$$q(t) = k(t) \cdot u(t) \tag{3}$$

Assuming a stationary (flow rates do not change along a road and over time) and homogeneously composed traffic (all EV agents are the same), the three variables are described graphically by the *fundamental diagrams*. The fundamental diagrams that describe the traffic on the avenue entities are presented in Fig. 3.

A triangular k-q relationship was assumed, as stated in Maerivoet and De Moor (2005). The density $k(t)$ of each avenue is calculated from Eq. (1) using the number of EV agents travelling on the avenue at time t and the *avenue* length. For densities smaller than the capacity density (k_c) the mean speed equals the free flow speed u_f and the flow rate is calculated from Eq. (3). In case the density is higher than the capacity density (but smaller than the jam density k_j), the mean speed is calculated from Eq. (3) and the flow rate is calculated from Eq. (4):

$$q(t) = \frac{q_c}{k_c - k_j} \cdot (k(t) - k_j) \tag{4}$$

The traffic flow variables are updated every minute according to the number of EV agents on the avenue.

3.2. The electricity grid environment

The considered electricity network follows the structure of the UK generic distribution network (Ingram et al., 2003), and is consisted of 6 types of elements. Each type was modelled as a "resource" entity. These are:

i. *HV Substations*
ii. *MV Feeders*
iii. *MV Substations*

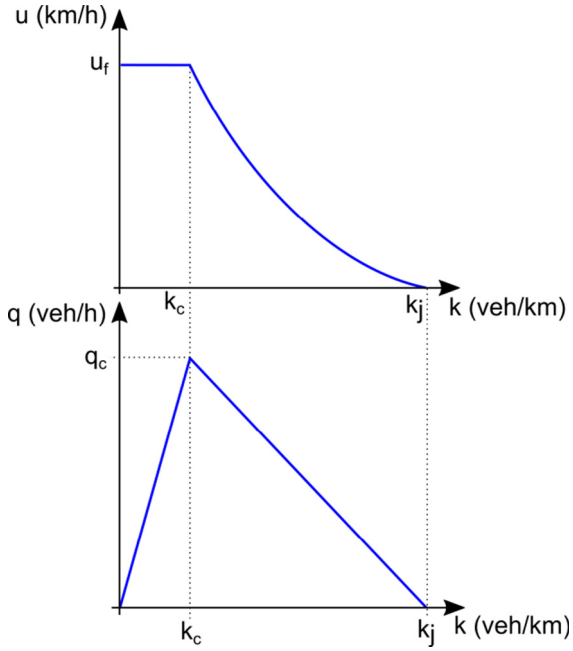

Fig. 3. The fundamental diagrams assumed in this work.

iv. *Non-EV loads*
v. *Home Chargers*
vi. *Public Chargers*

These elements were considered as black boxes and their detailed characteristics were not modelled. Such an abstraction level was considered acceptable in this study since the elements' purpose is to operate as aggregating points of electricity demand (entities i-iv) and points of EV connection to the AC network (entities v-vi). Nevertheless, efficiency factors in the range of (0–1) were considered to represent the energy losses from each element. More specifically:

The *HV Substations* are the highest level of electricity demand aggregation in our model. They represent the 132 kV/33 kV transformers connecting the transmission network to the distribution network. The HV Substations supply electricity to the districts through the *MV Feeders* and the *MV Substations*. The MV Feeders represent the 33 kV lines connecting the HV Substations to the MV Substations. The MV Substations represent the 33 kV/11 kV transformers and aggregate the electricity demand coming from all the *Non-EV loads* (residential, commercial etc.) and the *EV chargers* in a district entity. The considered network structure and components are shown in Fig. 4.

Based on this topology, the power demand aggregation is described by Eqs. (5) and (6).

$$P^{HV}_{33kV}(t) = \sum_{n=1}^{N_{MV}} P^{MV}_{33kV,n}(t) \tag{5}$$

$$P_{11kV,d}(t) = \sum_{l=1}^{N_{EV}} P^{AC}_{l,d}(t) + \sum_{l=1}^{N_L} P_{l,d}(t), \tag{6}$$

where

$P^{HV}_{33kV}(t)$ = the power demand at the secondary winding of the HV Substation
$P^{MV}_{33kV,n}(t)$ = the power demand at the primary winding of the MV Substation n
N_{MV} = the number of MV Substations connected to the HV Substation
$P_{11kV,d}(t)$ = the power demand at the secondary winding of the MV Substation of district d
$P^{AC}_{l,d}(t)$ = the power demand of an EV charger l of district d
$P_{l,d}(t)$ = the power demand of a non-EV load l of district d
NEV = the number of EV chargers connected to the MV Substation of district d
NL = the number of non-EV loads connected to the MV Substation of district d

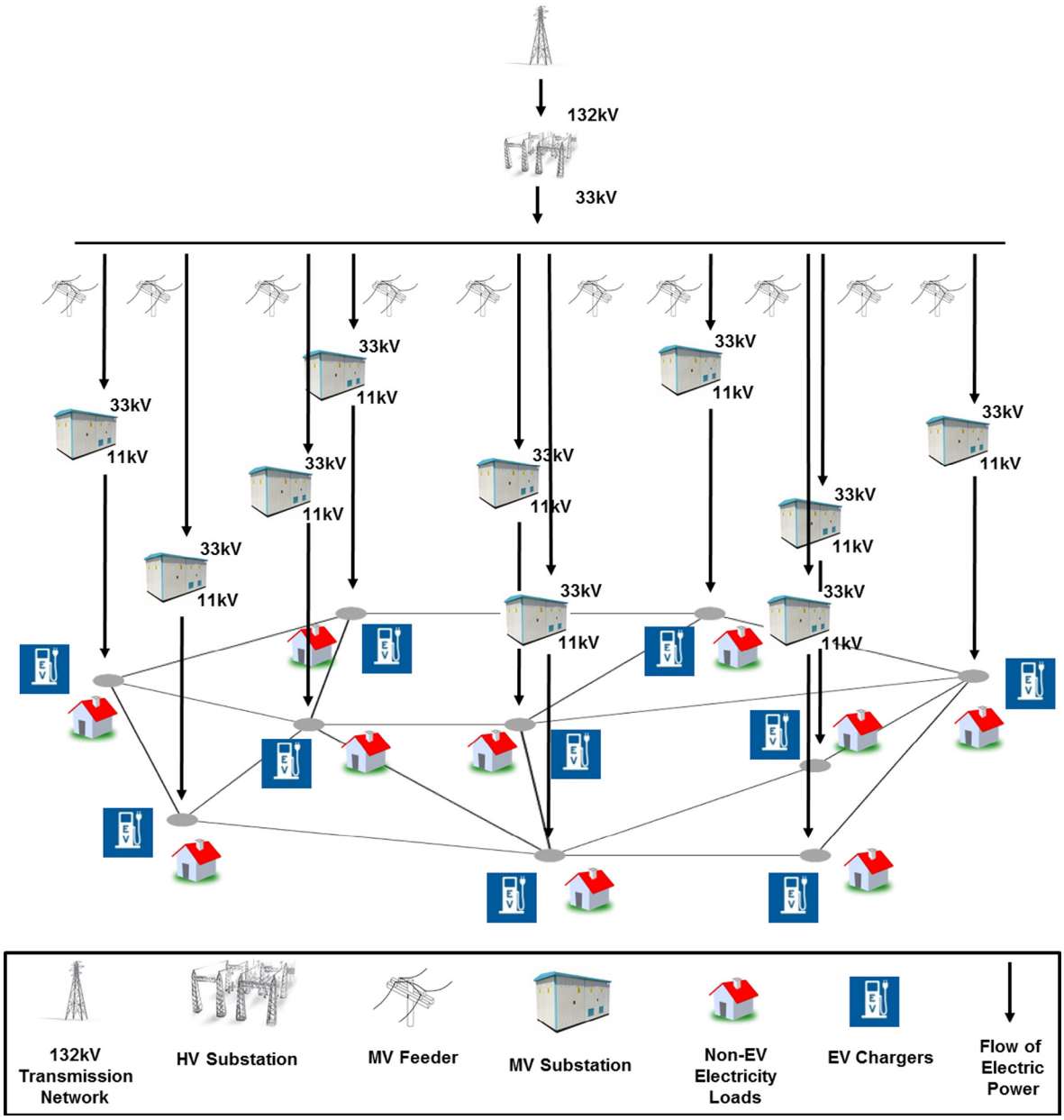

Fig. 4. The topology of the modelled electricity network in SeSAm.

Assuming an efficiency factor η_{FD} for the losses from the MV Feeders, Eq. (5) becomes as follows:

$$P^{HV}_{33kV}(t) = \eta_{FD} \cdot \sum_{n=1}^{N_{MV}} P^{MV}_{33kV,n}(t) \tag{7}$$

Considering also the power losses from the voltage transformation, Eqs. (8) and (9) are obtained.

$$P_{132kV}(t) = \eta_{HV} \cdot P^{HV}_{33kV}(t) \tag{8}$$

$$P^{MV}_{33kV}(t) = \eta_{MV} \cdot P_{11kV}(t), \tag{9}$$

where

$P_{132kV}(t)$ = the power demand at the primary winding of the HV Substation
η_{HV} = the efficiency factor of the HV Substation
η_{MV} = the efficiency factor of the MV Substation

The required energy to charge the EV batteries is supplied from the electricity grid through the charging stations (EV chargers). Two types of chargers were considered in this work: the *Home Chargers* and the *Public Chargers*. A Home Charger represents a private charging station which is installed at the EV owner's house; it is therefore unique for every EV and every EV owner was assumed to have one Home Charger. Depending on the number of EV owners living there, each district in our model can have more than one Home Chargers. The Public Chargers are chargers distributed throughout the districts and offer a recharging point to every EV. They were modelled with one charging connector allowing the charging of one EV at a time. Each Public Charger was designed with a queuing feature, so when more than one EV agent wants to use a Public Charger at the same time, a queue is created and each EV agent has to wait for the previous one to finish charging.

An efficiency factor was also considered in order to express the losses from the power conversion in the EV charger. An AC/DC converter is necessary to provide the DC power the battery needs. The maximum DC voltage that can be produced when connected to an AC network of 230 V is calculated from Eq. (10) for 1-phase and from Eq. (11) for 3-phase connection.

$$V_{\max}^{DC} = \frac{2}{\pi} \cdot \sqrt{2} \cdot V_{rms}^{AC} = \frac{2}{\pi} \cdot \sqrt{2} \cdot 230\ \text{V} = 207.07\ \text{V} \tag{10}$$

$$V_{\max}^{DC} = \frac{3}{\pi} \cdot \sqrt{2} \cdot V_{rms}^{AC} = \frac{3}{\pi} \cdot \sqrt{2} \cdot \sqrt{3} \cdot 230\ \text{V} = 537.99\ \text{V} \tag{11}$$

Depending on the charging voltage of the EV battery, a DC/DC converter might be necessary to adjust the voltage output of the charger. Considering separate efficiency factors for each conversion stage, the overall efficiency factor η_{EV} of the EV charger is given from Eq. (12).

$$\eta_{EV} = \eta_{AC/DC} \cdot \eta_{DC/DC} \tag{12}$$

Based on this factor, the grid side power demand of the charger is calculated from Eq. (13).

$$P^{AC}(t) = \eta_{EV} \cdot P^{DC}(t) \tag{13}$$

4. Modelling the characteristics of the EV agent

4.1. The EV agent's battery

A fundamental element of an EV is the battery. The EV agent battery operates in two modes: the charging mode and the discharging mode. In charging mode the battery stores energy drawn from a charging station (point of connection to the electricity grid) and thus acts as an electricity load. In discharging mode the battery acts as an electricity source and releases its stored energy to power the electric motor of the vehicle.

The modified Shepherd model of Tremblay and Dessaint (2009) was used in this work to model the behaviour of a Li-ion EV battery on a 1-min granularity. A 18650 Li-Ion battery cell with the characteristics of Tenergy (2009) was modelled with respect to its terminal voltage, discharge/charge current and state of charge. The model was used to simulate the behaviour of a battery pack similar to the one of a Tesla Roadster vehicle (https://www.teslamotors.com). According to Berdichevsky et al. (2007), such a battery pack is consisted of 6831 18650 Li-Ion battery cells following an 11S 9S 69P configuration. In this configuration 69 Li-Ion battery cells connected in parallel form 1 group, 9 groups connected in series form 1 module and 11 modules connected in series form the battery pack.

Assuming that the battery pack is consisted of the 18650 Li-Ion battery cells with the characteristics of Tenergy (2009), the battery pack specifications were calculated. For these calculations a battery cell management system was assumed to be in place to balance the battery cell utilisation, enabling the battery pack to behave like a single cell. The results are presented in Table 1. The modified Shepherd model was used to calculate the discharge characteristics of the battery pack for discharge rates of 0.2C, 0.5C, 1C and 2C (30.36A, 75.9A, 151.8A and 303.6A respectively). The characteristics are presented in Fig. 5.

4.2. The EV agent's energy consumption

When the EV agent is moving there is energy consumption from the EV battery. The power consumption of the EV agent was calculated following the approach described in Van Haaren (2012). According to this approach, the energy usage of an electric vehicle is distributed into 4 categories:

Table 1
EV agent battery pack specifications.

Maximum Capacity	151.8 A h
Nominal Capacity	144.9 A h
Nominal Voltage	366.3 V
Internal Impedance	0.05739 Ω
Standard Charge Conditions	Constant Current and Constant Voltage (CC/CV)
	Charge Current = 75.9 A (0.5C)
	End-up Voltage = 415.8 V
	End Current = 1.518 A
Standard Discharge Conditions	Constant Current (CC)
	Charge Current = 75.9 A (0.5C)
	End Voltage = 297 V

i. Aerodynamic Losses
ii. Tire Losses
iii. Drivetrain Losses
iv. Ancillary Losses

The aerodynamic losses depend directly on the driving speed. The force of air friction F_A on a moving object is a vector pointing to the opposite direction of movement and it has a magnitude of Eq. (14).

$$F_A = \frac{1}{2} \cdot C_d \cdot p \cdot A \cdot V^2, \tag{14}$$

where

F_A = air fiction (N)
C_d = drag coefficient
p = air density (1.225 kg/m^3)
A = frontal area of the moving object (m^2)
V = object speed (relative to air) (m/s)

Assuming that the EV agent is moving at a constant speed V, the power requirements P_A are described with Eq. (15).

$$P_A = F_A \cdot V \tag{15}$$

The drivetrain losses include those that the user doesn't typically control: the efficiency of the motor controller, the motor itself, the gearbox and generally all losses in converting the DC power from the battery pack into useful torque at the wheels of the car. This is proportional to speed due to spinning losses in the gearbox and motor and also proportional to power output due to conversion losses in the various subsystems. Compared to the aerodynamics, drivetrain losses are more difficult to

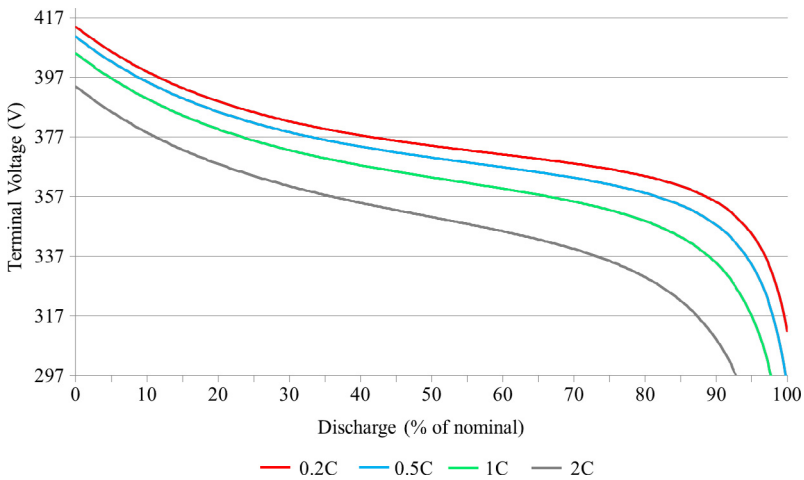

Fig. 5. Discharge characteristics for the EV agent battery.

Table 2
Data used in the power consumption calculations.

C_d	0.31
A	2.097 m^2
α	0.00096
β	0.193
γ	18.21
P_{stop}	0.375 kW
weight	13096.35 N
C_{rr}	0.0089
P_{anc}	2 kW

calculate using simple equations as the performance of each subsystem has to be individually modelled. In this work, the vehicle's speed is assumed to have a 3rd order polynomial relationship to the required drivetrain power P_{dr}, as mentioned in Van Haaren (2012). Eq. (16) describes this relationship:

$$P_{dr} = \alpha \cdot V^3 + \beta \cdot V^2 + \gamma \cdot V + P_{stop}, \tag{16}$$

where α, β, γ are the drivetrain coefficients and P_{stop} is the drivetrain power when the EV is not moving.

Tire losses are mainly determined by the weight of the vehicle and the rolling drag of its tires. The power required to overcome the rolling resistance is a function of the vehicle's weight N and rolling resistance coefficient C_{rr} and is proportional to the driving speed V. This power P_T is described by Eq. (17).

$$P_T = N \cdot C_{rr} \cdot V \tag{17}$$

All other electrical loads in the vehicle are considered as ancillary losses P_{anc}. These include losses from audio systems, electric windows, heating ventilation and air conditioning systems (HVAC), battery cooling and management systems as well as interior and exterior lightning. According to Van Haaren (2012), these losses are assumed to be independent to the vehicle's speed, and were considered constant in this study and equal to 2 kW.

Since the simulated EV agent carries a battery similar to the one in Tesla Roadster, the power consumption calculations were performed using data for the same model, and were obtained from TeslaMotors (no date). The data used in these calculations are presented in Table 2.

For vehicle speeds up to 150 km/h, the power consumption is presented in Fig. 6.

5. Modelling the behaviour of the EV agent

5.1. The behavioural profiles of the EV agent

The EV agent is an agent designed to simulate the behaviour of the EV owner/driver while driving and charging the EV. In real life, an EV driver drives the EV to various destinations and makes sure that the EV has sufficient energy to make the necessary trips. To simulate this behaviour the EV agent was designed to "think" like a human EV driver and take logical

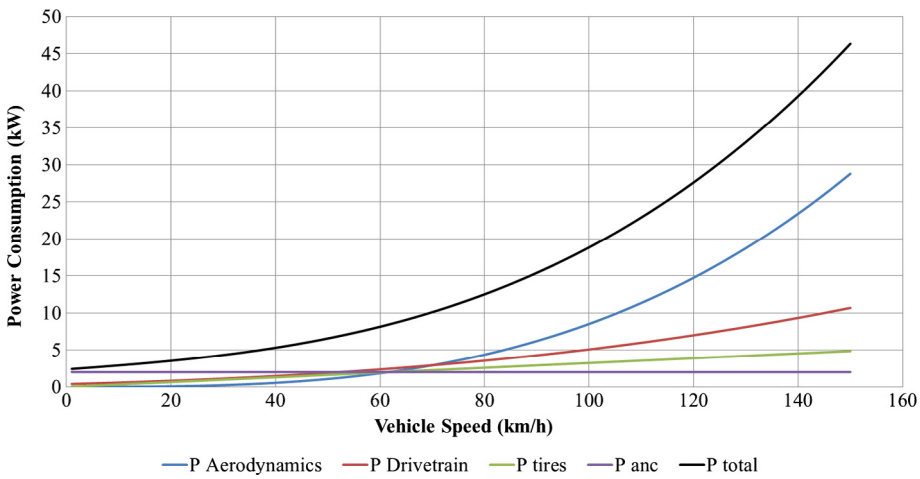

Fig. 6. Considered EV power consumption versus EV driving speed.

decisions according to the available information. Living in a complex environment (road transport and electricity grid), the EV agent operates in an intelligent way in order to achieve its goals. The goals of the EV agent are summarised below:

i. Find a route to my destination(s)
ii. Recharge my EV battery when the SoC is low
iii. Start the next day with a full battery

These goals describe the basic challenges an EV owner faces during the everyday use of its EV. The way that the EV owner achieves those goals affects its environment, both the road transport and the electricity grid.

Many factors affect the EV driver's behaviour. External factors like traffic data availability affect the route of the EV driver (e.g. information about a car accident could help the EV driver avoid traffic). The "range anxiety" feeling increases the frequency an EV driver recharges its vehicle and affects the distance an EV driver "thinks" the EV can make. The available charging infrastructure and the overall EV integration framework affects the EV driver charging awareness as well as its willingness to respond to economic incentives regarding their charging times and fashion. To model these factors two behavioural profiles were considered for the EV agent in this work: the Unaware and the Aware profile.

The Unaware EV agent represents an EV driver during the early stages of EV adoption, where the charging infrastructure and EV driver awareness is limited (Raab and Hartmann, 2012; Element Energy, 2013). This EV driver tries to find the best possible solution to its routing and charging challenges with limited access to information and with minimum interactions with its environment and the other EV agents. The "range anxiety" feeling is strong and the Unaware EV agent seeks to frequently recharge its EV- even when it is not absolutely necessary.

The Aware EV agent represents an EV driver during the mature stages of EV adoption, where advanced charging/communication infrastructure is in place to assist in the decision making process of the EV owner, and new business entities are emerged to provide economic incentives according to the charging fashion of the EV owners (Raab and Hartmann, 2012; Element Energy, 2013). Compared to the Unaware EV agent, the Aware EV agent has access to more information and interacts with its environment and the other Aware EV agents in order to find the best possible solution to its routing and charging challenges. The Aware EV agent is confident about the vehicle's range (the "range anxiety" feeling is low) and thus the Aware EV agent recharges its EV only when it is necessary.

Each behavioural profile was modelled separately and forms the EV agent's reasoning engine. The reasoning engine is consisted of activities (behavioural states) and transitions (links between activities). Each activity defines a sequence of actions that are executed and can trigger different procedures in the same entity and/or other entities. Time-dependent variables were defined to dynamically capture the state of the EV agent (e.g. terminal voltage of its battery) influenced by the interactions from the EV agent's environment. Independent variables were also used for the static characteristics of the EV agent (the parameters not affected by other agents or the environment). Such a parameter is the *SoC Threshold*, a parameter used to describe the "range anxiety" feeling, which defines the SoC level at which an EV agent expresses its need for recharging. All interactions among the EV agents follow request-response logic, thus each request must precede the corresponding response. Following this rule, all EV agents were modelled with an *idle* state in which they wait to receive an answer from another EV agent. This is critical for the EV agent coordination, as during this state, other EV agents perform various actions that need to be executed prior to this EV agent's next action e.g. one EV agent uses the result of another EV agent's calculation.

5.2. Interactions with the road transport network environment

The EV agent interacts with the road transport network of our model. It moves along the avenues to get to the district it wants. As mentioned in Section 3, it was assumed that the EV agent travels at a constant speed along an avenue, equal to the avenue's mean travelling speed when the EV agent enters it. Using this assumption, the EV agent affects the traffic of the avenue it is on, but also its moving speed is affected by the avenue's traffic. To simulate the routing *rationale* of an EV driver, a routing algorithm was developed for the EV agents. The routing algorithm is the procedure followed by the EV agent in order to calculate the route from the current location to its destination. This procedure is different according to the behavioural profile of the EV agent.

The Unaware EV agent has limited access to information and it doesn't use live traffic data during their path calculation. An exhaustive breadth-first search algorithm was used to calculate all the possible routes (unique sequence of avenues) to reach the defined destination district. For each possible route, the Unaware EV agent calculates the total trip distance by aggregating the lengths of all avenues in the route. It then selects the route with the minimum trip duration considering the free flow speed of each route according to Eq. (18):

$$\min T^{S\to D}_{Route_i}, \tag{18}$$

where

S = the starting district of the trip
D = the destination district of the trip
N = the number of possible unique routes from S to D

$i = 1 \ldots N$
$Route_i = \{a_1 \ldots a_k \mid K \text{ avenues connecting } S \text{ to } D\}$
$T^{S \to D}_{Route_i} = \sum_{k=1}^{K} \frac{d_{a_k}}{u_{af_k}}$
d_a = the length of avenue a of $Route_i$
u_{af} = the free flow speed of avenue a of $Route_i$

The Aware EV agent on the other hand has access to live traffic data and looks for a solution that would allow it to reach its destination district in the minimum time. Using the same search algorithm as the Unaware EV agent, the Aware EV agent calculates all the possible routes to the defined destination district. The difference is that the Aware EV agent uses live traffic data to identify the *quickest* path to its destination. The Aware EV agent estimates the total travelling time for each possible route to the destination district according to the current mean travelling speed on each avenue. It then selects the route with the minimum trip duration according to Eq. (19):

$$\min T^{S \to D}_{Route_i}, \tag{19}$$

where

S = the starting district of the trip
D = the destination district of the trip
N = the number of possible unique routes from S to D
$i = 1 \ldots N$
$Route_i = \{a_1 \ldots a_k \mid K \text{ avenues connecting } S \text{ to } D\}$
$T^{S \to D}_{Route_i} = \sum_{k=1}^{K} \frac{d_{a_k}}{u_{a_k}}$
d_a = the length of avenue a of $Route_i$
u_a = the current mean speed on avenue a of $Route_i$

In case the SoC of the EV agent's battery is lower than the pre-defined *SoC Threshold*, the EV agent seeks to recharge. If this need is expressed during a trip, the EV agent tries to find a Public Charger to make a recharging stop. In case there aren't Public Chargers along the EV agent's path, the EV agent would modify its trip to stop at a Public Charger. Trying to simulate a realistic EV driver behaviour, different methodologies to calculate this recharging stop were developed for each behavioural profile of the EV agent.

The Unaware EV agent follows again a "simplest solution" strategy to this problem using limited information. It seeks for the closest Public Charger. It acquires the location of all Public Chargers in the region and calculates the shortest path route from its current location to the location of each Public Charger. The Unaware EV agent then selects the Public Charger which requires the least travelling distance from its current location. As soon as a Public Charger is selected, the Unaware EV agent recalculates its route to include a recharging stop. When the Unaware EV agent reaches the Public Charger, it enters the queue and charges its battery until its SoC reaches 100%.

The Aware EV agent on the other hand follows a different approach which utilizes more information. It seeks for a recharging stop that minimises the total time needed to reach its initial destination district. In contrast to the Unaware EV agent, the Aware EV agent considers the live traffic of the avenues and the waiting time (queue) at the Public Chargers when calculating the recharging stop. It selects the Public Charger that minimises Eq. (20).

$$\min(T^{A \to PC}_{Route_i} + T^{PC}_{wait} + T^{PC}_{ch} + T^{PC \to B}_{Route_j}), \tag{20}$$

where

A = the current district of the Aware EV agent
PC = the district of the Public Charger
B = the destination district of the Aware EV agent
N = the number of possible unique routes from A to PC
$i = 1 \ldots N$
$Route_i = \{a_1 \ldots a_k \mid K \text{ avenues connecting } A \text{ to } PC\}$
$T^{A \to PC}_{Route_i} = \sum_{k=1}^{K} \frac{d_{a_k}}{u_{a_k}}$
d_{ak} = the length of avenue a of $Route_i$
u_a = the current mean speed on avenue a of $Route_i$
M = the number of possible unique routes from PC to B
$j = 1 \ldots M$
$Route_j = \{a_1 \ldots a_w \mid W \text{ avenues connecting } PC \text{ to } B\}$
$T^{PC \to B}_{Route_j} = \sum_{w=1}^{W} \frac{d_{a_w}}{u_{a_w}}$
d_{aw} = the length of avenue a of $Route_j$

u_a = the current mean speed on avenue a of $Route_j$
T^{PC}_{wait} = the waiting time at PC (before charging)
T^{PC}_{ch} = the charging time at PC

The Aware EV agent uses the live traffic data to estimate the travelling times ($T^{A\to PC}_{Route_i}$ and $T^{PC\to B}_{Route_j}$) for each Public Charger. In contrast to the Unaware EV agent, the Aware EV agents charge only for the necessary time in order to reach their destination. To this end the Aware EV agent estimates the energy requirements to get to its destination district and simulates the recharging cycle at that Public Charger. The energy requirements for each possible route are calculated using the live traffic data. To calculate the recharging time needed to cover these energy requirements, a "Virtual Battery Model" was developed for the Aware EV agent. The "Virtual Battery Model" is used by the Aware EV agent to simulate (in zero time) the whole recharging cycle of each recharging option and calculate the necessary recharging time at a particular Public Charger. When the appropriate Public Charger is selected, its queue is updated accordingly with the estimated recharging time of the Aware EV agent. To calculate the waiting time at a Public Charger, the Aware EV agent uses the aggregated recharging times of the Aware EV agents waiting at the Public Charger's queue.

5.3. Interactions with the electricity grid environment

The EV agent interacts with the electricity grid through the charging at the EV chargers. All EV chargers were modelled to operate on a constant current – constant voltage (CC-CV) charging cycle. Considering the EV chargers with the characteristics presented in Table 3, a full charging cycle of the EV agent's battery is presented in Fig. 7.

Depending on the nominal power rate and the efficiency factor of each charger, the charge current of the CC phase was calculated. Fig. 7 presents the EV battery voltage, current and SoC, as well as the charger's power demand from the AC grid.

The duration of charging is different for the two EV agent profiles. The Unaware EV agent charges its battery at a Public Charger until it is fully charged while the Aware EV agent charges its battery only for the time necessary to complete its daily trip. Longer charging durations affect the electricity grid, as the required energy for one charging event is more. In addition, the "range anxiety" feeling (expressed by the *SoC Threshold* variable), has an effect on the electricity grid as it defines the charging frequency for an EV agent. When the "range anxiety" feeling is strong (*SoC Threshold* is high), the EV agent charges its vehicle multiple times in a day trying to maintain the battery charge in levels above that threshold.

In the developed model, the EV agents charge at home every night. Trying to simulate the charging behaviour of unconcerned and concerned EV owners, the Unaware EV agent and the Aware EV agent were modelled to follow different charging regimes at home.

The Unaware EV agents follow an uncontrolled charging regime. As soon as they return home from their daily trips, they begin charging regardless the network's condition. Their charging stops when the EV battery is fully charged.

The Aware EV agents follow a different approach for their home charging. Their goal is to minimise the impact of their charging at a local level (district level). It was assumed that proper "smart" charging infrastructure is in place and the Aware EV agents are rewarded for their participation in a coordinated home charging scheme, aiming to reduce the impact of EV charging at the MV substation of a district. The Aware EV agents coordinate with the other Aware EV agents of the same district, and charge during the off-peak hours of the MV Substation of that district. To identify the off-peak hours, the expected day-ahead demand of a district was assumed known to the district's Aware EV agents. Upon its arrival at home, each Aware EV agent calculates the optimal start time (start minute since the simulation runs minute-wise) for its charging. The optimal start time t_s is the one which results in the minimum standard deviation of the expected day-ahead demand of the MV Substation. The Aware EV agent was modelled to solve the following problem:

$$\min \sqrt{\frac{\sum_{t=t_c}^{t_c+N}(X_t-\overline{X})^2}{N}}, \tag{21}$$

where

N = 1440 min (one day ahead)
t_c = the current minute
$\overline{X} = \frac{\sum_{t=t_c}^{t_c+N} X_t}{N}$

Table 3
The characteristics of the EV chargers.

Type	Home Charger	Public Charger
P^{AC}_{nom}	7.4 kW	22 kW
$\eta_{AC/DC}$	0.97	0.97
$\eta_{DC/DC}$	0.97	0.97
i_{cc} (calculated)	16.745 A	49.783 A

$$X_t = \begin{cases} P_{ch}(t - t_s) + P_{DA}(t) & , t_s < t \leqslant t_s + cd \\ P_{DA}(t) & , \text{otherwise} \end{cases}$$

cd = the necessary charging duration (in minutes)
t_s = the start time of charging
$P_{ch}(t)$ = the charging demand at minute t
$P_{DA}(t)$ = the day-ahead demand of the district's MV Substation

In order to calculate the charging demand, the Aware EV agent uses the "Virtual Battery Model" to simulate the charging procedure at its Home Charger. When the optimal start time is calculated, the Aware EV agent updates the expected day-ahead demand of the MV Substation accordingly. Eq. (22) was used to update the day-ahead demand.

$$P_{DA_new}(t) = \begin{cases} P_{ch}(t - t_s) + P_{DA_old}(t) & t_s < t \leqslant t_s + cd \\ P_{DA_old}(t) & , \text{otherwise} \end{cases}, \tag{22}$$

The next Aware EV agent that arrives at home in the same district uses the updated day-ahead demand to calculate the optimal time to charge its battery. After all Aware EV agents return home, the result is a coordinated charging with the minimum impact on the electricity grid.

6. Case study

6.1. Description of the scenarios

The developed model was used in order to study the impact of the EV agents' behavioural profiles in two different scenarios (one for Unaware behaviour and one for Aware behaviour). In the scenarios, 10,000 electricity consumers (houses) were considered for the whole network (geographical area). The consumers were evenly distributed in each district and were

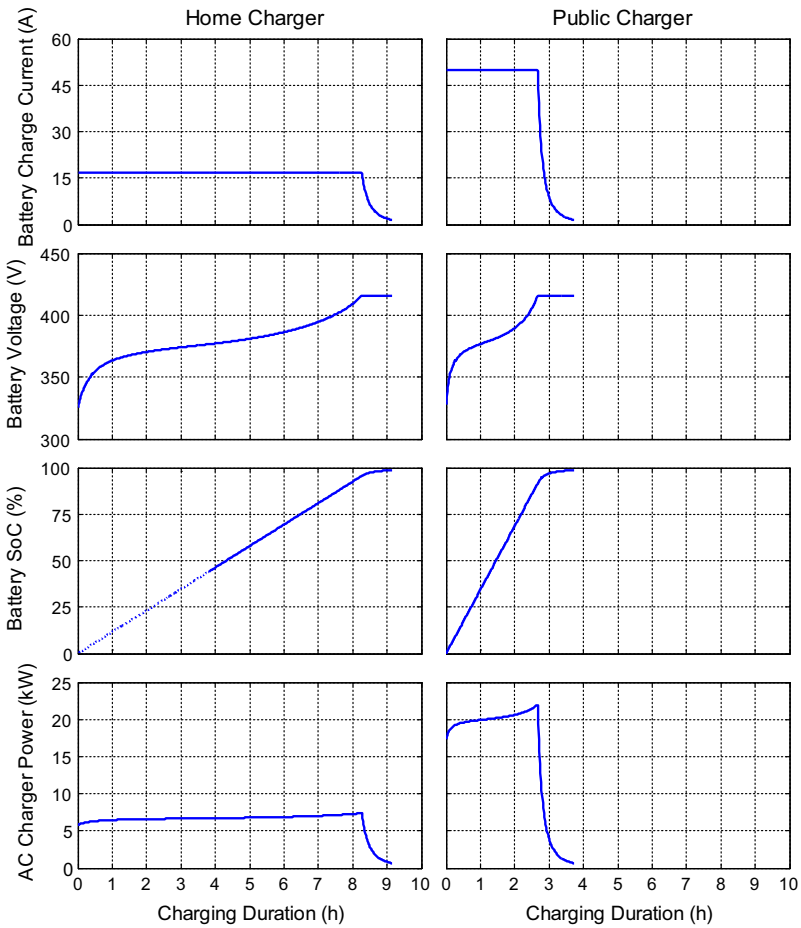

Fig. 7. The battery voltage, charge current and SoC of the EV battery, and the power demand of the EV charger.

Table 4
The distribution of the times spent for each activity.

Activity	Mean Value (μ)	Standard Deviation (σ)
Work 1	4 h	0.3 h
Lunch	1 h	0.25 h
Work 2	3 h	0.3 h
Shopping	1 h	0.25 h
Other	1 h	0.25 h

assumed to have different daily electricity demand profiles obtained from the UK Energy Research Centre (http://www.uk-erc.ac.uk/). An EV uptake of 10% was assumed, and a fleet of 1000 EVs (and EV agents) was created.

An activity-based travel pattern was assumed for all EV agents in our model. The travel pattern assumes a maximum of 5 activities in a day. Starting from Home the agents randomly choose a sequence of 3–5 activities from Table 4. After completing their activities, the EV agents return Home for the night. A random number generator was used to define the districts for each activity, with the assumption that these districts must be different from Home. The times each EV agent spent for each activity were assumed to be random numbers following a normal distribution (different for each destination). The distributions are presented in Table 4.

6.2. Results

The impact of the different behaviour of the EV agents on their environment and their battery characteristics was studied. Every dynamic variable of the model is monitored during the simulation. A sample of the simulation results was selected and is presented in this section.

As mentioned in the previous sections, the Home charging fashion is different for Unaware and Aware EV agents. The Unaware EV agents start charging immediately when they arrive at Home, while the Aware EV agents calculate the optimal start time for charging according to Eq. (21). The impact of EV charging at Home on the demand profile of the HV Substation is presented in Fig. 8 for both EV behavioural profiles.

As seen from Fig. 8, the Unaware EV agents start charging when they return home (around 17:30–18:00) and their charging demand coincides with the evening peak of the residential demand. Consequently, a 16.54% increase of the peak demand is caused, and the electricity network is stressed. On the other hand, the Aware EV agents place their charging during the off-peak hours (between 22:00 and 06:00) resulting in a valley-fill effect on the demand profile of the HV Substation. This "grid-sensitive" behaviour of the Aware EV agents not only avoids the increase of the peak demand, but also reduces the stress of the electricity network and postpones any unnecessary upgrades of the existing infrastructure. The impact of charging demand from Unaware and Aware EV agents was found similar to the Uncontrolled and Controlled charging demand profiles of Verzijlbergh et al. (2011), where a detailed model is presented to derive EV charging profiles from driving statistics.

As described before, the EV agents have a large battery pack (53 kW h). Assuming a full battery in the morning and a realistic SoC Threshold of 30%, the EV agents would not normally need a recharging stop during the day (especially when the trips are only five). In order to study the behaviour of the EV agents when a recharging stop at a Public Charger is required,

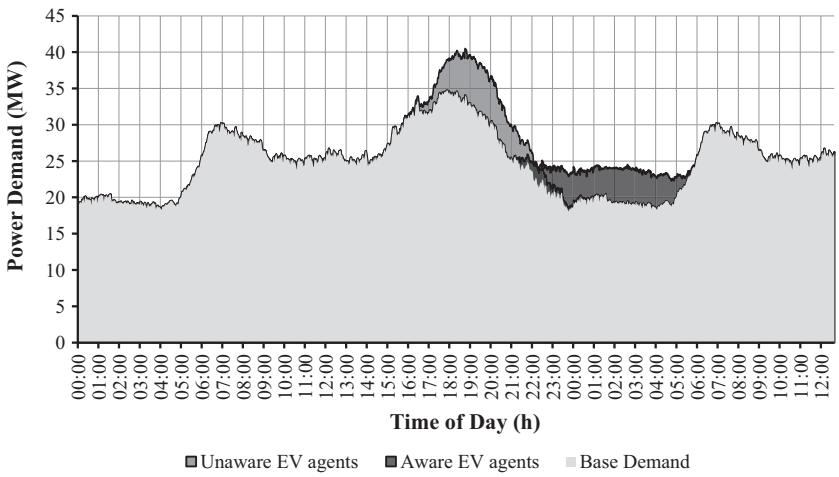

Fig. 8. Impact of EV charging at Home (aggregated).

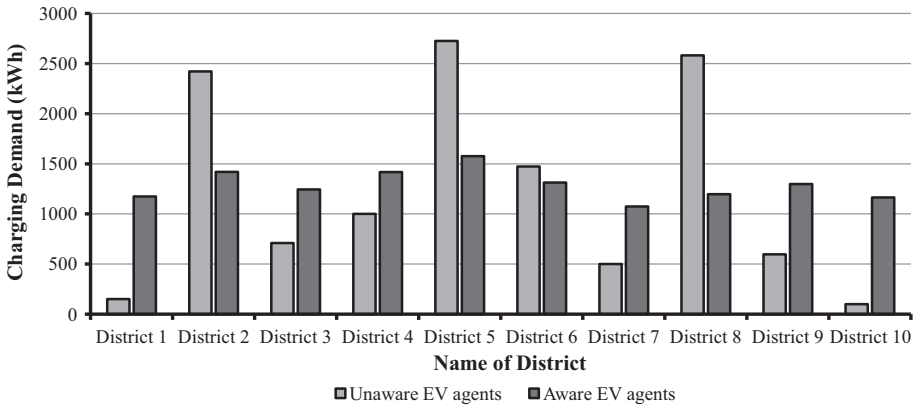

Fig. 9. Distribution of Public EV charging demand to the districts.

it was assumed that the need for a recharging stop is triggered at a much higher SoC level, at 70%. Although this value is unrealistic, it serves well the demonstrating purposes of this case study. To this end, 100 Public Chargers were distributed equally to the 10 Districts offering recharging services to the EV agents.

Fig. 9 presents the aggregated charging demand from the Public Chargers of each District. The Unaware EV agents look for the closest Public Charger when they need a recharging stop, while the Aware EV agents try to minimise the total duration of the recharging stop by considering the waiting times at a Public Charger. The Unaware EV agents were found to prefer the central nodes of the transport network (Districts 2, 5 and 8) for their public charging. The reason for this lies between their Unaware behaviour (looking for the closest Public Charger) and the structure of the road network. As seen from Fig. 2, the links of the network do not have the same length, and therefore some nodes are closer than others, even if they are only one "hop" away. The Unaware EV agents, looking for the closest Public Charger will prefer the nodes that are closer to them and they would not go to nodes at the other side of the road network. This causes an uneven utilisation of the Public Chargers (only the ones at central districts are used), as well as a stress at the local electricity grid. Queues are also created to the popular Public Chargers, delaying the charging procedure for the EV agents. On the other hand the Aware EV agents use the information regarding the availability of Public Chargers, and charge at Public Chargers in all Districts. This way they avoid the queues and reduce their recharging times. Moreover, the Aware EV agent behaviour increases the utilisation of the public charging facilities and offers an even distribution of the charging demand to all Districts, reducing the stress of the electricity grid.

The uneven distribution of the charging demand affects the electricity grid. The high charging demand stresses the distribution network infrastructure and causes increased line losses and deep voltage drops. As the distribution network has certain limits and load capacity, an upgrade might be necessary in order to facilitate this additional demand. In addition, the charging demand is directly related to the number of charging requests in the district. Increased number of charging requests in a district means that more EVs arrive to that district seeking to recharge, affecting the traffic on the roads of each district (not modelled in this work). The utilization rate of the public chargers is also affected by the distribution of charging requests. Considering third-party companies that own and manage these public chargers, the utilization rate has a significant effect on their income. The capital and operational costs of the public chargers are seen as investments by these companies, and an underused public charger reduces the efficiency of this investment. These companies need to understand the EV owners' behaviour and calculate the expected utilisation ratio of each public charger when planning its location to make sure that their investment will not be inefficient.

The EV agents affect the road transport network according to their behavioural profile and their recharging requirements. Fig. 10 presents the average number of EVs on a random road (avenue A1_2) of the transport network. Three traffic "peaks" are created from the EV agents. The first peak is during the morning hours, when all the EV agents go to their work. The second peak is in the early afternoon, when the EV agents go to lunch, following their pre-defined activity cycle. Due to the stochastic approach that was followed for the duration of each activity, the width of this peak is considerably wider than the first peak as not all the EV agents go for lunch at the exact same time. The same goes for the third peak in the evening hours, when the EV agents leave their work to go shopping and return home.

The Unaware EV agents choose the shortest route to their destination judging by the driving distance. The Aware EV agents on the other hand, consider the real time traffic information and choose the fastest route to their destination, avoiding the busy roads. Due to this behaviour, the traffic of avenue A1_2 was reduced as seen in Fig. 10. Of course, this is not the case with all the avenues in the transport network. The average traffic density in a day of all the avenues in the transport network is presented in Fig. 11.

The Unaware routing behaviour increased the traffic of popular avenues, and led to an uneven distribution of traffic throughout the network. The Unaware EV agents face delays in their return to home and the energy consumption of their

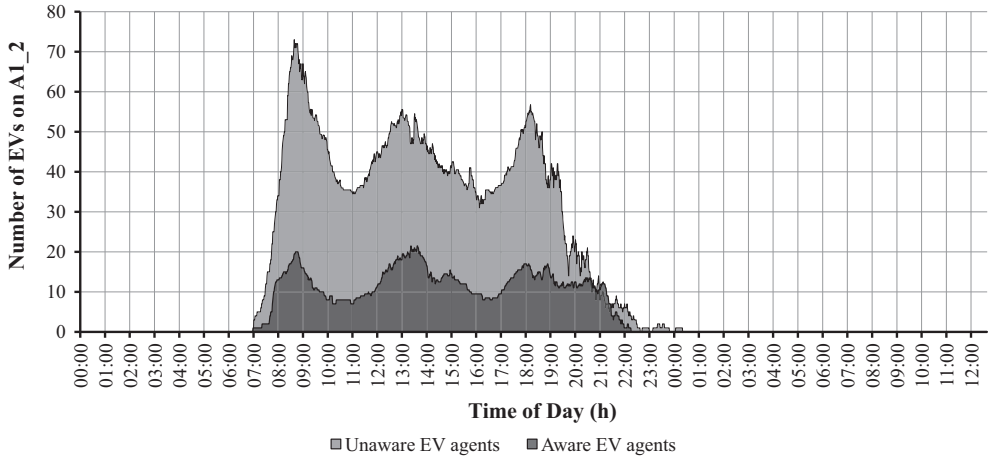

Fig. 10. Traffic distribution on avenue A1_2.

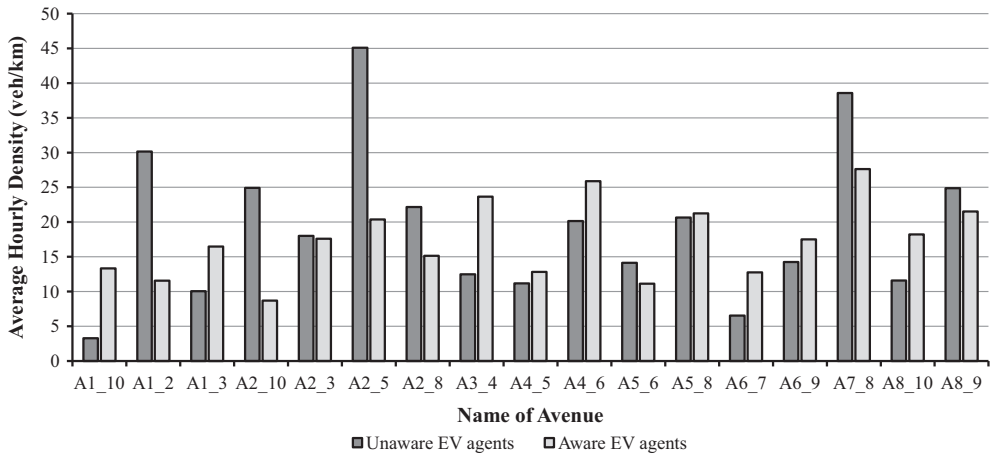

Fig. 11. Average traffic distribution of EVs on all avenues.

vehicles is increased. It was found that more than half the EV agents arrive home later in the Unaware scenario than in the Aware scenario. In average, the Unaware EV agents arrive home 81 min later than the Aware EV agents due to the increased traffic and the queues at Public Chargers. Their recharging requirements combined to their charging behaviour increases even more the traffic of the avenues which lead to the central districts. Due to a high SoC Threshold, the need for a recharging stop is frequent. Considering that the Unaware EV agents choose the closest Public Charger, many EVs arrive at the central districts seeking for an available Public Charger increasing the traffic of the surrounding avenues.

On the other hand, the Aware EV agents try to minimise the total duration of their trips. By using the avenues with reduced traffic, they distribute the traffic throughout the transport network. It was found that the standard deviation of traffic density in the avenues of the transport network was reduced by 41%. This reduces the risk of a traffic jam and enables a smooth and continuous flow of traffic. Their Aware charging behaviour and confidence on the EV range, allows the Aware EV agents to have less frequent recharging stops and when they do these are at available Public Stations at less popular districts. This helps in the disaggregation of traffic from the central districts of the network.

7. Conclusions

In this paper, a multi-agent system based simulator was developed for the integration of transport and electricity networks capable of reproducing the behaviour of an intelligent entity (electric vehicle) co-existing in both systems. The main components of both networks were modelled in a multi-agent simulation platform to simulate the environment of the EV. The main EV characteristics were also modelled in detail, allowing a more in-depth approach to the EV's interdependencies

with its environment. One of the main aims of this simulator is to enable a variety of possible scenarios to understand the EV context, bringing together two distinctly different but highly inter-related infrastructures. To this end, two realistic behavioural profiles (Unaware/Aware) were considered to describe the way an EV driver deals with the everyday challenges.

Considering a fleet of 1000 EV agents, two scenarios were considered to understand the impact of different EV driver behaviour to the road transport and the electricity grid. The scenarios represent the different stages of EV integration, starting with Unaware EV drivers when the public acceptance of EVs is limited, and developing to Aware EV owners as the electrification of road transport is promoted in an overall context. Following a realistic activity-based trip pattern, the EV agents move and stay at random destinations for durations that were stochastically defined. The results showed that the EV agents' behavioural profile has direct and indirect impact on both the road transport network and the electricity grid, affecting the traffic of the roads, the stress of the distribution network and the utilization of the charging infrastructure. The awareness of the EV drivers should be supported (and incentivised) by the authorities as it reduces the impact of EVs on road transport and electricity networks and ensures a smooth electrification of road transport.

Observing EV behaviour under different situations with multi-agent simulations will help understand the impact of future EV integration on both systems and to better understand how a variety of differing roles within both networks could co-exist. Therefore, authorities will have knowledge of possible irregularities or needs for adjustments/re-configuration in order to allow and support the EV adoption in the future. With the existing model, more scenarios can be considered to analyse the overall system in depth. By changing the number of the EVs within the model, the limitations of the existing electric power network in terms of charging capability will be investigated. By changing the location and the number of charging stations at the transport network, the EVs' travel behaviour will show the utility value of each location, indicating the most and least visited stations. By applying the model on larger networks the results become more interesting, as the EVs could travel longer distances needing more than one recharging stop. The simulation can also be improved by considering a more detailed traffic congestion model. Additional stochastic parameters can be introduced in the transport network (e.g. a road becomes unavailable due to an unexpected event), to observe the agents' reactions and understand the impact on both the transport and electric power network.

In future work, the authors will extend the model and run simulations in a larger scale. A bigger road network will be considered, based on real data from a geographical area. More details will be included in the electricity grid, and distributed generation will be considered in different nodes offering public charging services in order to investigate the EV agents' reaction to "environment-friendly" charging facilities. Additional features will be included such as the stochastic assignment of activity sequences and behavioural profiles to the EV agents. This will allow the study of scenarios that include a mix of Unaware and Aware EV agents, covering the intermediate stages of EV adoption.

Acknowledgement

The authors would like to acknowledge EPSRC-NSFC project "Grid Economics, Planning and Business Models for Smart Electric Mobility" (EP/L001039/1) for supporting this work.

References

Arentze, T., Feng, T., Timmermans, H., Robroeks, J., 2012. Context-dependent influence of road attributes and pricing policies on route choice behavior of truck drivers: results of a conjoint choice experiment. Transportation 39 (6), 1173–1188. http://dx.doi.org/10.1007/s11116-012-9391-z.

Bae, S., Kwasinski, A., 2012. Spatial and temporal model of electric vehicle charging demand. IEEE Trans. Smart Grid 3 (1), 394–403. http://dx.doi.org/10.1109/TSG.2011.2159278.

Balmer, M., Cetin, N., Nagel, K., Raney, B., 2004. Towards truly agent-based traffic and mobility simulations. Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagent Systems, vol. 1, pp. 60–67. http://dx.doi.org/10.1109/AAMAS.2004.242235.

Bazzan, A.L.C., Klügl, F., 2013. A review on agent-based technology for traffic and transportation. Knowl. Eng. Rev. 29 (May), 1–29. http://dx.doi.org/10.1017/S0269888913000118.

Berdichevsky, G., Kelty, K., Straubel, J., Toomre, E., 2007. The Tesla Roadster Battery System, *Tesla* Motors Inc. Available at: <http://esmuc.info/dispara2/TeslaRoadsterBatterySystem.pdf>.

Bhat, C.R., 1997. Work travel mode choice and number of non-work commute stops. Transp. Res. Part B: Meth. 31 (1), 41–54. http://dx.doi.org/10.1016/S0191-2615(96)00016-1.

Cavadas, J., de Almeida, Homem, Correia, G., Gouveia, J., 2015. A MIP model for locating slow-charging stations for electric vehicles in urban areas accounting for driver tours. Transp. Res. Part E: Logist. Transp. Rev. 75, 188–201. http://dx.doi.org/10.1016/j.tre.2014.11.005.

Clement-Nyns, K., Haesen, E., Driesen, J., 2010. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Trans. Power Syst. 25 (1), 371–380. http://dx.doi.org/10.1109/TPWRS.2009.2036481.

Coninx, K., Holvoet, T., 2014. A microscopic traffic simulation platform for coordinated charging of electric vehicles. In: Advances in Practical Applications of Heterogeneous Multi-Agent Systems. The PAAMS Collection, pp. 323–326. http://dx.doi.org/10.1007/978-3-319-07551-8_29.

van Dam, K.H., Lukszo, Z., 2006. Modelling energy and transport infrastructures as a multi-agent system using a generic ontology. In: 2006 IEEE International Conference on Systems, Man and Cybernetics. IEEE, pp. 890–895. http://dx.doi.org/10.1109/ICSMC.2006.384502.

Doniec, A., Mandiau, R., Piechowiak, S., Espié, S., 2008. A behavioral multi-agent model for road traffic simulation. Eng. Appl. Artif. Intell. 21 (8), 1443–1454. http://dx.doi.org/10.1016/j.engappai.2008.04.002.

Element Energy, 2013. Pathways to high penetration of electric vehicles - Report prepared for Committee on Climate Change. Cambridge.

Galus, M.D., Waraich, R.A., Noembrini, F., Steurs, K., Georges, G., Boulouchos, K., Axhausen, K.W., Andersson, G., 2012. Integrating power systems, transport systems and vehicle technology for electric mobility impact assessment and efficient control. IEEE Trans. Smart Grid 3 (2), 934–949. http://dx.doi.org/10.1109/TSG.2012.2190628.

Ghamami, M., Zockaie, A., Nie (Marco), Y., 2016. A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel. Transp. Res. Part C: Emerg. Technol. 68, 389–402. http://dx.doi.org/10.1016/j.trc.2016.04.016.

Van Haaren, R., 2012. Assessment of Electric Cars ' Range Requirements and Usage Patterns based on Driving Behavior recorded in the National Household Travel Survey of 2009.

He, F., Wu, D., Yin, Y., Guan, Y., 2013. Optimal deployment of public charging stations for plug-in hybrid electric vehicles. Transp. Res. Part B: Meth. 47, 87–101. http://dx.doi.org/10.1016/j.trb.2012.09.007.

He, F., Yin, Y., Zhou, J., 2015. Deploying public charging stations for electric vehicles on urban road networks. Transp. Res. Part C: Emerg. Technol. 60, 227–240. http://dx.doi.org/10.1016/j.trc.2015.08.018.

He, S.Y., Kuo, Y.-H., Wu, D., 2016. Incorporating institutional and spatial factors in the selection of the optimal locations of public electric vehicle charging facilities: a case study of Beijing, China. Transp. Res. Part C: Emerg. Technol. 67, 131–148. http://dx.doi.org/10.1016/j.trc.2016.02.003.

Ingram, S., Probert, S., Jackson, K., 2003. The impact of small scale embedded generation on the operating parameters of distribution networks, PB Power Technical Report K/EL/00303/04/01. Available online at: <http://webarchive.nationalarchives.gov.uk/20100919181607/www.ensg.gov.uk/assets/22_01_2004_phase1b_report_v10b_web_site_final.pdf>.

Karfopoulos, E.L., Hatziargyriou, N.D., 2016. Distributed coordination of electric vehicles providing V2G services. IEEE Trans. Power Syst. 31 (1), 329–338. http://dx.doi.org/10.1109/TPWRS.2015.2395723.

Karfopoulos, E.L., Marmaras, C.E., Hatziargyriou, N., 2012. Charging control model for electric vehicle supplier aggregator. In: 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe). IEEE, pp. 1–7. http://dx.doi.org/10.1109/ISGTEurope.2012.6465716.

Klügl, F., Herrler, R., Fehler, M., 2006. SeSAm: implementation of agent-based simulation using visual programming. In: Proceedings of the Fifth International Joint Conference on Autonomous Agents and Multiagent Systems – AAMAS '06, p. 1439. doi:http://dx.doi.org/10.1145/1160633.1160904.

Li, S., Huang, Y., Mason, S.J., 2016. A multi-period optimization model for the deployment of public electric vehicle charging stations on network. Transp. Res. Part C: Emerg. Technol. 65, 128–143. http://dx.doi.org/10.1016/j.trc.2016.01.008.

Lin, J., Leung, K.-C., Li, V.O.K., 2014. Optimal scheduling with vehicle-to-grid regulation service. IEEE Internet Things J. 1 (6), 556–569. http://dx.doi.org/10.1109/JIOT.2014.2361911.

Maerivoet, S., De Moor, B., 2005. Traffic Flow Theory, (May), p. 35. Available at: <http://arxiv.org/abs/physics/0507126>.

Marmaras, C., Corsaro, M., Xydas, E., Cipcigan, L.M., Pastorelli, M.A., 2014. Vehicle-to-building control approach for EV charging. In: Proceedings of the Universities Power Engineering Conference. http://dx.doi.org/10.1109/UPEC.2014.6934639.

Momber, I., Gómez, T., Rivier, M., 2013. Regulatory framework and business models integrating EVs in power systems. In: Electric Vehicle Integration into Modern Power Networks. Springer, New York, New York, NY, pp. 251–271. http://dx.doi.org/10.1007/978-1-4614-0134-6_8.

Nicholas, M.A., Tal, G., Woodjack, J., 2013. California Statewide Charging Assessment Model for Plug-in Electric Vehicles: Learning from Statewide Travel Surveys. Davis, California.

Olivella-Rosell, P., Villafafila-Robles, R., Sumper, A., Bergas-Jané, J., 2015. Probabilistic agent-based model of electric vehicle charging demand to analyse the impact on distribution networks. Energies 8 (5), 4160–4187. http://dx.doi.org/10.3390/en8054160.

Papadopoulos, P., Skarvelis-Kazakos, S., Grau, I., Cipcigan, L.M., Jenkins, N., 2012. Electric vehicles' impact on British distribution networks. IET Electric. Syst. Transp. 2 (3), 91. http://dx.doi.org/10.1049/iet-est.2011.0023.

Pieltain Fernandez, L., Gomez San Roman, T., Cossent, R., Mateo Domingo, C., Frias, P., 2011. Assessment of the impact of plug-in electric vehicles on distribution networks. IEEE Trans. Power Syst. 26 (1), 206–213. http://dx.doi.org/10.1109/TPWRS.2010.2049133.

Putrus, G.A., Suwanapingkarl, P., Johnston, D., Bentley, E.C., Narayana, M., 2009. Impact of electric vehicles on power distribution networks. In: 2009 IEEE Vehicle Power and Propulsion Conference. IEEE, pp. 827–831. http://dx.doi.org/10.1109/VPPC.2009.5289760.

Raab, A.F., Hartmann, N., 2012. Mobile Energy Resources in Grids of Electricity – Final Recommendations.

Raveau, S., Muñoz, J.C., de Grange, L., 2011. A topological route choice model for metro. Transp. Res. Part A: Policy Pract. 45 (2), 138–147. http://dx.doi.org/10.1016/j.tra.2010.12.004.

Rodrigue, J.-P., Comtois, C., Slack, B., 2009. The Geography of Transport Systems. Routledge.

Schücking, M., Jochem, P., Fichtner, W., Wollersheim, O., Stella, K., 2017. Charging strategies for economic operations of electric vehicles in commercial applications. Transp. Res. Part D: Transp. Environ. 51, 173–189. http://dx.doi.org/10.1016/j.trd.2016.11.032.

Soares, J., Canizes, B., Lobo, C., Vale, Z., Morais, H., 2012. Electric vehicle scenario simulator tool for smart grid operators. Energies 5 (6), 1881–1899. http://dx.doi.org/10.3390/en5061881.

Strehler, M., Merting, S., Schwan, C., 2017. Energy-efficient shortest routes for electric and hybrid vehicles. Transp. Res. Part B: Meth. Article in. doi:http://dx.doi.org/10.1016/j.trb.2017.03.007.

Tenergy, 2009. Tenergy 30003 Li-Ion 18650 Cell Available at: <www.TenergyBattery.com>.

TeslaMotors (no date) *Tesla Roadster Features and Specifications*. Available at: <https://my.teslamotors.com/en_GB/roadster/specs> (accessed: 23 November 2015).

Tremblay, O., Dessaint, L.a., 2009. Experimental validation of a battery dynamic model for EV applications. World Electric Veh. J. 3 (1), 1–10.

Tu, W., Li, Q., Fang, Z., Shaw, S., Zhou, B., Chang, X., 2016. Optimizing the locations of electric taxi charging stations: a spatial–temporal demand coverage approach. Transp. Res. Part C: Emerg. Technol. 65, 172–189. http://dx.doi.org/10.1016/j.trc.2015.10.004.

Verzijlbergh, R.A., Lukszo, Z., Veldman, E., Slootweg, J.G., Ilic, M., 2011. Deriving electric vehicle charge profiles from driving statistics. In: 2011 IEEE Power and Energy Society General Meeting. IEEE, pp. 1–6. http://dx.doi.org/10.1109/PES.2011.6039609.

Yao, E., Morikawa, T., 2005. A study of on integrated intercity travel demand model. Transp. Res. Part A: Policy Pract. 39 (4), 367–381. http://dx.doi.org/10.1016/j.tra.2004.12.003.