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

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1 ABSTRACT

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

14 INTRODUCTION

15 Electric vehicles use

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

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

25 The problem receives more than pure technical attention. White-House-NSTC (1) states:
26 *President Obama has set a national goal of generating 80% of [the] electricity from clean energy*
27 *sources by 2035 and has reiterated his goal of putting one million electric vehicles on the road by*
28 *2015.*

30 Activity-based models to predict energy demand by electric vehicles

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

39 This paper explores the case for Flanders. The region counts 6 million inhabitants on
40 13000 square kilometers and is part of Belgium (Europe) (11 million inhabitants on 30000 square
41 kilometers). The area is subdivided in 2368 zones. A synthetic population of actors has been built
42 to mimic each inhabitant of the area to be studied. Actor behavior is determined by characteristics
43 of the surroundings like road transportation network, distance between locations suited for specific
44 types of activities, public transport availability, delays induced by congestion. The *Feathers*
45 ActBM described in (2) has been used. Within *Feathers*, actor behavior is modeled by 26
46 decision trees, each one of which takes as input attributes of both the individual actor and the
47 environment as well as the outcome of decisions already made. The decision trees have been
48 trained by means of the CHAID method using data from regional time specific travel behavior
49 OVG surveys. A single survey covers up to 8800 respondents. The decision trees are used to
50 predict (in the order specified) attributes for work episodes, work locations, work-travel mode,
51 fixed non-work activities, flexible non-work activities, non-work locations, non-work-travel mode.
52 At this moment *Feathers* does not adapt actor behavior to car type (ICEV, EV). Car type is
53 determined after schedule prediction. Resulting schedules are used to predict time and location for
54 travel related electric energy consumption.

55 First we explain what hypotheses about EV drivers behavior have been made and how
56 EV characteristics have been determined from literature and from available statistical data. Next,
57 calculation details are described. Finally, results for the Flemish region are presented: area specific

58 energy and power requirements as a function of time identify critical parts in the electric grid. The
59 fraction of the household transportation market that can be served by EV without range extenders,
60 is calculated.

61 **Related work**

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

83 **CONTEXT**

84 **Smart grids and transport engineering**

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

101 **Electric energy demand evolution - Power demand**

102 *Energy demand*

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

106 For a Flemish household, the estimated yearly amount of electric energy required by the
107 car (0.2 kWh/km, 15000 km) is of the same order of magnitude as the amount of electric energy
108 consumed by the household for other purposes (current electric energy consumption value). Ac-
109 cording to figures published in *Oxford University Environmental Change Institute* website statistics
110 pages (14) the average yearly consumption for a Belgian household amounts to 3899 [kWh/year].
111 A similar figure (3500 [kWh/year]) for Belgium is mentioned by (15). As a consequence, the rel-
112 ative contribution of transport in the overall demand, will grow significantly with increasing EV
113 market penetration.

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

118 *Power demand*

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

126 **The use of activity based models**

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

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

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

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

145 ELECTRIC VEHICLE FLEET ATTRIBUTES

146 Since the EV market is only emerging, predictions cannot be based on extensive statistics. As-

147 sumptions made in the paper have been explained and argued below.

148 Vehicle categories

149 Electric cars are subdivided into the categories *small*, *medium*, *large* similar to what is

150 done in (13). In order to estimate the energy requirement, one needs to know the contribution of

151 each category to the complete vehicle fleet. Belgian government statistics provide the distribution

152 of registered cars along a classification based on the ICEV cylinder volume. We state the one-to-

153 one mapping of categories given in table 1 that shows market share and technical characteristics

154 for each category. Vehicle characteristics in the table have been derived from data in (13) and (18),

155 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 (<i>kWh</i>)	10	20	35
Range (km)	100	130	180
Energy consumption (<i>kWh/km</i>) : lower limit	0.090	0.138	0.175
Energy consumption (<i>kWh/km</i>) : 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

157 Available Chargers

158 Locally available 3.3 [kVA] and 7.2 [kVA] chargers are considered. Our model distinguishes be-

159 tween *home* and *work location* chargers. Charger type occurrence probability is given in table 1.

160 The power value for home chargers is assumed to depend on the car category: smaller cars are

161 equipped with a less powerful charger. On the other hand, companies offering car charging facili-

162 ties are assumed to provide powerful chargers in order to save time and to extend the distance that

163 can be bridged during one day. The company investment in a powerful charger is assumed to be a

164 profitable one.

165 **Company cars in Belgium - Vehicle ownership**

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

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

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

184 **Relation between EV ownership and EV type**

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

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

193 **SIMULATIONS**

194 **Method overview**

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

201
202 Energy and power demand are computed from `Feathers` results as follows:

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

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

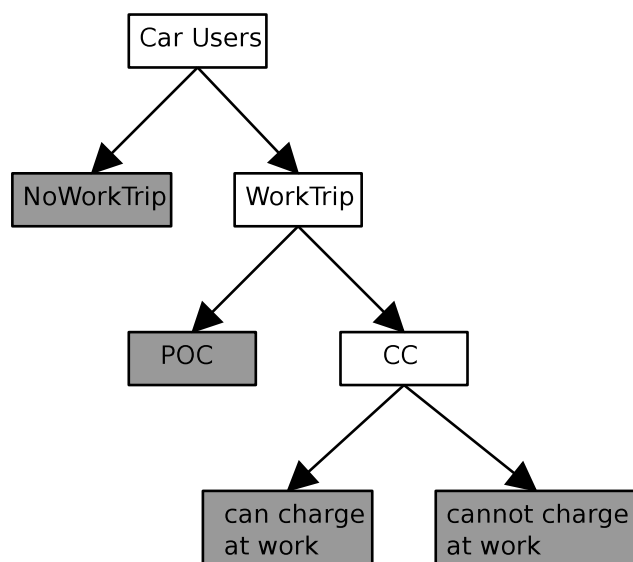


FIGURE 1 : Car users partitioning. (1) workTrip based partitioning follows from the AB-Model-generated schedules. (2) ownership (POC, CC) and canChargeAtWork are specified by parameters.

215

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

220 **Vehicle characteristics determination**

221 Vehicle characteristics for each schedule are determined by random selection using the joint prob-
222 abilities shown in the Bayesian network in figure 2 . Arrows designate dependencies between
223 probability densities. For example, the EV *type* depends on the *ownership* and on the fact that the
224 schedule can be executed using a BEV (block *BEV-feasibility*). The shaded rectangle *Electrified*
225 represents the probability density from which EV are sampled. The shaded rectangle *EnergyReq*
226 represents the probability density for the electric energy required to complete all trips in the sched-
227 ule. The ovals represent *change of variable functions*. Function $f(\text{schedule}, \text{consumption})$ calculates
228 whether or not the sequence of trips in a given schedule can be driven by a BEV given the stochas-
229 tic value for the distance specific consumption of the vehicle and the charge opportunities in the

230 schedule. Function $f(\text{schedule}, \text{consumption})$ corresponds to the conditions detailed in equations 1
 231 and 2.

232 The function $g(\text{schedule}, \text{consumption})$ calculates the stochastic value for the energy re-
 233 quired during each minute of the day for the given schedule.

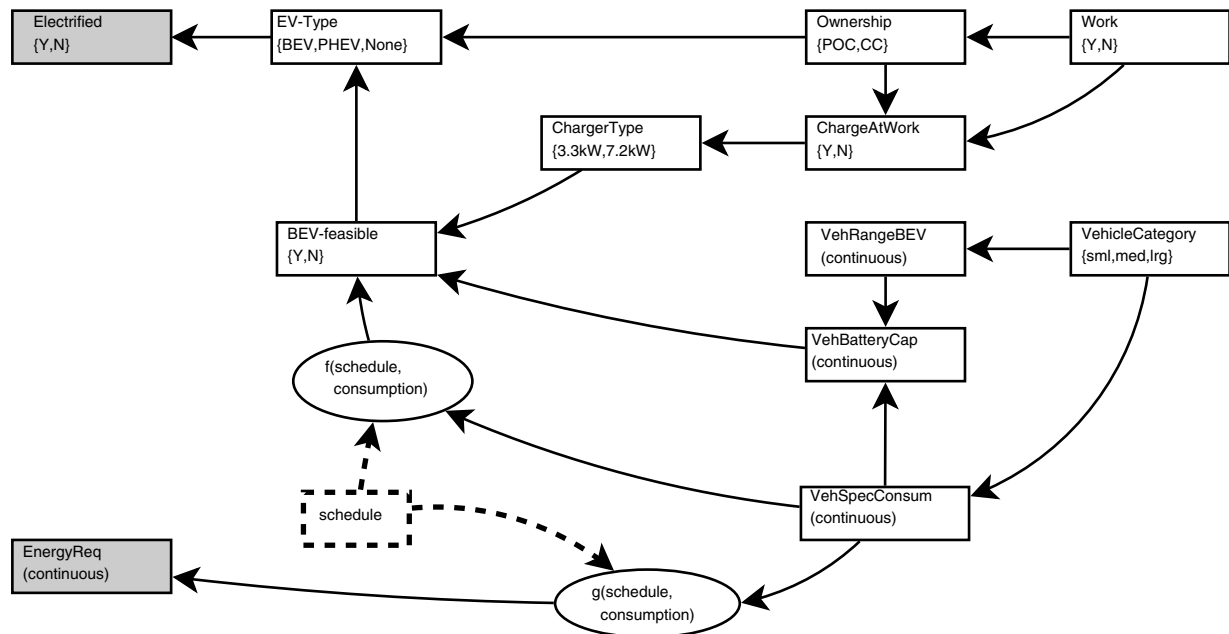


FIGURE 2 : Bayesian network showing conditional dependencies for stochastic variables. Continuous line rectangles designate probability densities. The domain for the variable is listed between curly braces. Each continuous line arrow designates a conditional dependency. Ovals designate *change of variable*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

234

235 Vehicle characteristics are determined as follows:

236

- Vehicle *category* is randomly selected from the distribution specified in table 1

237

- Vehicle *range* is selected from table 1.

238

239

240

- 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.

241

242

243

244

- 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.

245

246

- 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

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

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

259 BEV-feasibility

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

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

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

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

269 Vehicle sampling

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

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

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

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

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

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

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

279 **Charging parameters - Scenarios**

280 *Assumptions valid for all scenarios concerned*

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

289 For each schedule and each charging opportunity, the *required* charge duration for full recharge
 290 and the *available* charge period are calculated. The available charge period is determined from the
 291 arrival and departure times at the charge location. If the available period length is larger than the
 292 required charge duration, their difference is the *slack time* (otherwise slack time equals zero). A
 293 non-zero slack time implies a degree of freedom for selecting the time to start charging. In many
 294 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
 295 same.

296 *Scenario specific assumptions*

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

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

311 *Aggregation of microsimulation results*

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

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

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

319 **SUMMARY OF RESULTS FOR FLEMISH REGION**

- 320 • *Feathers* statistics and energy demands have been summarized in table 2. Scenarios
 321 are identified by the ratio of the EV fleet being a PHEV for company cars (CC) and
 322 privately owned cars (POC) respectively. Replacing BEV by PHEV increases power
 323 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.

324

- 325 • Table 3 shows the fractions of BEV-feasible schedules determined in the second step
 326 (accounting for work location recharge). Note that only 10% of the schedules having a
 327 work trip have been assigned a company car in the scenarios considered. Almost 78%
 328 of the trips is BEV-feasible when the EV category coincides with actual ICEV market
 329 shares given in table 1.

- 330 • Figure 3 shows the power demand for an area with 5835 inhabitants for scenarios *Unifor-*
 331 *mDist*, *LastHome* and *AlwaysAtHome*. The power peak for *UniformDist* (individual actor
 332 cost minimizing) is the bigger one and the peak shifts from about 20:00h to about 02:30
 333 between scenarios. Note that the power demand shown is to be added to the already
 334 existing *zone-specific* demand but at the time of writing only countrywide aggregated
 335 time dependent electricity consumption data are available; hence data have not yet been
 336 presented geographically to pinpoint problematic areas. The result shows that it is worth
 337 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

- 338 • 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
339 using a timer. This peak is expected to cause problems for the electric grid and has not
340 been included in the diagram.
341
- 342 • Table 4 shows the fraction of charge opportunities used and the daily charge frequency
343 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)

- 344
- 345 • Table 5 shows absolute and relative energy demand for the scenario where 10% of the
346 cars are EV and BEV/PHEV ratio is 50/50. Almost 60% of the energy consumption is
347 by PHEV, almost 94% by privately owned cars.

348 CONCLUSION

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

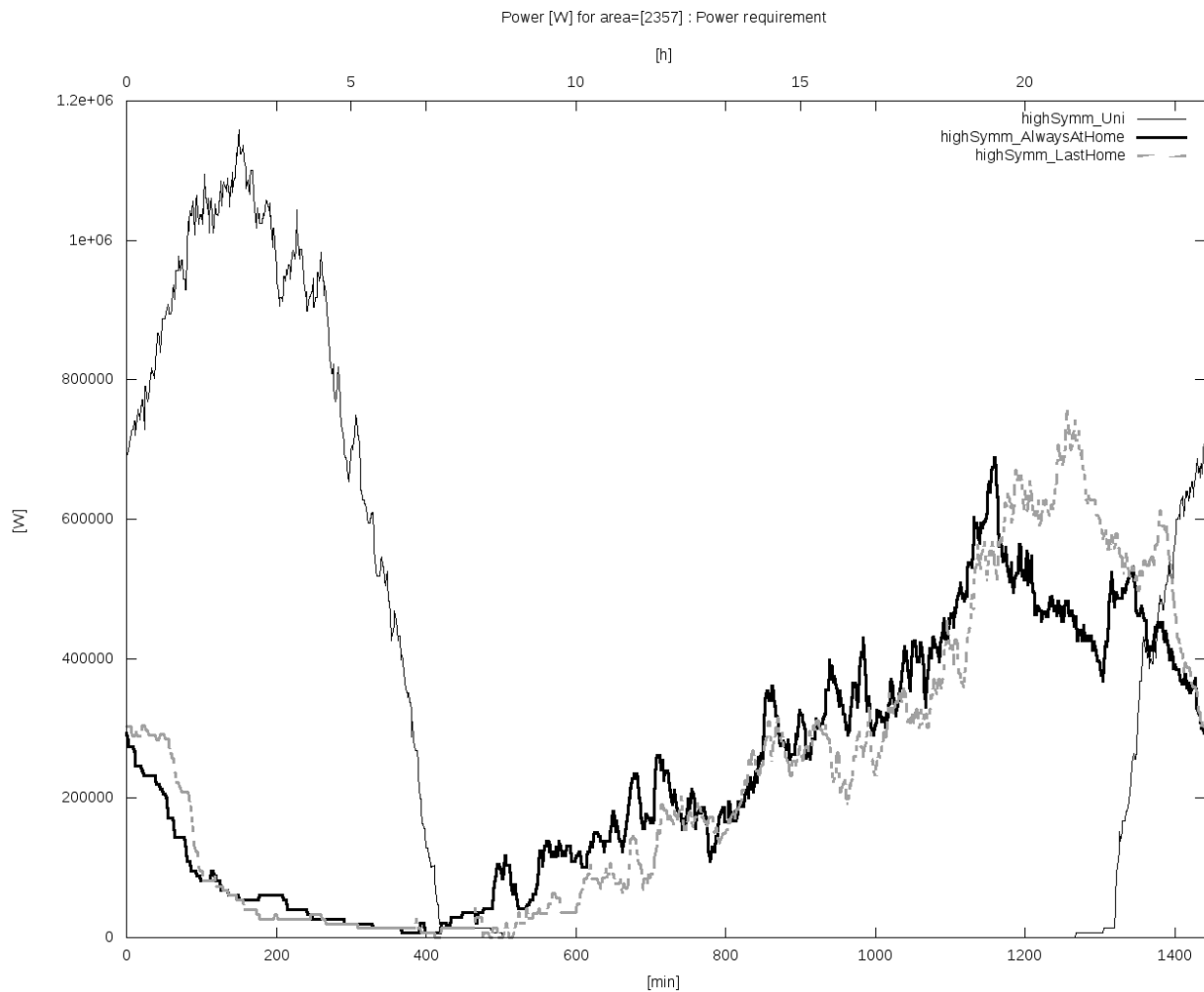


FIGURE 3 : Power demand for EV charging as a function of time. The thin line holds for *UniformDist* (cost minimising, random), the thick line for *AlwaysAtHome* and the dashed line for *LastHome*.

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*

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

357 **FUTURE RESEARCH**

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

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

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

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

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