Using activity-based modeling to predict spatial and temporal electrical vehicle power demand in Flanders

Using Activity-Based Modeling to Predict Spatial and Temporal Electrical Vehicle Power demand in Flanders

Luk Knapen, Bruno Kochan, Tom Bellemans, Davy Janssens, Geert Wets*
Transportation Research Institute (IMOB)
Hasselt University
Wetenschapspark 5, bus 6
B-3590 Diepenbeek
Belgium
Fax: +32 (0) 11 26 91 99

ir Luk Knapen
Email: luk.knapen@uhasselt.be
Tel: +32 (0) 11 26 91 26
ir Bruno Kochan
Email: bruno.kochan@uhasselt.be
Tel: +32 (0) 11 26 91 47
Prof dr ir Tom Bellemans
Email: tom.bellemans@uhasselt.be
Tel: +32 (0) 11 26 91 27
Prof dr Davy Janssens
Email: davy.janssens@uhasselt.be
Tel: +32 (0) 11 26 91 28
Prof dr Geert Wets
Email: geert.wets@uhasselt.be
Tel: +32 (0) 11 26 91 58
Corresponding author : Geert Wets (*)

Number of words = 5499
Number of tables = 5
Number of figures = 3
Words counted : 5499 + 5*250 +3*250 = 7499 words

November 13, 2011

ABSTRACT

Electric power demand for household generated traffic is estimated as a function of time and space for the region of Flanders. An activity-based model is used to predict traffic demand. Electric vehicle (EV) type and charger characteristics are determined on the basis of car ownership and by assuming that EV categories market shares will be similar to the current ones for internal combustion engine vehicles (ICEV) published in government statistics. Charging opportunities at home and work locations are derived from the predicted schedules and by estimating the possibility to charge at work. Simulations are run for several EV market penetration levels and for specific BEV/PHEV (battery-only/pluggable hybrid) ratios. A single car is used to drive all trips in a daily schedule. Most of the Flemish schedules can be driven entirely by a BEV even after reducing published range values to account for range anxiety and for the over-estimated ranges resulting from tests according to standards. The current low tariff electricity period overnight is found to be sufficiently long to allow for individual cost optimizing while peak shaving overall power demand.

INTRODUCTION

Electric vehicles use

The economy's dependency on fossil combustibles is attempted to be decreased for both environmental and strategic reasons. Resulting effects are an expected increase of electric vehicle (EV) use and use of alternative sources for electric energy production. Sustainable electric energy sources (wind, solar) deliver power at variable rates that cannot easily be predicted. Furthermore, storing electric energy is a major problem.

The use of EV generates challenging questions but also opportunities: when EV are used in a *vehicle to grid (V2G)* configuration, they can serve as electric energy storage devices. Designing and operating an electricity grid having lots of small unpredictable producers combined with relocatable storage capacity that is time dependent, is a complex problem.

The problem receives more than pure technical attention. White-House-NSTC (*1*) states: *President Obama has set a national goal of generating 80% of [the] electricity from clean energy sources by 2035 and has reiterated his goal of putting one million electric vehicles on the road by 2015.*

Activity-based models to predict energy demand by electric vehicles

Activity-based modeling (ActBM) predicts daily schedules for people based on the behavioral characteristics for each individual. As a result, each individual actor can be designed to adapt in its own specific way to changes applied in scenarios when using feedback mechanisms during simulation. Activity-based models therefore allow for policy evaluation. The schedules generated by ActBM contain information about the transport modes used and about the activity kind, duration and location. As a result they provide the tools to investigate the feasibility of goals like the one stated in (1) both by modeling in a closed loop, individual behavior change (adaptation) and the effect thereof on the public infrastructure.

This paper explores the case for Flanders. The region counts 6 million inhabitants on 13000 square kilometers and is part of Belgium (Europe) (11 million inhabitants on 30000 square kilometers). The area is subdivided in 2368 zones. A synthetic population of actors has been built to mimic each inhabitant of the area to be studied. Actor behavior is determined by characteristics of the surroundings like road transportation network, distance between locations suited for specific types of activities, public transport availability, delays induced by congestion. The `Feathers` ActBM described in (2) has been used. Within `Feathers`, actor behavior is modeled by 26 decision trees, each one of which takes as input attributes of both the individual actor and the environment as well as the outcome of decisions already made. The decision trees have been trained by means of the CHAID method using data from regional time specific travel behavior OVG surveys. A single survey covers up to 8800 respondents. The decision trees are used to predict (in the order specified) attributes for work episodes, work locations, work-travel mode, fixed non-work activities, flexible non-work activities, non-work locations, non-work-travel mode. At this moment `Feathers` does not adapt actor behavior to car type (ICEV, EV). Car type is determined after schedule prediction. Resulting schedules ar used to predict time and location for travel related electric energy consumption.

First we explain what hypotheses about EV drivers behavior have been made and how EV characteristics have been determined from literature and from available statistical data. Next, calculation details are described. Finally, results for the Flemish region are presented: area specific energy and power requirements as a function of time identify critical parts in the electric grid. The fraction of the household transportation market that can be served by EV without range extenders, is calculated.

Related work

Many research projects are driven by the goals to reduce greenhouse emissions. Recently european research focuses on the problem of matching the supply and demand of electric energy from sustainable sources (solar, wind). Cui et al. (*3*) use a car selection model, a budget prediction model and an agent based simulator (stigmergy) to predict pluggable hybrid electric vehicle (PHEV) market penetration for Knox County (190k households). Davies and Kurani (*4*) predict the electric power demand for the PHEV used by 25 households from data recorded in an experiment and from a PHEV car design game conducted by the households: the effect of work location charging is simulated. Kang and Recker (*5*) and Recker and Kang (*6*) use an activity based model for California based on statewide travel diaries and several charging scenarios to predict the power demand for the whole area as a function of time. Bliek et al. (*7*) describe how PowerMatcher predicts electric energy in a smartgrid containing small unpredictable solar and wind energy sources and tries to match supply and demand using an agent based auction for electric energy. Clement-Nyns et al. (8) evaluate *coordinated charging* strategies for a belgian case. In such systems customers need to specify time limits for charging (which can be produced by ActBM). Waraich et al. (9) evaluate energy tariff effects on charging behavior for the city of Berlin by coupling `MATSim-T` (travel demand simulator framework) to `PMPSS` (PHEV Management and Power Systems Simulation). Binding and Sundstroem (*10*) describe an agent based simulator for an auction based energy pricing system aimed at matching sustainable power supply and demand: they plan to integrate the V2G (Vehicle to Grid) concept to temporary store energy in car batteries. Hadley and Tsvetkova (*11*) predefine a charging profile and analyse the effect on power demand when applying it to 13 US regions at different times of the day.

CONTEXT

Smart grids and transport engineering

Smart grids are required when trying to meet electric energy demand in networks containing many small production units exposing difficult to predict behavior (solar, wind energy). Several techniques are used to try smoothing power requirement over time and to adapting it to uncontrollable time dependent production. With central coordination based schemes, the energy provider is allowed to turn on/off electric loads remotely. Other schemes rely on intelligence local to the consumer to determine electric demand at any moment in time: auction based configurations try to adapt demand to production by negotiating location specific prices every 15 minutes. Each one of those schemes requires intelligent components but also a lot of information about the environment and efficient adequate short time forecasting techniques. ActBM in transport engineering can contribute to the problem solution by creating adequate tools to forecast the energy and power demand as a function of time and location in order to decide when and where energy can be delivered proactively or stored in batteries for later retrieval. Several papers mentioned under **Related Work** predict energy demand: they do so either for a small population or as an aggregated value for a wide region. Related work on smartgrid design, shows that the auction based pricing system simulators need predictions about *when* and *where* electric power is demanded. Therefor, this paper estimates the electric energy and power requirements for Flanders using activity based modeling.

Electric energy demand evolution - Power demand

Energy demand

According to several sources ((12),(13)) the total amount of energy drawn from the grid by electric vehicles is relatively small: a 30% market share EV would represent 3% of the total annual electric energy consumption for the region of Milan, Italy.

For a flemish household, the estimated yearly amount of electric energy required by the car (0.2 kWh/km, 15000 km) is of the same order of magnitude as the amount of electric energy consumed by the household for other purposes (current electric energy consumption value). According to figures published in *Oxford University Environmental Change Institute* website statistics pages (14) the average yearly consumption for a belgian household amounts to 3899 [kWh/year]. A similar figure (3500 [kWh/year]) for Belgium is mentioned by (15). As a consequence, the relative contribution of transport in the overall demand, will grow significantly with increasing EV market penetration.

The evolution of electric energy demand per sector for Belgium is given in (16). Total consumption in 2005 was 80.2 TWh. The transport sector contribution increases but amounted to only 2.12% in 2005. According to several sources ((17), (12)) the energy demand by EV is not expected to cause problems on the electricity grid provided it is distributed over time.

Power demand

Activity-based models help to assess where and when peak power demand would exceed limits imposed by the grid. Perujo and Ciuffo (13) studied power demand for the Milan region using the assumptions that people will not charge their car batteries everyday but only when needed and that charging starts between 16:00h and 19:00h in the evening obeying a uniform distribution over time. Parque and Ciuffo (*12*) recognize the need for statistical values (estimated distributions) on daily commuter trips for a particular region. Our study uses ActBM to calculate charging time and location resulting in a prediction of EV power demand.

The use of activity based models

Electric energy demand estimates require detailed data about location and timing as well as trip purpose and activity information for each simulated individual. This paper investigates following scenarios for charging of both battery-only EV (BEV) and pluggable hybrid EV (PHEV) in order to calculate peak power demand as a function of time and location starting from `Feathers` predicted schedules:

- Scenario **EarlyLowTariff**: people start charging as soon as possible during the low tariff period (night-time, reduced-rate electricity).
- Scenario **UniformLowCost**: people start charging at a uniformly distributed moment in time but so that their cost is minimal (maximum use of low tariff period).
- Scenario **LastHome**: people start charging batteries as soon as the car gets parked at the *last* home arrival of the day irrespective of any low-tariff period.
- Scenario **AlwaysAtHome**: people charge batteries immediately after *each* home arrival.

In all cases, charging period is assumed to be contiguous (uninterrupted) which means that no auction based dynamic pricing for fifteen minute charging blocks has been considered. Furthermore we hypothesize

- that everyone recharges batteries everyday due to *range anxiety*
- that all cars are charged at home with additional charging at the work location in well defined cases only

ELECTRIC VEHICLE FLEET ATTRIBUTES

Since the EV market is only emerging, predictions cannot be based on extensive statistics. Assumptions made in the paper have been explained and argued below.

Vehicle categories

Electric cars are subdivided into the categories `small, medium, large` similar to what is done in (13). In order to estimate the energy requirement, one needs to know the contribution of each category to the complete vehicle fleet. Belgian government statistics provide the distribution of registered cars along a classification based on the ICEV cylinder volume. We state the one-to-one mapping of categories given in table 1 that shows market share and technical characteristics for each category. Vehicle characteristics in the table have been derived from data in (13) and (18), the market share figures have been taken from the belgian federal government 2009 *PARC010 Transport Indicator* statistics (19)

	Vehicle categories		
Equivalent engine cylinder volume [cc] (ICEV category)	$V < 1400$	$1400 \leq V \leq 2000$	$2000 < V$
Market share (from belgian government statistics)	0.496	0.364	0.140
EV category	small	medium	large
Battery capacity (kWh)	10	20	35
Range (km)	100	130	180
Energy consumption (kWh/km) : lower limit	0.090	0.138	0.175
Energy consumption (kWh/km) : upper limit	0.110	0.169	0.214
Charger type at home : prob(3.3[kW])	0.8	0.4	0.1
Charger type at home : prob(7.2[kW])	0.2	0.6	0.9
Charger type at work : prob(3.3[kW])	0.1	0.1	0.1
Charger type at work : prob(7.2[kW])	0.9	0.9	0.9

TABLE 1 : Correspondence between EV and ICEV for categories specified in Belgian Government statistics

Available Chargers

Locally available 3.3 [kVA] and 7.2 [kVA] chargers are considered. Our model distinguishes between *home* and *work location* chargers. Charger type occurrence probability is given in table 1. The power value for home chargers is assumed to depend on the car category: smaller cars are equipped with a less powerful charger. On the other hand, companies offering car charging facilities are assumed to provide powerful chargers in order to save time and to extend the distance that can be bridged during one day. The company investment in a powerful charger is assumed to be a profitable one.

Company cars in Belgium - Vehicle ownership

Employers are believed to allow company car (CC) drivers to charge at the work location because that is less expensive than providing fuel cards to employees. However, for technical reasons, not all companies can provide the required infrastructure. The fraction of actors who can charge batteries at the work location has been determined as a fraction of company car drivers. It has been assumed that 50% of the CC drivers can charge at the work location.

The `Feathers` ActBM predicts trips and provides information about car availability but not about car ownership (private vs. company owned). In order to estimate the number of people able to charge batteries at the work location, we need to estimate the fraction of work trips traveled by company car. The COCA (Company Car analysis) report (20) states that depending on the context, multiple definitions of a *company car* (voiture de société) are in use because both fiscal and operational aspects are concerned. The COCA definition (*A company car is made available by a company to an employee for both professional and private use*) is used in our study. The same COCA report states that, based on two belgian reports (*OVG* for Flanders and *ERMMW* for Wallonia), it can be concluded from data up to 2005, that 6% . . . 7% of the car fleet in use by belgian households, is company owned (source (20) page 31/80). The OVG42 report (21) estimates the fraction of company cars available to households in 2009 to 10%.

Our model assumes that 10% of the actors driving to work, make use of a company car. Cars used in schedules without any any work trips, are assumed to be privately owned cars (POC).

Relation between EV ownership and EV type

The portions of EV being PHEV are assumed to differ between privately owned and company cars. Currently no data about the respective expected market shares are available. PHEV rates 0.0, 0.5 and 1.0 for both CC and POC have been combined to run simulations.

PHEV do not have practical range limitations but long All-Electric-Range (AER) versions are more expensive than BEV. Temporal unavailability of a car induces high hourly costs for a company: the investment in a more expensive PHEV is assumed to be a profitable one. Private owners, on the other hand, are assumed to be more reluctant against large initial investments for private use.

SIMULATIONS

Method overview

The `Feathers` ActBM (2) created by the Transportation Research Institute (IMOB) has been used to generate *activity-travel schedules* (daily agenda for each individual of the flemish population). Each schedule consists of trips and activities. For each trip, departure time, trip duration, origin and destination zones are predicted. For each activity, the purpose (work, shop, bring-get, . . .) is predicted. In this study, only work and non-work activities are distinguished. `Feathers` results apply to a single 24-hour period. A working day simulation has been used.

Energy and power demand are computed from `Feathers` results as follows:

- In a first step, schedules having at least one car trip are extracted and data structures are set up.
- In the second step, car ownership, possibility of work location charging, car characteristics (range, distance specific energy consumption, battery capacity) and the types of home

and work location charger used, are determined. Both a BEV and a PHEV belonging to a same category, are assigned to the schedule. A feasibility indicator is calculated which tells whether or not the schedule can be executed using the assigned BEV electric car (PHEV always is feasible since the internal combustion engine (ICE) always is available as a range extender). Each individual schedule is assumed to be executed using a single car and a predefined fraction of the company cars can get recharged at the work location. The set of schedules is partitioned as specified in figure 1. For each one of the leaf node parts, the market share has been specified: the results shown in this report hold for 10% *no-work trip* and 10% *work trip* electrification.

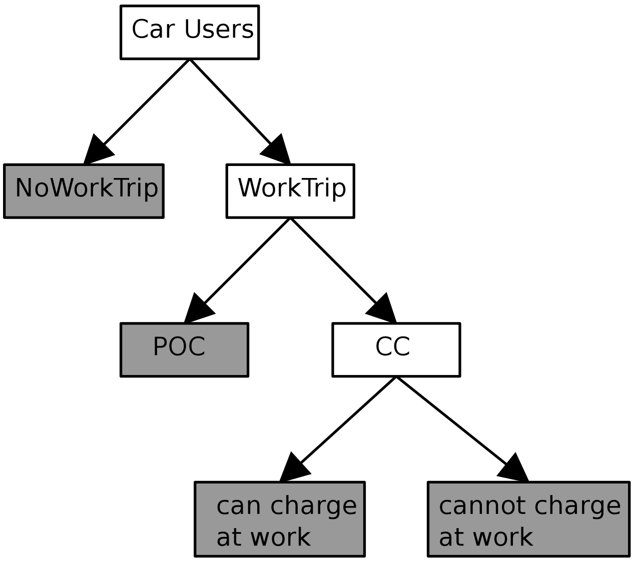

FIGURE 1 : Car users partitioning. (1) workTrip based partitioning follows from the AB-Model-generated schedules. (2) ownership (POC, CC) and canChargeAtWork are specified by parameters.

- In the third step, *charging scenarios* are evaluated. Schedules are sampled from the partitions set up in the second step and the start time for each charging operation is determined. Energy requirement and power demand are accumulated for every minute of the day for each one of the 2368 zones in Flanders.

Vehicle characteristics determination

Vehicle characteristics for each schedule are determined by random selection using the joint probabilities shown in the Bayesian network in figure 2 . Arrows designate dependencies between probability densities. For example, the EV *type* depends on the *ownership* and on the fact that the schedule can be executed using a BEV (block *BEV-feasibility*). The shaded rectangle *Electrified* represents the probability density from which EV are sampled. The shaded rectangle *EnergyReq* represents the probability density for the electric energy required to complete all trips in the schedule. The ovals represent *change of variable functions*. Function *f(schedule,consumption)* calculates whether or not the sequence of trips in a given schedule can be driven by a BEV given the stochastic value for the distance specific consumption of the vehicle and the charge opportunities in the schedule. Function *f(schedule,consumption)* corresponds to the conditions detailed in equations 1 and 2.

The function *g(schedule,consumption)* calculates the stochastic value for the energy required during each minute of the day for the given schedule.

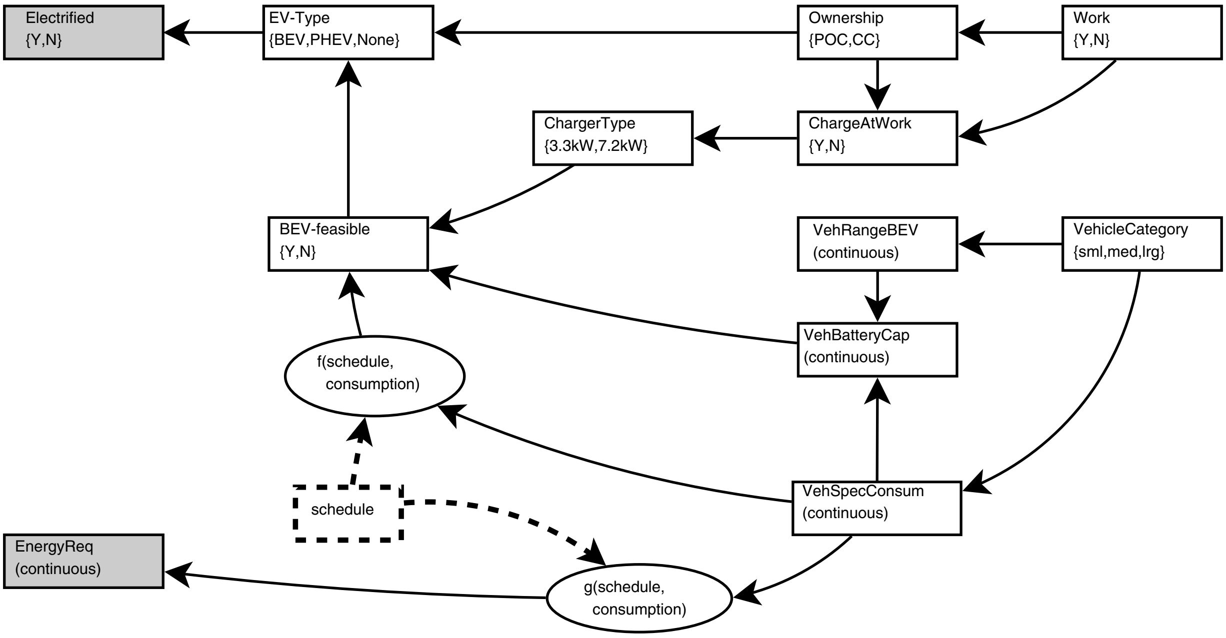

FIGURE 2 : Bayesian network showing conditional dependencies for stochastic variables. Continuous line rectangles designate probability densities. The domain for the variable is listed between curly braces. Each continuous line arrow designates a conditional dependency. Ovals designate *change of variable* functions. Dashed lines represent regular functional dependencies.

Vehicle characteristics are determined as follows:

- Vehicle *category* is randomly selected from the distribution specified in table 1
- Vehicle *range* is selected from table 1.
- Work location charging is allowed for 0.50 of the company car drivers. Privately owned cars cannot be recharged at work. The charger power is randomly selected for both home and work location chargers using the distribution specified in table 1.
- Vehicle *consumption* is randomly selected using a uniform distribution in the interval specified for the vehicle category (from table 1). This is the consumption determined by official US and European standard (FTP, WP.29) test suites that do not account for cabin clima (heating, airco) nor for frequent acceleration and deceleration.
- The specific energy consumption as determined by european (UNECE WP.29 R101) and US standard methods is argued to be an underestimation (Elgowainy et al. (*22*)). The

standardized test conditions differ from operating conditions: hence, a *range reduction coefficient* of 0.75 has been applied. The range reduction coefficient is used to adjust the specific consumption (which is used in schedule feasibility and energy demand calculations). This is done for both BEV and PHEV in the same way.

- The battery capacity is derived from range and distance specific consumption and has been verified with data found in literature ((18),(23),(24)).
- PHEV categories PHEV48, PHEV64 and PHEV96 are considered and have been mapped to the categories *small*, *medium* and *large* respectively in order to determine the relative market shares (see table 1). The number in the category identifier designates the AER in kilometers.
- Finally, the charger power is randomly selected for both home and work location chargers using the distribution specified in table 1.

BEV-feasibility

In order to be feasible for a BEV, each location in the schedule shall be reachable when starting with a fully charged battery in the morning: this is expressed by the condition (set of $\#\mathbb{L}$ inequalities)

$$\forall i,j \in [1,\#\mathbb{L}] : C_b - d_{O,i} * cons + \sum_{j=1}^{j<i} t_j * p_j \geq C_b * DCD \tag{1}$$

where i and j are location indexes, C_b is the battery capacity, $\mathbb{L}$ is the set of all locations used in the schedule, t_j is the charge-period duration at the j-th location and p_j is corresponding power, $d_{O,i}$ is the total distance from the first origin to the i-th destination, $cons$ is the distance specific energy consumption and $DCD = 0.1$ is the maximal *deep charge depletion* coefficient. DCD has been applied to specify the minimal battery level that shall be available at all times; it is used to model *range anxiety* and is used in BEV-electrification feasibility calculation only. The condition that the battery cannot get over-charged is given by following set of inequalities using the same symbols

$$\forall i,j \in [1,\#\mathbb{L}] : C_b - d_{O,i} * cons + \sum_{j=1}^{j\leq i} t_j * p_j \leq C_b \tag{2}$$

Vehicle sampling

The vehicle type (BEV, PHEV) is determined using the conditional probability values specified under *Relation between EV ownership and EV type* above. The probability for a vehicle to be a PHEV is given following expressions containing given probabilities in the right hand sides

$$P_{EV} = P(EV|CC) \cdot P_{CC} + P(EV|POC) \cdot P_{POC} \tag{3}$$

$$P_{PHEV} = P_{CC} \cdot P(EV|CC) \cdot P(PHEV|EV \wedge CC) + \tag{4}$$

$$P_{POC} \cdot P(EV|POC) \cdot P(PHEV|EV \wedge POC) \tag{5}$$

where *EV* designates Electric Vehicle, *CC* designates Company Car, *POC* designates Privately Owned Car, *PHEV* designates Pluggable Hybrid Electric Vehicle. It follows that

$$P_{BEV} = P_{EV} \cdot (1 - P(PHEV|EV)) = P_{EV} \cdot (1 - P_{PHEV}/P_{EV}) = P_{EV} - P_{PHEV} \tag{6}$$

where *BEV* designates Battery Electric Vehicle. Let N_v be the number of cars. A set of $P_{BEV} \cdot N_v$ elements is sampled from the set of schedules that can be executed by a BEV (the *BEV-feasible* schedules); then $P_{PHEV} \cdot N_v$ cars are sampled from all remaining schedules (BEV-feasible and BEV-infeasible ones).

Charging parameters - Scenarios

Assumptions valid for all scenarios concerned

- Energy cost is assumed to conform to the current tariff scheme used in Belgium: it consists of one contiguous *regular tariff* period and one contiguous *low tariff* period during the night (from 22:00h to 07:00h).
- The schedules apply to a working day and schedules are assumed to repeat on successive days. This assumption allows to determine the period of time available for recharging overnight. Everyone is assumed to recharge batteries everyday.
- When plugged to the electric grid, charging occurs during a single uninterrupted period of time.

For each schedule and each charging opportunity, the *required* charge duration for full recharge and the *available* charge period are calculated. The available charge period is determined from the arrival and departure times at the charge location. If the available period length is larger than the required charge duration, their difference is the *slack time* (otherwise slack time equals zero). A non-zero slack time implies a degree of freedom for selecting the time to start charging. In many cases, there is an interval $\Delta t = [t_0, t_1]$ of starting times t_s such that $\forall t_s \in \Delta t$ the energy cost is the same.

Scenario specific assumptions

- Scenario **EarlyLowTariff**: If Δt is contained in the low tariff period, the actor starts charging as soon as possible; otherwise (the case where the charge period contains the low-tariff period), the actor starts charging as late as possible thereby pushing energy demand to the morning hours. This scenario conforms to the situation where people are using simple timers to start charging.
- Scenario **UniformLowCost**: Each actor tries to minimize energy cost by charging during the low tariff period as much as possible. The charge period start time t_s is chosen from Δt by random selection using a uniform distribution.
- Scenario **LastHome**: All actors ignore the existence of a low-tariff period and start charging immediately when ariving at home after the last trip of the day.
- Scenario **AlwaysAtHome**: All actors ignore the existence of a low-tariff period and start charging immediately when ariving at home after each home arrival.

Note that scenarios *EarlyLowTariff* and *UniformLowCost* are energy cost minimising scenarios at the individual actor level, but the other ones are not.

Aggregation of microsimulation results

Battery charging opportunities are identified during micro-simulation and inserted in the schedules according to the applied scenario. For each charge opportunity, the required power is accumulated and recorded for each minute in the charging period. This process results in a power requirement time series for each zone. Plots are generated for the zones having

- maximal energy requirement (power integrated over time)
- maximal power peak value

for the full day, the normal-tariff period and the low-tariff periods respectively.

SUMMARY OF RESULTS FOR FLEMISH REGION

- `Feathers` statistics and energy demands have been summarized in table 2. Scenarios are identified by the ratio of the EV fleet being a PHEV for company cars (CC) and privately owned cars (POC) respectively. Replacing BEV by PHEV increases power demand since longer distances are driven on electricity. PHEV can exhaust the full AER while BEV can drive distances strictly smaller than the *anxiety reduced* range only.

Scenario	Feathers ActBM prediction	
All	Fraction of actors performing work trips	0.406
All	Fraction of actors performing car trips	0.555
All	Fraction of car using schedules containing work activity	0.531
All	Average work related car trip distance (km)	19.376
All	Fraction of trips that are work trips	0.160
	EV Energy demand calculation	
CC=0.0 and POC=0.0	Total energy demand	1380[MWh]
CC=0.5 and POC=0.5	Total energy demand	1652[MWh]
CC=1.0 and POC=1.0	Total energy demand	1829[MWh]

TABLE 2 : **`Feathers` Results Statistics.**

- Table 3 shows the fractions of BEV-feasible schedules determined in the second step (accounting for work location recharge). Note that only 10% of the schedules having a work trip have been assigned a company car in the scenarios considered. Almost 78% of the trips is BEV-feasible when the EV category coincides with actual ICEV market shares given in table 1.
- Figure 3 shows the power demand for an area with 5835 inhabitants for scenarios *UniformDist*, *LastHome* and *AlwaysAtHome*. The power peak for *UniformDist* (individual actor cost minimizing) is the bigger one and the peak shifts from about 20:00h to about 02:30 between scenarios. Note that the power demand shown is to be added to the already existing *zone-specific* demand but at the time of writing only countrywide aggregated time dependent electricity consumption data are available; hence data have not yet been presented geographically to pinpoint problematic areas. The result shows that it is worth extending the ActBM actor behavior model to make it sensitive to electricity prices.

Partition	Fraction of the car using schedules	
	When charging after last home arrival	When charging at each home arrival
BEV-feasible schedules without work trips POC (NW)	0.364	0.371
BEV-feasible schedules with work trips POC (W_POC)	0.357	0.371
BEV-feasible schedules with work trips CC, chargeAtWork (W_CC_CAW)	0.020	0.021
BEV-feasible schedules with work trips CC, no chargeAtWork (W_CC_NCAW)	0.024	0.024
BEV-Infeasible	0.235	0.213

TABLE 3 : **Car-using Schedule Partitions with respect to Feasibility for Electrification**

- The power peak for scenario *EarlyLowC* at 22:00h amounts to eight times the *UniformDist* peak value because everyone is assumed to start charging at the same moment using a timer. This peak is expected to cause problems for the electric grid and has not been included in the diagram.
- Table 4 shows the fraction of charge opportunities used and the daily charge frequency for each usecase partition and scenario. BEV and PHEV owners are assumed to share the same charging behavior.

Partition	Home charging scenario							
	EarlyLowTariff		UniformLowCost		LastHome		AlwaysAtHome	
	FracOp	NumCh	FracOp	NumCh	FracOp	NumCh	FracOp	NumCh
NW	0.853	1.000	0.850	1.000	0.854	1.000	1.000	1.196
W_POC	0.822	1.000	0.822	1.000	0.823	1.000	1.000	1.262
W_CC_CAW	0.911	2.194	0.914	2.199	0.905	2.203	1.000	2.450
W_CC_NCAW	0.817	1.000	0.828	1.000	0.821	1.000	1.000	1.260

TABLE 4 : **Fraction of charge opportunities used (*FracOp*) and number of charge operations per day (*NumCh*) for each scenario and partition (N: No, W: Work, POC: Privately Owned Car, CC: Company Car, CAW:Can Charge at Work)**

- Table 5 shows absolute and relative energy demand for the scenario where 10% of the cars are EV and BEV/PHEV ratio is 50/50. Almost 60% of the energy consumption is by PHEV, almost 94% by privately owned cars.

CONCLUSION

Schedules predicted by the `Feathers` ActBM have been used to predict energy demand and power peaks due to electric vehicle charging as a function of time and location for several EV market penetration scenarios and PHEV/BEV ratios. For the Flanders case, 78% of distances travelled

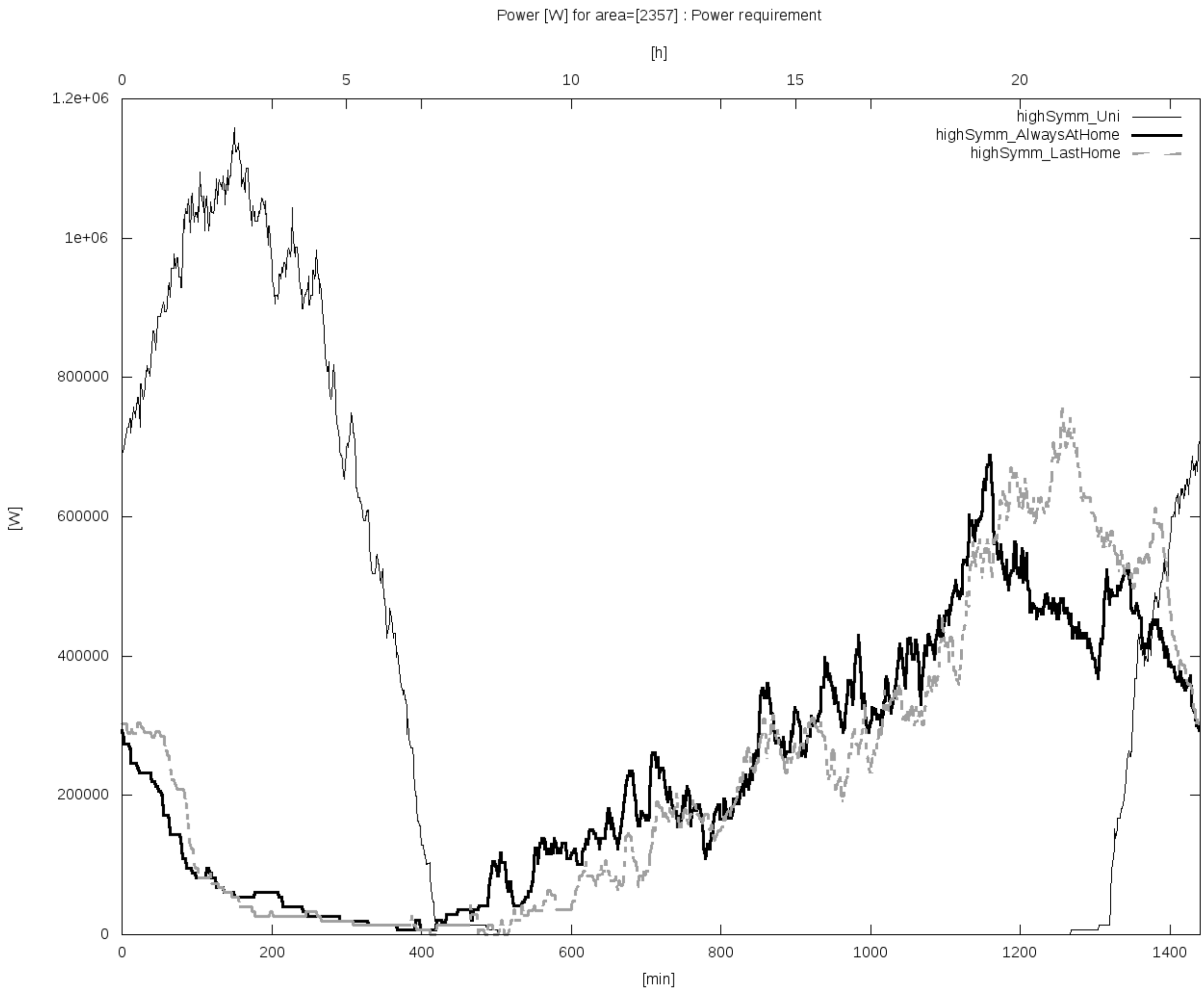

FIGURE 3 : **Power demand for EV charging as a function of time. The thin line holds for *UniformDist* (cost minimising, random), the thick line for *AlwaysAtHome* and the dashed line for *LastHome*.**

Partition	Energy [MWh]			Relative
	BEV	PHEV	Total	
NW	280.346	414.969	695.315	0.421
W_POC	363.328	486.132	849.460	0.515
W_CC_CAW	25.846	31.915	57.761	0.035
W_CC_NCAW	20.126	28.110	48.236	0.029
Total	689.647	961.126	1650.773	
Relative	0.418	0.582		1.000

TABLE 5 : **Absolute and relative daily energy demand when 10% of cars are EV and 50% of the EV are PHEV both for POC (privately onwed cars) and CC (company cars) for scenario *AlwaysAtHome***

daily using a single car on working days, seem to be BEV-feasible assuming that EV categories deployment conforms to current one for ICEV. Secondly, replacing BEV by PHEV increases electric energy consumption because PHEV can exploit their full electric range. Finally, the current reduced rate electricity period is sufficiently long to allow for charging period distribution over time in order to avoid unwanted power peak demand while allowing people to minimize cost.

FUTURE RESEARCH

Although activity based models have a firm statistical basis, some aspects of reality do not yet have been translated to AB-model parameters. Therefore, this study shall be the base for following research paths.

On one hand, more accurate technical and market related data need to be determined from literature, surveys and experimentation. Data about distance specific energy consumption in real situations are based on measurements based on standards and are underestimated: they need to be refined (cabin clima effects). The amount of car users who are able to charge at home has not been considered a limiting factor for the current study but could be one of the main factors when estimating EV market share.

The software be extended to remove the constraint of using a single vehicle for schedule trips executed by multi-car households. The behavioral model is to be extended to integrate car selection decisions based on the actor specific charging decision strategy.

Finally, AB-models and smartgrid models need to get integrated in a closed loop. Since typical activity based models account for price elasticity and allow for learning, results feedback allows for evaluation of smartgrid strategies for *charging timeslot* allocation. Evaluation of the *vehicle to grid* (V2G) concept requires integration of smartgrid controllers with AB-models.

References

[1] White-House-NSTC, *A policy framework for the 21st century grid : Enabling our secure energy future (www.whitehouse.gov/sites/default/files/microsites/ostp/nstc-smart-grid-june2011. pdf)*, 2011.

[2] Bellemans, T., B. Kochan, D. Janssens, G. Wets, T. Arentze, and H. Timmermans, Implementation Framework and Development Trajectory of FEATHERS Activity-Based Simulation Platform. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. Volume 2175, No. Volume 2175 / 2010, 2010, pp. 111–119.

[3] Cui, X., C. Liu, H. K. Kim, S. Kao, M. Tuttle, and B. Bhaduri, A Multi Agent-Based Framework for Simulating Household PHEV Distribution and Electric Distribution Network Impact, 2011.

[4] Davies, J. and K. Kurani, Estimated Marginal Impact of Workplace Charging on Electricity Demand and Charge Depleting Driving. Scenarios based on Plausible Early Market Commuters' Use of a 5kWh Conversion PHEV, 2011.

[5] Kang, J. E. and W. Recker, An activity-based assessment of the potential impacts of plug-in hybrid electric vehicles on energy and emissions using 1-day travel data. *Transportation Research Part D: Transport and Environment*, Vol. 14, No. 8, 2009, pp. 541 – 556.

[6] Recker, W. W. and J. E. Kang, *An Activity-Based Assessment of the Potential Impacts of Plug-In Hybrid Electric Vehicles on Energy and Emissions Using One-Day Travel Data*. University of California Transportation Center, Working Papers 1593422, University of California Transportation Center, 2010.

[7] Bliek, F., A. van den Noort, B. Roossien, R. Kamphuis, J. de Wit, J. van de Velde, and M. Eijgelaar, PowerMatching City, A living lab smart grid demonstration. IEEE, Goteborg, Sweden, 2010.

[8] Clement-Nyns, K., E. Haesen, and J. Driesen, Analysis of the Impact of Plug-In Hybrid Electric Vehicles on Residential Distri bution Grids by using Quadratic and Dynamic Programming. *World Electric Vehicle Journal*, Vol. 3, 2009.

[9] Waraich, R. A. and M. Galus, *Plug-in Hybrid Electric Vehicles and Smart Grid: Investigations Based on a Micro-Simulation*, 2009.

[10] Binding, C. and O. Sundstroem, A simulation environment for Vehicle-to-grid Integration Studies. In *Summer Computer Simulation Conference 2011*, SCSC, Den Haag, NL, 2011, p. 248.

[11] Hadley, S. and A. Tsvetkova, *Potential Impacts of Plug-in Hybrid Electric Vehicles on Regional Power Generation*. OAK RIDGE NATIONAL LABORATORY, 2008.

[12] Parque, A. P. M. D. and B. Ciuffo, Potential Impact of Electric Vehicles on the Electric Supply System. A Case Study for the Province of Milan, Italy. *OPOCE*, , No. JRC53390, 2009.

[13] Perujo, A. and B. Ciuffo, The introduction of electric vehicles in the private fleet: Potential impact on the electric supply system and on the environment. A case study for the Province of Milan, Italy. *Energy Policy*, Vol. 38, No. 8, 2010, pp. 4549 – 4561.

[14] UO_ECI, *Country pictures Belgium (http://www.eci.ox.ac.uk/research/energy/)*, 2011.

[15] EABEV, *Energy consumption, CO2 emissions and other considerations related to Battery Electric Vehicles (http://www.going-electric.org/)*, 2010.

[16] D'haeseleer, W., P. Klees, J. Albrecht, J. D. Ruyck, P. Tonon, J. Streydio, R. Belmans, L. Dufresne, B. Leduc, S. Proost, J. van Ypersele, J. Chevalier, W. Eichhammer, and P. Terzian, *Commission ENERGY 2030 — FINAL REPORT : Belgium's Energy Challenges Towards 2030*, 2007.

[17] Ramage, M., *Transitions to Alternative Transportation Technologies–Plug-in Hybrid Electric Vehicles*. National Academies Press, Committee on Assessment of Resource Needs for Fuel Cell and Hydrogen Technologies, Washington, DC 20001, 2010.

[18] Nemry, F., G. Leduc, and M. Almudena, *Plug-in Hybrid and Battery-Electric Vehicles: State of the research and development and comparative analysis of energy and cost efficiency*, 2009.

[19] Federal Planning Bureau, B., *Transportdatabanken : Indicator PARC010 (http://www.plan.be/)*, 2009.

[20] Cornelis, E., A. Malchair, T. Asperges, and K. Ramaekers, *COCA : Company Cars Analysis (Rapport final)*, 2007.

[21] Cools, M., K. Declercq, D. Janssens, and G. Wets, *Onderzoek Verplaatsingsgedrag Vlaanderen 4.2 (2009-2010)*. Universiteit Hasselt, IMOB, 2011.

[22] Elgowainy, A., J. Han, L. Poch, M. Wang, A. Vyas, M. Mahalik, and A. Rousseau, *Well-to-Wheels Energy Use and Greenhouse Gas Emissions Analysis of Plug-In Hybrid Electric Vehicles*. Argonne National Laboratory, 2010.

[23] Wu, D., D. Aliprantis, and K. Gkritza, *Electric Energy and Power Consumption by Light-Duty Plug-In Electric Vehicles*, 2010.

[24] Kromer, M. and J. Heywood, *Electric Powertrains: Opportunities and Challenges in the U.S. Light-Duty Vehicle Fleet*, 2007.