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Potential of Vehicle-to-Grid Ancillary Services Considering the Uncertainties in Plug-in Electric Vehicle Availability and Service/Localization Limitations in Distribution Grids

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Abstract

The aim of the paper is to propose an approach for statistical assessment of the potential of plug-in electric vehicles (PEV) for vehicle-to-grid (V2G) ancillary services, where it focuses on PEVs doing daily home-work commuting. In this approach, the possible ancillary services (A/S) for each PEV fleet in terms of its available V2G power (AVP) and flexible intervals are identified. The flexible interval is calculated using a powerful stochastic global optimization technique so-called "Free Pattern Search" (FPS). A probabilistic method is also proposed to quantify the impacts of PEV's availability uncertainty using the Gaussian mixture model (GMM), and interdependency of stochastic variables on AVP of each fleet thanks to a multivariate modeling with Copula function. Each fleet is analyzed based on its aggregated PEV numbers at different level of distribution grid, in order to satisfy the ancillary services localization limitation. A case study using the proposed approach evaluates the real potential in Niort, a city in west of France. In fact, by using the proposed approach an aggregator can analyze the V2G potential of PEVs under its contract.

Keywords: Vehicle-to-grid, Ancillary services, Distribution grid, Gaussian Mixture model, Copula function, Free Pattern Search

1. Introduction

Massive production perspective of plug-in electric vehicles (PEVs) causes serious challenges and grid congestion for the utility grids. The researches have shown that electricity distribution grid can be highly affected by arbitrary charging demand of electric vehicles [1–3]. However, vehicle-to-grid (V2G) technology and charging coordination during off-peak hours of local distribution grids have been proposed as solutions [4–7]. In addition, V2G enabled PEVs, which have the ability to inject power to the grid, have been presented as grid supporters [8] and potential ancillary service (A/S) providers, where eventually make the transportation electrification beneficial for the grids [9].

Nomenclature

PEV	Plug-in Electric Vehicle	BC2	Bidding Capacity 2
V2G	Vehicle-to-Grid	BC3	Bidding Capacity 3
G2V	Grid-to-Vehicle	MLE	Maximum Likelihood Estimation
A/S	Ancillary Service	MCS	Monte Carlo Simulation
AVP	Available V2G Power	RF	Reliability Factor
FPS	Free Pattern Search	BS	Bidding Start time
GMM	Gaussian Mixture Model	HJPS	Hooke and Jeeves Pattern Search
HV	High Voltage	FS	Free Search
MV	Medium Voltage	DLP	Daily Load Profile
LV	Low Voltage	BM	Balancing Mechanism
TSO	Transmission System Operator	PPSMV	Peak Power Shaving - Medium Voltage
DSO	Distribution System Operator	PPSLV	Peak Power Shaving - Low Voltage
SOC	State Of Charge	VRMV	Voltage Regulation - Medium Voltage
pdf	probability distribution function	VRLV	Voltage Regulation - Low Voltage
FIS	Fuzzy Inference System	LM	Losses Minimization
NEDC	New European Driving Cycle	ETCM	Energy Transmission Cost Minimization
DoD	Depth of Discharge	FR	Frequency Regulation
BC1	Bidding Capacity 1	<i>DUR</i>	Duration, input for Fuzzy system

32 In the literature, the economic [10–13] and technical [14, 15] feasibilities of PEV fleet as the energy storage
33 and service providers are discussed. They are considered in different services markets such as, regulation,
34 spinning reserve [16], peak power support [17] and power quality [18] and more from economic point of
35 view. While, technical analyses are mainly limited to capacity estimation, optimal coordination, aggregator
36 communication architectures and battery degradation impacts [15, 17, 19, 20]. The points related to aggre-
37 gator volume requirements, grid/services localization limitations and PEVs availability uncertainty impacts
38 on bidding capacities are not discussed or less explored. In addition, the aggregator volume in terms of the
39 required number of vehicles for providing each ancillary service is not analyzed up to now.

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40 In term of the energy management systems for plug-in electric vehicles and V2G technologies, different
41 scheduling and management schemes are developed. An adaptive intelligent system using fuzzy logic con-
42 troller and adaptive neuro-fuzzy inference system (ANFIS) is developed in [21]. In [22] an intelligent energy
43 management using cloud computing network is proposed. These technics reduce operation of electric vehicle,
44 grid and parking lot as well as the load demand prediction. A large scale fuzzy logic based intelligent control
45 for V2G is also proposed in [23] which provides different services such as, peak power, balancing control, load
46 levelling and voltage regulation. For specific services, different control strategies are developed. For instance,
47 a preventive control strategy for controlling static voltage stability is proposed in [24, 25] which maintains the
48 static voltage stability of power system under the V2G concept and evaluates the V2G response capability
49 with different charging strategies during a whole day.

50 The innovative aspects of this paper compared to the aforementioned papers is considering the uncer-
51 tainty impact on the V2G capacity, and scalability of the flexible V2G power capacity for different level of
52 distribution grid by considering localization limitation of different services. Hence the service assessment
53 can be applicable up to the low voltage (LV) distribution grid services such as voltage regulation and load
54 levelling at LV grid. Interdependency of stochastic variables such as arrival time, departure time and driving
55 distance are also modelled and their impacts on the contracted power are analyzed.

56 The novelty of the paper is that it has provided a multi-level methodological approach in order to assess the
57 V2G potential, suitable for regional distribution system operators. In this approach, the PEVs' availability
58 uncertainty and localization/limitation are considered as the main factors affecting the potential of V2G for
59 grid ancillary service participation. A probabilistic model is developed in order to estimate the availability
60 uncertainty using only daily trips probability data. The interdependency of the stochastic variables are also
61 modeled using a copula function. This modeling approach, takes into account the impact of uncertainty
62 on the bidding capacities and improve the reliability of the contracted bidding. In addition, in order to
63 be realistic, the distribution of electric vehicles in the distribution grid is estimated using real customers'
64 distribution data to estimate the real potential of PEV fleet for different ancillary services.

65 A/S providers at the distribution grid level are faced with the localization limitation for each type of
66 service. Such limitations make difficult to achieve the services' requirements for PEV aggregators, as the
67 aggregated number of PEVs at the different level of the grid is not always sufficient. Moreover, the aggregators
68 need to have sufficient information for offering a reliable bidding capacity, which depend upon the type of
69 services for which they would be the candidate. However, the general requirements are the amount of energy
70 in form of power and time interval. These are predefined by grid actors based on the grid characteristics in
71 different countries¹. The constraints related to PEVs aggregation such as, available aggregated power and
72 PEVs availability uncertainty should be taken into account in order to be competitive in the markets. These

¹From August 2014, RTE, the French transmission system operator (TSO), announced that industrial consumers henceforth could be reserve service providers with a minimum power of 2 MW [26]. This is also estimated for the distributed energy storage systems at the distribution grid level with a minimum of 1 to 2 MW power [27].

73 constraints are the main concerns of this paper, where the effort is to propose an approach for potential
74 assessment of a candidate PEV fleet under an aggregation contract, particularly at the level of distribution
75 grid by considering; **1)** Available V2G power of the fleet, **2)** Availability uncertainty of the fleet and its
76 impacts on the bidding capacities' reliability, **3)** The flexibility of the available power interval under bidding
77 capacity contracts and **4)** Distribution grid services/localization limitations.

78 In this paper, at first the general approach for ancillary service assessment of V2G enabled PEVs at the
79 distribution grid level is introduced. Afterwards, all necessary input data for the assessment are identified.
80 The methodology is applied on Niort, a city in west of France, considering its mobility statistics and distribu-
81 tion grid topology. The methodologies for available V2G power modeling, availability uncertainty modeling,
82 the flexibility of the bidding capacities' calculation and the service assessment system will be explained thor-
83 oughly in the next sections. A general research background is presented to show actual solutions and the
84 main contribution of paper for V2G ancillary service assessment.

85 **2. Research background**

86 Different methods have been proposed for capacity estimation of PEV fleet, but none of them consider
87 the localization limitation of the services. Reference [15] calculates achievable power capacity by binomial
88 distribution of clustered PEVs. Reference [28] uses the survey data to identify the location of PEVs during
89 the day. In [29] Monte Carlo simulation is used to estimate the probability of transition between different
90 states, e.g. parked or movement for different parking location. A non-homogeneous semi-Markov process is
91 used in [30] for PEV availability and identifying the charging load, while in [31] a continuous time non-Markov
92 chain is chosen as the mobility patterns do not fulfill the Markov property (memorylessness). Reference [32]
93 uses the trip chains for mobility modeling of PEV fleet and concluded that the home and office car parks
94 have maximum availability among other place parkings. Among all of these researches backgrounds and our
95 case study mobility survey, we concluded that the PEVs are parked in home and office parkings mostly a
96 day and their service providing potential at these time intervals is relatively higher than other places, such
97 as parking lots of shopping centers or the streets, which are highly stochastic and periodically short.

98 The second limitation is the uncertainties associated with availability of the PEVs for service providing.
99 Reference [33] defines the uncertainty sources as the model based uncertainties and forecasting based uncer-
100 tainties. The model-based uncertainties come from the aggregated battery model instead of the individual
101 battery model ². The second source is related to forecasting data such as arrival, departure time, driving
102 behavior and arrival state of charge (SOC) of PEVs. In [34], the driving behavior uncertainty is modeled
103 with individual driving behavior with the non-Markov chain process by the states' transition probabilities
104 defined based on mobility survey data. In [35], a two-state single node Monte Carlo simulation is used to
105 represent the uncertainty in driving behavior by concentrating on stochastic variables with the independent

²In modeling large number of PEVs it would be impractical to model all batteries' dynamics in detail.

106 sampling process. While in this paper, interdependency of stochastic variables are modeled in a multivariate
107 manner using copula function.

108 The predictable sources of uncertainties are normally following a particular probability distribution. These
109 are known as arrival time, departure time and driving distance distribution. In addition, in the future smart
110 grid, the communication infrastructures will facilitate accessibility and predictability of such information.
111 Therefore, considering highly enough accurate prediction system, the uncertainties associated with prediction
112 errors can be negligible. In the other side, there are some sources of uncertainty, which are not predictable
113 at all, like the unforeseen departure of PEVs during their stationing time (plug-in time). Considering that,
114 a probabilistic approach is proposed for this study, that can provide the probability distribution function
115 (pdf) of availability uncertainty. The advantage with this approach is the ability to quantify the availability
116 uncertainty impact on the bidding capacities by only knowing the daily trips percentage, arrival and departure
117 time probability of the fleet.

118 3. General Approach

119 The general approach consists of 6 sub-blocks, each doing a particular task for the final objective (Fig.
120 1):

121 **Available V2G power modeling (AVPM)** is designed to model the available V2G power for PEVs
122 arriving at office in the morning and PEVS arriving at home in the afternoon. Fundamental parameters for
123 modeling the available V2G power are calculated in **Fundamental parameters estimation FPE** block,
124 which contain arrival SOC, V2G energy, G2V energy and plug-in interval. These parameters which are
125 the indirect parameters will be calculated using the output parameters of MMSV block and averaged PEV
126 characteristic parameters such as, driving efficiency, charging, discharging efficiency, NEDC autonomy and
127 averaged battery capacity of the fleet. In **Multivariate modeling of stochastic variables (MMSV)**
128 block, correlation between arrival time, departure time and driving distance is explored for PEVs doing daily
129 home-work commuting using copula function. This issue is considered as one of the possible uncertainty on the
130 contracted V2G power. A novel approach is proposed in **Probabilistic availability uncertainty modeling**
131 **(PAUM)** block, which uses only the daily trips percentage data in order to associate a probability density
132 function to the availability uncertainty phenomena. Afterwards, the flexibility of each bidding capacity will be
133 calculated in **Bidding flexibility calculation (BFC)** block using a global stochastic optimization method
134 so-called "Free Pattern Search", which is chosen for its robustness and convergence quality for high dimension
135 stochastic problems. Finally, in **Fuzzy inference system service assessment (FISSA)** block, a fuzzy
136 inference system (FIS) is designed for service assessment of each PEV fleet based on the PEVs population
137 provision of the city under study. This system uses the AVP of each bidding and its flexibility as FIS inputs
138 and will generate a potential factor of 0 to 1 in order to evaluate the fleet potential for each service. In
139 addition, a grid service/localization limit factor is considered to evaluate the aggregated number of PEVs at
140 the appropriate location of the grid.

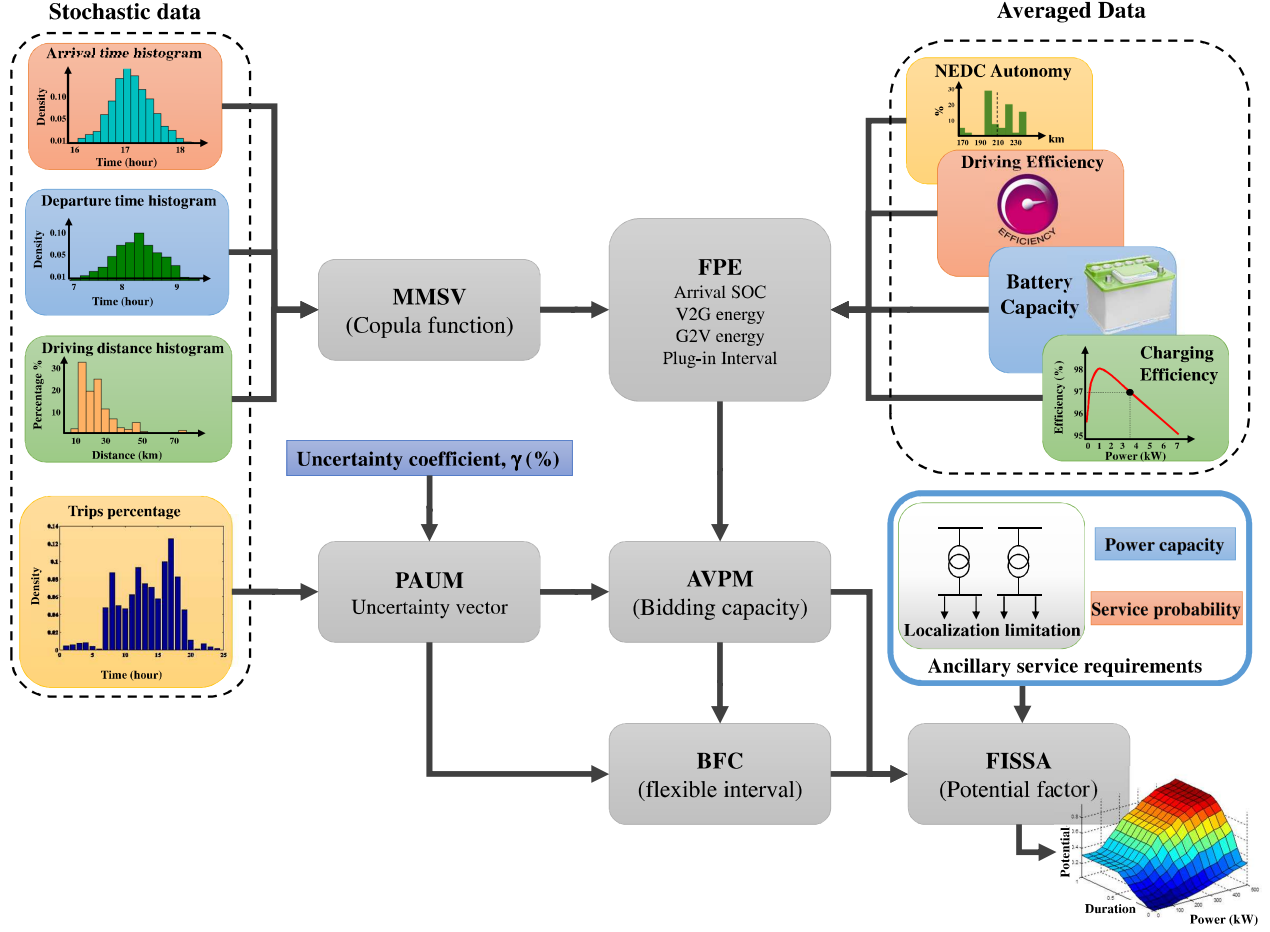


Fig. 1: General framework of V2G ancillary service assessment approach.

141 4. Case study and Input data

142 It is assumed, the statistical information about the place under study is available, where the approach will
 143 be applicable when the data can be available via the smart grid communication. This approach is practical
 144 for local DSO, managing the middle cities' grid operations. The statistical data of Niort city in France are
 145 considered as case study [36]. The two evolution scenarios of EVs in France up to 2030 are considered in this
 146 study [37, 38] (Table 1). Having the vehicle fleet statistics of Niort and its population, the PEV evolution can
 147 be calculated for this city. The cars-per-capita quota is used in order to transfer the unit from population to
 148 the car number [39]. The PEV case study scenarios are brought in Table. 2.

Table 1: PEV evolution scenarios in France (PEV numbers in Million).

Evolution horizon	2013	2015	2020	2025	2030
Low Scenario	0.042	0.05	0.8	1.7	2.5
High Scenario	0.05	0.3	0.2	5.5	9

Table 2: PEV evolution scenarios for Niort city.

Evolution horizon	2020	2025	2030
Low Scenario (PEV number)	851	1808	2659
High Scenario (PEV number)	2127	5849	9572

149 The input data are divided in two main natures; averaged data and stochastic data. Averaged data
150 are containing the vehicle characteristics, which help to estimate the available and consumed energy of the
151 vehicle’s battery. For this study, based on the actual French electric vehicles market, the values are considered
152 as in Table. 3. The stochastic variables sampled from statistical survey are; **Arrival time distribution,**
153 **Departure time distribution, Daily Driving distance distribution** and **Daily trips percentage.**

Table 3: Averaged PEV characteristics in French market.

Parameter	Symbol	Value
Battery Capacity	E_{ev}	22 kWh
Charging/Discharging efficiency	η_{cd}	97.5%
Charging/Discharging power	P_{ch}	3.7 kW
NEDC autonomy	A	210 km
Driving efficiency	η_{ev}	97% (9.2 km/kWh)
Admissible depth of discharge	DoD	80%

154 The arrival and departure time’s distribution of both home and office scenario are following approximately
155 a Gaussian distribution with the parameters as follows; Home departure ($\mu=07h45$), Home arrival ($\mu=17h15$),
156 Office Arrival ($\mu=08h15$), Office departure ($\mu=16h45$), Home-work trips ($\mu=08h00$) and Work-home trips
157 ($\mu=17h00$) and the $\sigma=30$ min for all cases. The daily driving distance distribution of home scenario takes into
158 account a daily round trip and for office scenario, a single way trip to the office and both are approximated
159 to follow the same distribution (Fig. 2).

160 Daily trips percentage data show the hourly percentage of the trips for a working day done by personal
161 vehicles for the Niort city. This distribution is used in order to model the availability uncertainty of the
162 PEVs (Fig. 3).

163 5. Available V2G power modeling (AVPM)

164 In this study, AVP of home-work commuting PEV fleet has been evaluated in two potential intervals.
165 First V2G at work only and second V2G at home only. The main assumptions behind the work are as follows:

- 166 • Charging/discharging rate at normal level (16A, 230 V, 3.7 kW).
- 167 • The PEV will provide V2G service once in a day and will be fully charged once in a day.

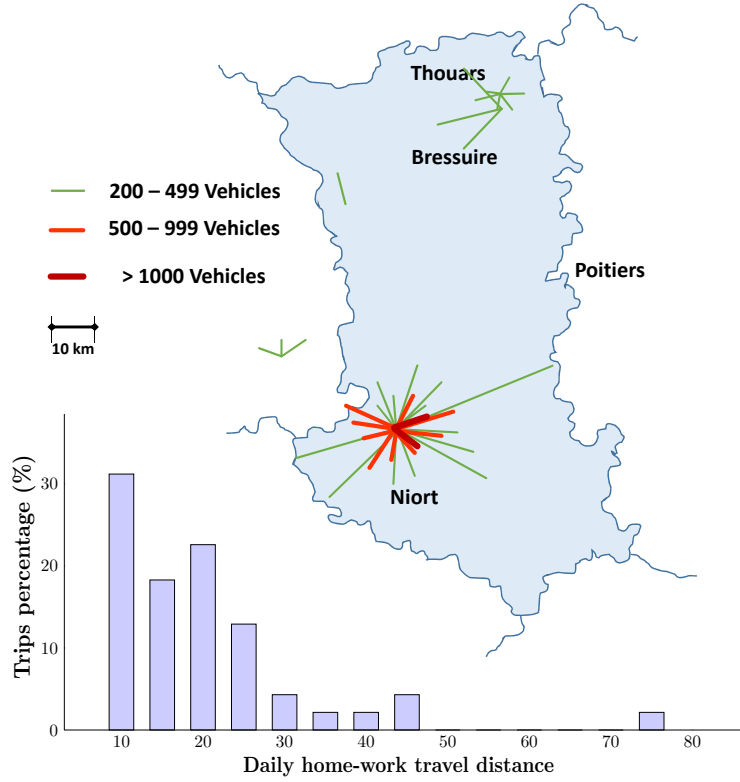


Fig. 2: Daily driving distance for home-work commuting in Niort [36].

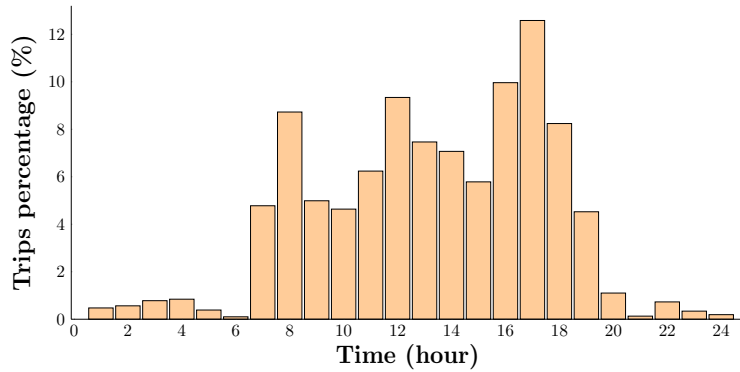


Fig. 3: Daily trips percentage in Niort city [40].

- 168 • 2 scenarios for V2G service assessment have been considered:
 - 169 – V2G at home (the PEV will make a round trip and then provide V2G at home only).
 - 170 – V2G at work (the PEV after arrival to the office will provide V2G at work, considering energy
 - 171 need for its return and minimum energy of 20% as constraint to reduce the degradation impact of
 - 172 V2G, i.e. 80% Depth of Discharge (DoD)).

173 For home scenario, PEVs will be fully charged at departure time, while at the office scenario, PEVs have

174 sufficient energy for the return trip plus 20% energy in battery. These assumptions were made to evaluate the
 175 maximum possible potential for aggregated V2G power during each interval. The fact is that, if we consider
 176 that PEVs will provide V2G services both at home and office, leading to portioned aggregated V2G power
 177 between home and office intervals.

178 *5.1. Fundamental parameter estimation (FPE)*

179 AVP modeling flowchart is provided in Fig. 4. Availability of each PEV in the V2G enabled parking,
 180 and its stored battery energy at arrival time are the key information in defining the AVP. Availability of
 181 PEVs will be identified by their arrival time to home/work parking and departure time from home/work for
 182 home/work V2G scenarios. Assuming N PEVs with full-charged battery at home departure moment, the
 183 arrival state of charge ($SOC_{arrival}^i$) of the i^{th} PEV battery can be estimated as follows:

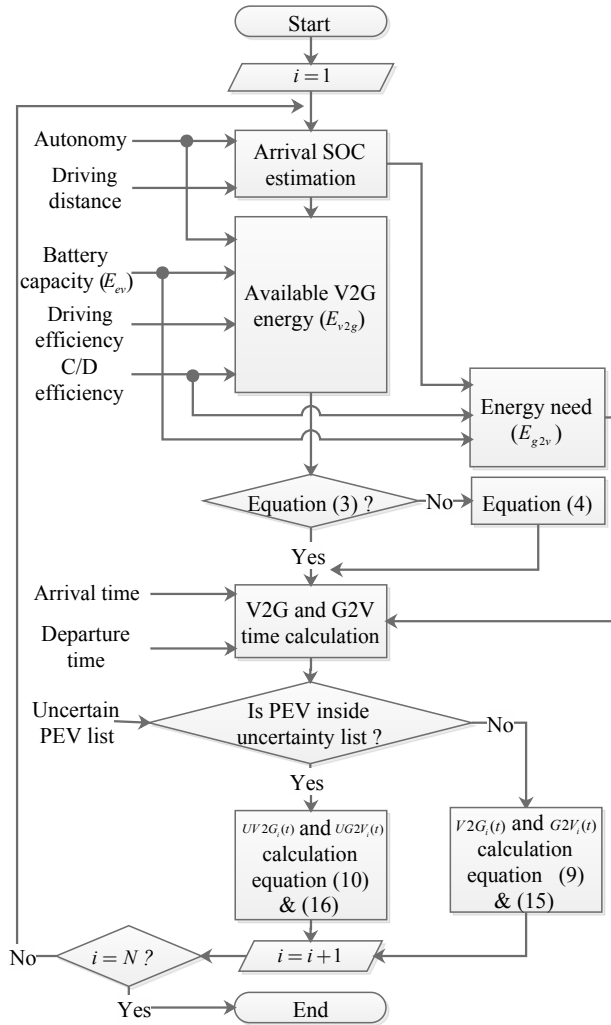


Fig. 4: The flowchart of AVPM.

$$SOC_{arrival}^i = (1 - \frac{D_d^i}{A^i}) \times 100\% \quad (1)$$

184 This is under the assumption of linear SOC drop with travel distance [41]. D_d^i denotes the driving
185 distance of i^{th} PEV from home to work for work scenario and round trip for home scenario. The probability
186 densities of arrival time ($T_{arrival}$), departure time ($T_{departure}$) and driving distance (D_d) have been presented
187 in the previous section. In this section, the steps to model AVP are presented. The interdependency of
188 these stochastic variables and their impacts on AVP will be analyzed afterwards. In current calculation, the
189 averaged correlation coefficients are considered, where their calculations will be explained in MMSV block
190 section. After the SOC estimation, Available V2G energy should be estimated for each V2G scenario.

$$E_{v2g}^i = (D_oD \times E_{ev} - \frac{D_d^i}{\eta_{ev}}) \eta_{cd} \quad (2)$$

191 For estimated V2G energy the following constraint should be satisfied:

$$2E_{v2g}^i + \frac{D_d^i}{\eta_{ev}} \leq T_{plug-in}^i \times P_{ch} \quad (3)$$

192 Where $T_{plug-in}$, is the plug-in interval of the PEV. If constraint (3) is not satisfied, the V2G energy
193 should be recalculated as follows:

$$E_{v2g}^i = \frac{(T_{plug-in}^i \times P_{ch})}{2} - E_{g2v}^i \quad (4)$$

194 For office scenario, we consider the vehicle needs to have the same amount of energy as it has already
195 consumed for arrival at work, plus 20% SOC to limit DOD at 80%.

$$E_{v2g-work}^i = (D_oD \times E_{ev} - \frac{2D_{d-work}^i}{\eta_{ev}}) \eta_{cd} \quad (5)$$

196 The duration of V2G and G2V action can be easily calculated by dividing the energy by charging/discharging
197 rate:

$$T_{v2g}^i = \frac{E_{v2g}^i}{P_{ch}} \quad (6)$$

$$T_{g2v}^i = \frac{E_{g2v}^i}{P_{ch}} \quad (7)$$

198 After identifying the V2G and G2V energy, the planning should be applied. The charging and discharging
199 planning should be done in a way to have maximum difference and minimum overlap between V2G and G2V
200 power curves. The reason behind this choice is to be able to estimate the maximum achievable V2G power
201 capacity of the fleet. This leads to analyze the potential services with respect to the maximum achievable
202 V2G power of each bidding capacity, which will be presented afterwards. Overlapping of V2G and G2V
203 power or mixed planning, i.e. charging/discharging at the same time horizon, leads to reduced V2G capacity

204 of the fleet from aggregator capacity point of view. For home V2G planning, the plug-in interval ($PI_i(t)$)
 205 and V2G interval ($V2G_i(t)$) are defined as follows:

$$PI_i(t) = \begin{cases} 1, & T_{arrival}^i < t < T_{departure}^i \\ 0, & elsewhere \end{cases} \quad (8)$$

$$V2G_i(t) = \begin{cases} 1, & T_{arrival}^i < t < T_{arrival}^i + T_{v2g}^i \\ 0, & elsewhere \end{cases} \quad (9)$$

206 It means that, the PEVs are asked to be discharged upon their arrival, to have time to be fully charged
 207 up to departure time. In fact, after discharging period the PEV has time to recharge its battery and being
 208 full-charged for departure.

209 We define here the uncertain V2G time vector to complete formulation, where the complete approach to
 210 the uncertainty modeling is explained in the next section. Uncertain V2G time vector is:

$$UV2G_i(t) = UA_i(t) \times PI_i(t) \times V2G_i(t) \quad (10)$$

211 Where $UA_i(t)$, is the unavailability vector and the output of PAUM block. We define γ as the uncertainty
 212 coefficient, the portion of PEVs fleet, which have uncertain behavior potential.

$$K = \gamma \times N, \forall K \in Q \quad (11)$$

$$M = N - K, \forall M \in E \quad (12)$$

213 Where Q is the integer set of uncertain PEVs numbers, and E is the integer set of certain PEVs, where
 214 the following law is consistent:

$$E \cup Q = N \quad (13)$$

215 Finally, the V2G power called AVP for home scenario is as follows:

$$P_{v2g}(t) = \sum_{i=1}^K (UV2G_i(t) \times P_{ch}) + \sum_{i=1}^M (V2G_i(t) \times P_{ch}) \quad (14)$$

216 The G2V interval for calculation of G2V power should be defined as follows:

$$G2V_i(t) = \begin{cases} 1, & T_{departure}^i - (T_{g2v}^i + T_{v2g}^i) < t < T_{departure}^i \\ 0, & elsewhere \end{cases} \quad (15)$$

217 Uncertain G2V time vector is necessary for uncertain PEV and is obtained using:

$$UG2V_i(t) = UA_i(t) \times PI_i(t) \times G2V_i(t) \quad (16)$$

218 Using uncertain G2V vector and G2V vector, the G2V power of the fleet is estimated by using equation
 219 (17):

$$P_{g2v}(t) = \sum_{i=1}^K (UG2V_i(t) \times P_{ch}) + \sum_{i=1}^M (G2V_i(t) \times P_{ch}) \quad (17)$$

220 The final output of this block for a case of 1000 PEV fleet is depicted in Fig. 5 and 6. The potential
 221 bidding capacities from AVP at home and office are explained afterwards.

222 5.2. Bidding capacities (BC)

223 Based on the distribution function of arrival time, we have proposed three indicative intervals, so-called
 224 "potential interval (pi)", where there is a considerable cumulated number of PEVs and the V2G capacity
 225 of the fleet can be contracted. These three capacities, proportional with the number of available PEVs, are
 226 called bidding capacity for service market participation. We define the bidding capacity z , ($1 \leq z \leq 3 \in \mathbb{N}$)
 227 and its function, $BC_z(t)$, with its capacity value, Cap_z during its interval from t_1 to t_2 .

$$BC_z(t) = \begin{cases} Cap_z, & t_1 < t < t_2 \\ 0, & elsewhere \end{cases} \quad (18)$$

228 The three indicative times have been chosen in order to propose biding start times BS_z for each bid as
 229 follows:

$$BS_z = \begin{cases} \mu - \sigma, & z = 1 \\ \mu, & z = 2 \\ \mu + \sigma, & z = 3 \end{cases} \quad (19)$$

230 The potential interval for each bid will be started from bidding start time until the power capacity equals
 231 to $BC_z(BS_z)$ as it is shown in the figures for both scenarios. In the Fig. 5, the V2G power called AVP, is
 232 starting right after the availability of the fleet shown in form of the arrival time histogram. It increases up to
 233 its maximum value corresponding to the whole fleet available PEVs, which is 3.7 MW active power. Due to
 234 the constraints of the PEVs such as, maximum battery DoD and their availability interval, the AVP decreases
 235 to zero until around 22:00 PM. The G2V power which corresponds to PEVs charging is completely separated
 236 from V2G power starting from 2:00 AM ending by the departure of the whole fleet at around 9:00 AM. From
 237 the modeled AVP, three candidates bidding capacities are extracted with the characteristics represented in
 238 Table. 4. In Fig. 6, the AVP is modeled with the same strategy while the constraints are minimum required
 239 energy for return trip and minimum battery DoD. These two modeled AVPs will be analyzed for V2G A/S
 240 potential assessment.

241 6. Multivariate Modeling of stochastic variables (MMSV)

242 In the probabilistic analysis with stochastic variables, the correlation between the variables should be
 243 taken into account even by knowing the marginal distribution of each single variable to avoid inconsistent

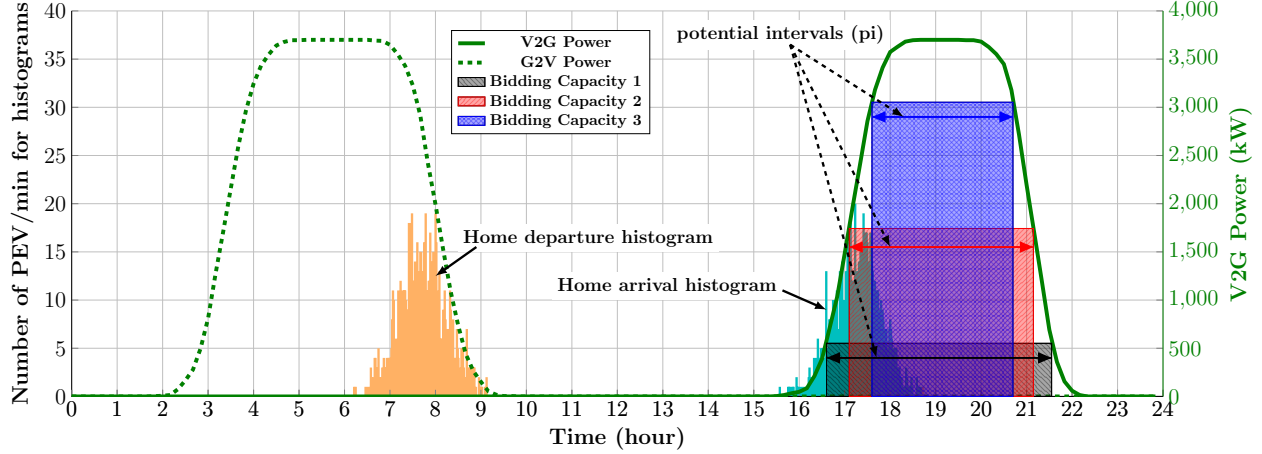


Fig. 5: The output of AVPM algorithm for home scenario, a fleet of 1000 PEV.

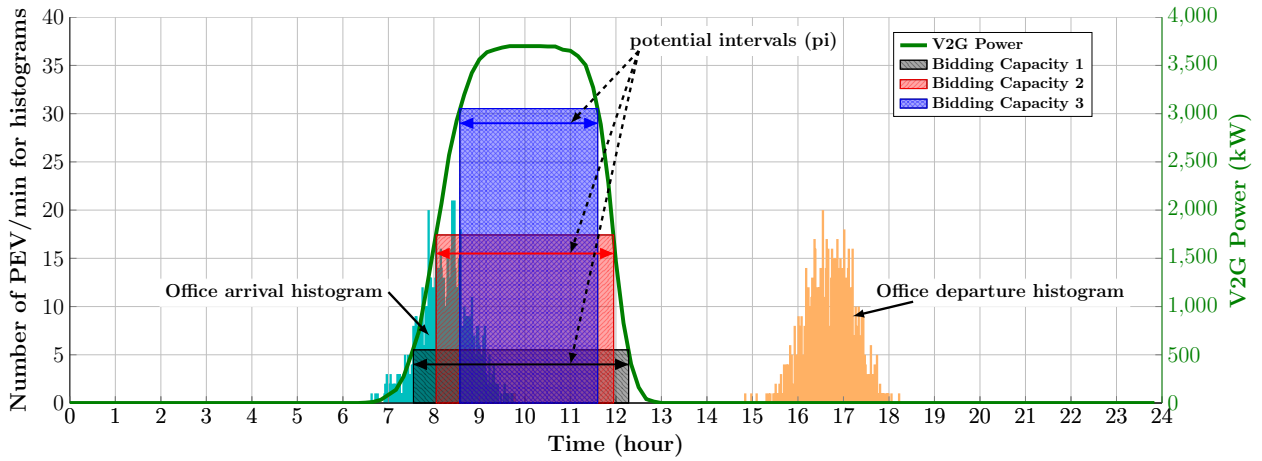


Fig. 6: The output of AVPM algorithm for office scenario, a fleet of 1000 PEV.

244 and unreliable estimation [42]. For the PEV fleet of daily home-work commuting, dependency of their
 245 departure times, arrival times and driving distances should be taken into consideration as they have key roles
 246 in modeling AVP and V2G energy capacity. However, the correlation between these stochastic variables can
 247 be estimated through statistical data as in [43] but their dependency impact on AVP and V2G energy should
 248 also be considered to provide a reliable marginal power capacity for aggregators. The latter is the case of this
 249 section. These dependencies can be analyzed with copula function. The approach of generating correlated
 250 samples using t copula sampling process is used in this paper where the notion and copula-based sample
 251 generation are explained thoroughly in [43]. t copula is used as it has tailed dependence modeling ability
 252 and is more suitable for real data modeling [43].

253 6.1. The t copula

254 A d -dimensional copula C is a d -dimensional distribution function on $[0, 1]^d$ with standard uniform
 255 marginal distributions [44]. For each random variable x , copula functions are used to correlate univariate

Table 4: Bidding capacities' characteristics for home and office scenarios.

Scenario	BC1		BC2		BC3	
	pi (h)	Power (kW)	pi (h)	Power (kW)	pi (h)	Power (kW)
Home Scenario	5.5	550	4.2	1750	3	3050
Office Scenario	5.2	550	4	1750	2.9	3050

marginal cumulative distribution functions (CDF), $F_1(x_1), F_2(x_2), \dots, F_d(x_d)$, to their joint CDF, $F(x_1, x_2, \dots, x_d)$ [43]:

$$C(F_1(x_1), F_2(x_2), \dots, F_d(x_d)) = F(x_1, x_2, \dots, x_d) \quad (20)$$

Conversely, any copula C can be used to join any type of marginal distribution and construct a multivariate distribution function with the same marginal. The unique t copula for any uniform random variable $u = (u_1, u_2, \dots, u_d) \in [0, 1]^d$ is given by:

$$C_{\nu, P}^t(u) = \int_{-\infty}^{t_{\nu}^{-1}(u_1)} \int_{-\infty}^{t_{\nu}^{-1}(u_2)} \dots \int_{-\infty}^{t_{\nu}^{-1}(u_d)} \frac{\Gamma(\frac{\nu+d}{2})}{\Gamma(\frac{\nu}{2})\sqrt{(\pi\nu)^d |P|}} \left(1 + \frac{x' P^{-1} x}{\nu}\right)^{-\frac{\nu+d}{2}} dx \quad (21)$$

Where t_{ν}^{-1} denotes the inverse CDF function of a standard univariate t_{ν} distribution with degree of freedom ν and symmetric positive definite correlation matrix P with unity diagonal elements.

6.2. AVP variation calculation

Generally, using the historical data or datasets gathered from statistical surveys, the correlation between arrival/departure time and driving distance can be easily estimated by fitting the multivariate distribution function to the datasets. This approach leads to the extraction of correlation matrix elements, which are representative of correlation degree between each two single marginal distribution [43]. In this study, an approach is proposed to quantify the impact of stochastic variable's dependencies on AVP. Afterwards, the correlation matrix elements associated with average AVP variation are considered as the case study. We assume that the working hours are fixed for whole fleet. In this case the dependency of the variables rationally should be either blue or red transition lines between possible linguistic correlations' states defined in Fig. 7. While, the other transitions will not provide reliable samples to take into account for daily home-work driving pattern estimation. It means that, for a PEV departing soon from home and arriving late to home, the driving distance should have been long and vice versa.

These correlations frame, present a linear direct correlation between driving distance and arrival time and a linear indirect correlation between departure and arrival time. Using a t copula function, the univariate marginal distribution of departure, arrival and driving distance can be related to their joint distribution as follows:

$$C(F_1(T_{departure}), F_2(T_{arrival}), F_d(D_d)) = F(T_{departure}, T_{arrival}, D_d) \quad (22)$$

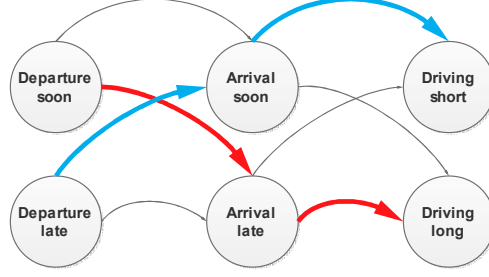


Fig. 7: Possible correlation states' transitions.

279 Considering the possible mentioned transitions, the elements of correlation matrix P will vary as follows:

$$P_{3 \times 3} = \begin{bmatrix} 1 & \rho_{12} & \rho_{13} \\ \rho_{21} & 1 & \rho_{23} \\ \rho_{31} & \rho_{32} & 1 \end{bmatrix} \quad (23)$$

where,

$$\begin{aligned} \rho_{12} &= \rho_{21} \in [-1, 0] \\ \rho_{13} &= \rho_{31} \in [-1, 0] \\ \rho_{23} &= \rho_{32} \in [0, 1] \end{aligned} \quad (24)$$

280 Where ρ_{12} indicates the correlation between departure time and arrival time, ρ_{23} indicates the correlation
 281 between arrival time and driving distance and ρ_{13} denotes the correlation between departure time and driving
 282 distance. In order to measure the sensitivity of AVP to the different possible correlation, an optimization
 283 approach is proposed where the variables will be the correlation matrix elements associated with maximum
 284 variation of AVP;

$$\min_{\substack{\rho_{12}, \rho_{23}, \rho_{32} \\ \rho'_{12}, \rho'_{23}, \rho'_{32}}} \left(\sum |P_{v2g}^w(t) - P_{v2g}^v(t)| \right)^{-1} \quad (25)$$

Subject to:

$$\begin{aligned} \{\rho_{12}, \rho_{13}, \rho'_{12}, \rho'_{13}\} &\in [-1, 0] \\ \{\rho_{23}, \rho'_{23}\} &\in [0, 1] \\ x^T P x &\geq 0 \end{aligned} \quad (26)$$

285 Where w and v are the two extreme cases of AVP affected by possible correlation between variables. The
 286 last constraint checks if the correlation matrix is positive definite or not for any possible x . This approach
 287 is tested on home V2G scenario as the case study where it is applicable on work V2G scenario as well. The
 288 results of optimization are brought in Table. 5.

289 Using the obtained results, the AVP of the two extreme cases is calculated where these two cases will
 290 never happen (Fig. 8). Considering the realistic case, there is always a correlation between three variables.

Table 5: Results of optimization for effect of correlation coefficients

Parameter	ρ_{12}	ρ_{13}	ρ_{23}	ρ'_{12}	ρ'_{13}	ρ'_{23}
Optimum value	-0.3960	-0.4950	0.99	-0.5940	-0.6930	0

291 The average value considered as the case study while in real case, the statistic's data or smart metering
 292 communication data can help to estimate the best correlation coefficients. The results show that the peak of
 293 AVP during its p_i is the same for all three cases and there is only a negligible variation in power descending
 294 period.

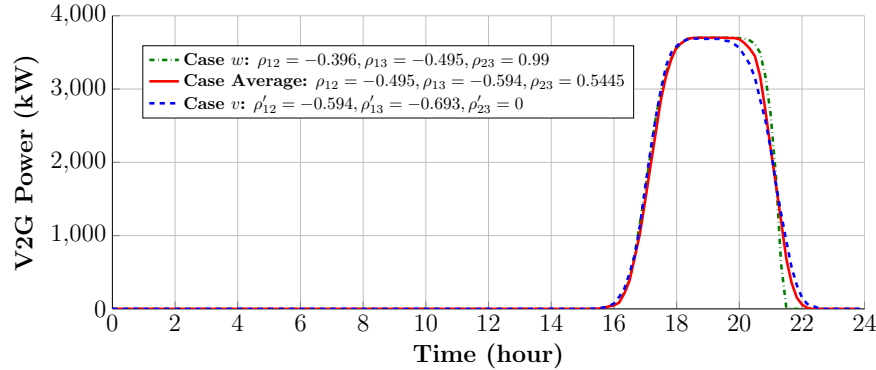


Fig. 8: Effect of various possible correlation between stochastic variables on the AVP.

295 In this paper, the parameters for average variation of AVP are considered as the case study, where the
 296 impacts of correlation between variables are illustrated in Fig. 9. As it is shown, the marginal distributions
 297 for both non-correlated and correlated variables are approximately the same, while the orientation patterns
 298 in 2D copula surface between each pair of stochastic variables are different. The orientation differences are
 299 justifiable considering the correlation states transitions shown in Fig. 7. In other word, the vehicles departing
 300 soon in the morning have potential to arrive late as they have had longer driving distance and *vice versa*.
 301 This effect is considered in AVP modeling procedure. The other effect, coming from unpredictable availability
 302 uncertainties, which is modeled using a probabilistic model, is explained in the next section.

303 7. Probabilistic availability uncertainty modeling (PAUM)

304 Availability uncertainty can have different reasons: Later arrival or sooner departure compared to the
 305 estimated or declared arrival and departure time, sudden departure in case of an urgent during the plug-in
 306 interval or any partial unavailability due to the leisure motives. Whatever the case, the PEV's unavailability
 307 from the aggregator point of view will be considered as V2G power unavailability and will impose negative
 308 impacts on contracted bidding capacity. Therefore, it is necessary to take into account the availability
 309 uncertainty factor prior to the capacity announcement.

310 The PEVs unavailability during their plug-in interval is highly stochastic and difficult to model. How-

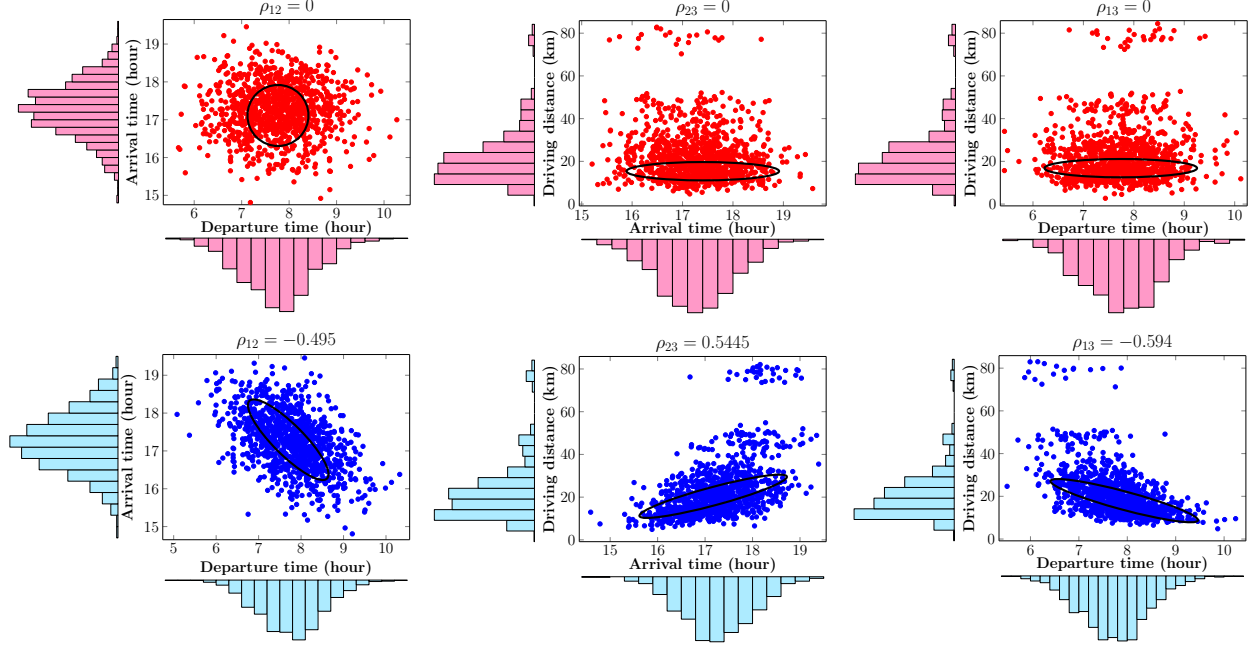


Fig. 9: Upper subplots: non-correlated stochastic variables, Lower subplots: correlated stochastic variables with averaged coefficients (Considered as the case study for AVP calculation).

311 ever, its stochastic nature follows a particular probability distribution which can be detected in daily trips
 312 percentage data. In this paper, an approach is proposed to model availability uncertainty knowing only the
 313 daily trips percentage and the fact that the trips leading to unavailability are included in trips probability
 314 distribution. Two parameters have been considered for each PEV in order to model its unavailability:

- 315 1. Departure moment as $T_{depstart}$
- 316 2. Unavailability period as DUR_{UN}

317 In addition, an uncertainty coefficient has been introduced as, $\gamma = [0, 1] \in \mathbb{R}$, which is the portion of PEVs
 318 fleet, that have potential of availability uncertainty. In another word, $\gamma = 1$, means that all of the PEVs inside
 319 the fleet will experience at least a short departure during the plug-in time. Monte-Carlo simulation (MCS) is
 320 used to generate samples with given trips percentage and prepare inputs for Gaussian mixture model (GMM)
 321 with a given number of components. Two major Gaussian components will be considered as trips related to
 322 departure from home to work in the morning and departure from work to home in the afternoon. By filtering
 323 these two components, the probability of the other motives' trips leading to availability uncertainty can be
 324 detected. In the second step, using a uniform distribution by lower bound as home arrival time and upper
 325 bound as V2G interval, the sampling process of $T_{depstart}$ will be bounded over V2G interval and conducted
 326 by filtered GMM probability distribution. For DUR_{UN} , sampling a uniform distribution between 30 minutes
 327 to 3 hours is used. This is the maximum time length a PEV will be unavailable based on the mobility
 328 survey information. In this approach, we assume that the amount of PEV battery energy used during the
 329 unavailability interval is the same as the energy amount that would be provided as V2G, if PEV was available

330 in the parking. In the following, the formulation of different steps of the approach is provided along with the
 331 modeling framework in Fig. 10.

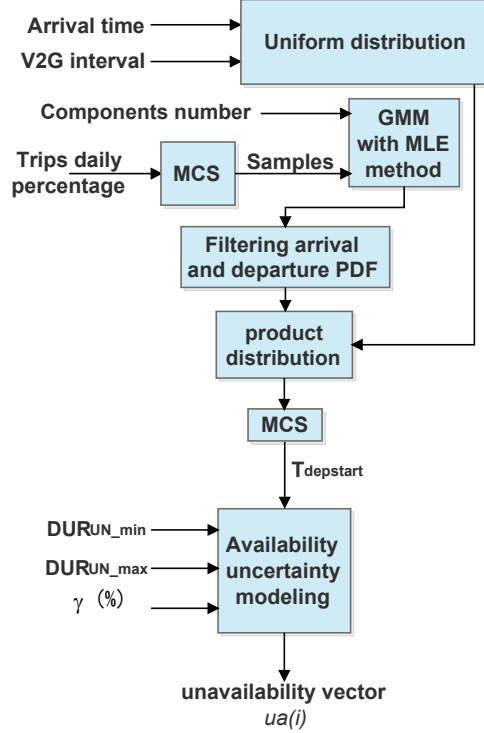


Fig. 10: The PAUM framework.

332 7.1. Gaussian mixture model

333 In this study Mixture model is used to find the sub-populations of daily trips percentage to associate
 334 an availability uncertainty probability distribution to the unknown sub-populations. These sub-populations
 335 are modeled as Gaussian components in GMM. For this reason, MCS is used to provide samples based on
 336 daily trips percentage and their probability distribution is estimated using kernel density estimation. The
 337 estimated probability density is used in MLE in order to estimates the parameters of GMM components with
 338 maximum likelihood percentage (Fig. 11).

339 One-dimensional GMM density function for a set of C components and their parameter sets as $\Theta =$
 340 $(\alpha_1, \alpha_2, \dots, \alpha_c, \sigma_1, \sigma_2, \dots, \sigma_c, \mu_1, \mu_2, \dots, \mu_c)$ is represented as follows [45];

$$f(x_s|\Theta) = \sum_{j=1}^c \alpha_j \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{(x_s - \mu_j)^2}{2\sigma_j^2}\right) \quad (27)$$

341 We assume that $\alpha_j \geq 0$, for $j \in [1, \dots, c]$ and $\sum_{j=1}^c \alpha_j = 1$. x_s represents the samples. The best likelihood
 342 is obtained with 6 components with parameters shown in Table. 6.

343 The last two components can be considered as trips related to departure from home to work in the morning
 344 and departure from work to home in the afternoon since their parameters are near to the ones which have

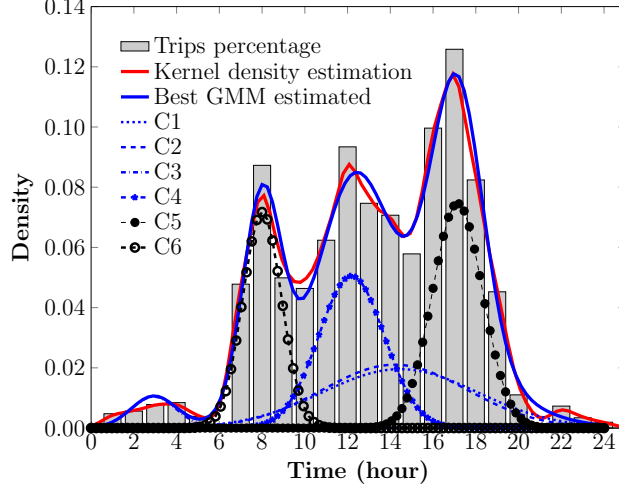


Fig. 11: Kernel density fitted to trips percentage along with best GMM fit with 6 components.

Table 6: parameters of GMM components.

Component j	C_1	C_2	C_3	C_4	C_5	C_6
$\mu_j (hh : mm)$	14:27	14:13	02:55	12:25	17:08	08:00
$\sigma_j (minutes)$	217	202	63	92	45	36

345 been considered in the previous section. By filtering these two components from GMM, the density function
 346 of other motives trips can be found (Fig. 12).

347 7.2. Uniform distribution

348 Using a uniform distribution, the sampling process for parameter $T_{depstart}$ can be bounded on the V2G
 349 time interval in order to emphasize uncertainty over AVP. In flexibility study in the next section, the interval
 350 will be adapted by a flexibility interval. The filled intervals in Fig. 12 show the products of uniform
 351 distribution and filtered GMM density function, which will be considered as uncertainty density function
 352 for uncertainty sampling process. In other words, the sampling process will be done randomly considering
 353 the obtained uncertainty density as the probability of selection. This density function can be represented as
 354 follows:

$$g_{un}(x_s|\Theta) = \begin{cases} \sum_{j=1}^4 \alpha_j \frac{1}{\sqrt{2\pi\sigma_j^2}} \exp\left(-\frac{(x_s-\mu_j)^2}{2\sigma_j^2}\right) & T_{arrival} < x_s < T_{arrival} + T_{v2g} \\ 0 & elsewhere \end{cases} \quad (28)$$

355 Where $T_{arrival}$ will be arrival time of first PEV at work for work V2G scenario and at home for home
 356 V2G scenario. For the unavailability period, a uniform distribution is considered with cumulative distribution
 357 function as follows:

$$F(DUR_{UN}; a(i), b(i)) = \frac{DUR_{UN}(i) - a(i) + 1}{b(i) - a(i) + 1} \quad (29)$$

358 Where $a(i) = 30min$, $b(i) = 3hours$ and $DUR_{UN}(i) \in [a(i), b(i)]$. The outputs of the model for two scenarios
 359 are depicted in Fig. 12. This density function will be used as inputs for uncertainty sampling process, and
 360 it will affect the V2G vector as in (10). The impact of modeled uncertainty on each bidding capacity during
 361 its p_i is studied using a reliability factor (RF), which is the ratio of available V2G energy with uncertainty
 362 divided by V2G energy without uncertainty. The results depicted in Fig. 13, show intensive impacts on BC3,
 363 particularly for home scenario. The BC1 remains mostly reliable even with the highest γ value. This analysis
 364 helps to choose the most reliable BCs where the procedure will be completed by assessing the flexibility of
 365 each BC in next section.

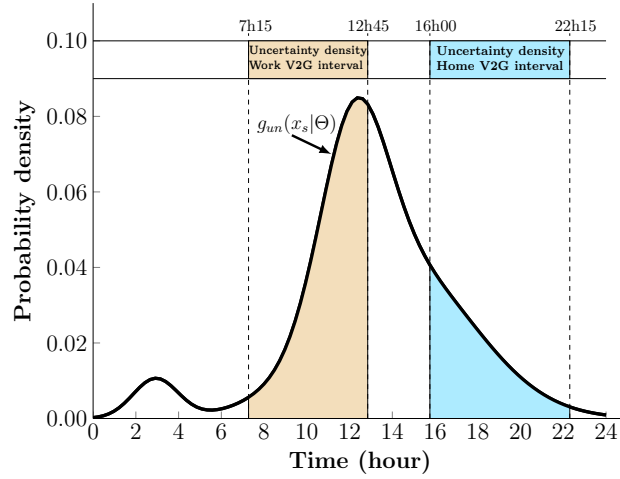


Fig. 12: Uncertainty probability density function for two V2G scenarios at work starting from 7h15 and at home starting at 16h00.

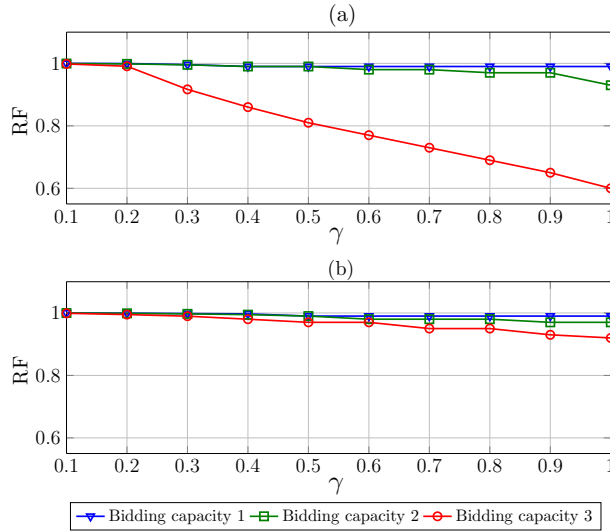


Fig. 13: Impact of uncertainty on reliability factor for, (a) home scenario, (b) work scenario.

366 8. Bidding flexibility calculation (BFC)

367 As we modeled the AVP upon the arrival of the PEVs, it would also be possible to coordinate the
 368 discharging time in order to prolong the bidding capacity interval. This so-called "bidding capacity flexibility"
 369 is analyzed in this section under a stochastic global optimization problem approach. Considering the BCs
 370 defined in previous sections by (18) and (19), the only way to maximize these capacities is to maximize the
 371 potential interval and for this goal, the only degree of freedom is to coordinate the V2G time of PEVs.

372 8.1. Flexibility problem formulation

373 The purpose of this optimization is to maximize the BC time interval, starting from its availability. For
 374 instance, for bidding 1 starting at 16h45, the objective is to maximize the capacity interval using V2G start
 375 time coordination of PEVs. This maximization is under constraints of respecting the G2V capacity of the
 376 fleet (for home scenario) and possible flexible range of V2G start time. In order to simplify the calculation
 377 one parameter per PEV is considered, and it is the V2G start time which varies between arrival time and
 378 G2V start time minus V2G time interval. We define the $k(t)$ function as the counter of sample times having
 379 a capacity more than each BC .

$$K(t) = \begin{cases} 1 & P_{v2g}(t) \geq BC_z(t) \\ 0 & elsewhere \end{cases} \quad (30)$$

Objective function:

$$\max_{T_{VS}(i,i+1,\dots,N)} \sum_{t_1}^{t_2} K(t) \quad (31)$$

Subject to:

$$\begin{aligned} P_{v2g}(t) &\geq BC_z(t), \forall t \in [t_1, t_2] \\ T_{arrival}(i) &\leq T_{VS}(i) \leq T_{departure}(i) - T_{g2v}(i) - 2 \times T_{v2g}(i) \end{aligned} \quad (32)$$

380 Where $T_{VS}(i)$ is the V2G start time of PEVs arriving after BS_z that should be coordinated in order to
 381 maximize the available interval of $BC_z(t)$. Considering the normal distribution empirical rule (three sigma)
 382 and number of PEVs per fleet, the number of parameters that has to be optimized can be calculated as
 383 follows for a fleet with N PEV, $P_1 = 0.6827$ and $P_2 = 0.997$:

$$Param_{num} = \begin{cases} \frac{P_1+P_2}{2} \times N & z = 1 \\ 0.5 \times N & z = 2 \\ \frac{P_2-P_1}{2} \times N & z = 3 \end{cases} \quad (33)$$

384 For instance, for a fleet with 1000 PEV, in order to calculate flexibility of bidding $z = 1$, 838 parameters
 385 correspond to the PEVs arriving after BS_1 should be optimized. This expression shows that we face with a
 386 relatively large optimization problem which needs a powerful algorithm.

387 8.2. Methodology

388 The major challenge for this optimization problem is finding the best feasible solutions (global optimum),
389 knowing the potential of high dimension problem and stochastic nature of the problem, which makes difficult
390 to use deterministic and gradient based optimization algorithms. The latter using derivative free algorithms
391 seem effective. In [46], it is shown that Free Pattern Search (FPS) algorithm is scalable to the dimension
392 increasing and performs better compared to the other evolutionary algorithms. This algorithm employs the
393 HJPS method as a local search algorithm and two operators from FS to guarantee the diversity of search
394 in order to inherit the global search. Long et al. showed that FPS has very fast convergence speed, better
395 solution accuracy, swarm management ability and robustness to the dimension compared to the similar
396 evolutionary algorithms.

397 In this paper, we have implemented FPS algorithm on bidding flexibility problem, and its functionality
398 is assessed in both quality of result and dimension increment.

399 8.3. Free Pattern search

400 FPS is a population-based global optimization algorithm with three main parts; initialization, exploration
401 and termination. In exploration part, there are three operators: search operator for local search based on
402 HJPS, acceleration operator to avoid trapping in local optimums and a throw operator, which ensures the
403 diversity of population. A single individual, $X_j, \{1 \leq j \leq m \in \mathbb{N}\}$, will do the search based on HJPS algorithm
404 in all of its dimensions, $1 \leq i \leq n \in \mathbb{N}$, bounded between lower and upper limits, Low_i and Up_i . The flowchart
405 of the FPS algorithm is illustrated in Fig. 14 and the different operators are explained afterwards.

406 **Search operator** uses the HJPS algorithm to find local optimum for each individual. HJPS is a single-
407 point search method which uses a pattern to search around the base point. There are three types of points in
408 HJPS; the current point Ψ , the base point ϕ , and previous point θ . The current point is the actual solution
409 of algorithm. The base point is for finding the better solution, and the previous point is the last current point.
410 The HJPS contains two parts: exploration move (EMove) and pattern move (PMove). EMove will search
411 in all dimensions of the base point to find the best trial. If the best trial is better than current point, the
412 PMove will be implemented.

413 **Acceleration operator** separates the population in two groups. The first group are the individuals
414 trapped in local optimum and need to be accelerated. Using a sensibility factor S , the individuals will be
415 polarized into two groups and the first group individuals X_j^1 will be accelerated thanks to the randomly
416 selected second group individuals X_r^2 .

417 **Throw operator** detects the individuals that would gather and search in the same small space. It
418 scatters them by adding or subtracting a $\Delta_{i,init}$ length to every dimension of the start position $X_{i,start}$ of
419 gathered individuals. Throw operator keeps the population diversity in the search space. After finishing
420 all operations the algorithm will be terminated facing with maximum step or maximum function call and
421 accuracy of the solution.

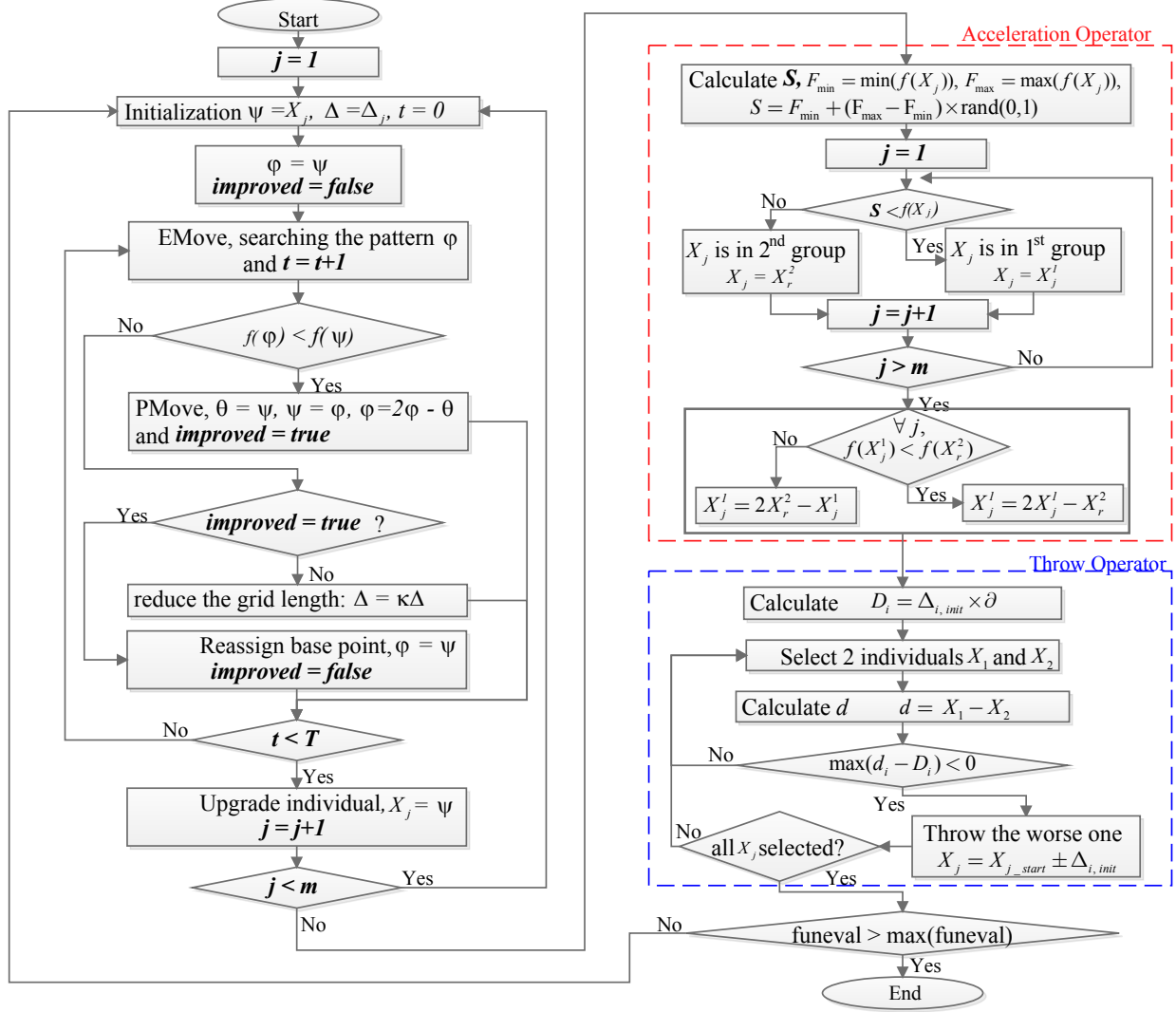


Fig. 14: FPS algorithm flowchart.

422 8.3.1. Results

423 The method is implemented on different PEV fleet numbers. Fig. 15 shows the function evaluation per all
424 individuals for the fleet of 50, 200 and 500 PEVs. The result shows a complete convergence of all individuals
425 for all cases. This shows the robustness of the algorithm to the dimension increment. The convergence and
426 exploration intervals are indicated on the function evaluation windows. By increasing the dimension, the
427 exploration is also prolonged. The optimization is stopped when all the individuals in each evaluation are
428 converged to a single value and there is no further improvement in term of optimum result. The best value is
429 obtained 10.5 hours. In fact, as the problem is stochastic, the optimization is repeated to have all cases with
430 the same optimum values while the final results for bidding capacity 1 is almost around 10 hours for all the
431 PEV fleet cases. This optimization is done in presence of different values of uncertainty coefficient, and the
432 results are presented in Fig. 16. The impact of uncertainty shows a linearly drop on the flexibility interval

433 and more important on home scenario biddings. The BC3 for both scenarios has a flexibility less than 3
 434 hours after 20% uncertainty ($\gamma = 0.2$). It shows that BC3 compared to BC1 and BC2 has less reliability in
 435 terms of interval flexibility even by having a power more than them. Since the minimum time requirement
 436 for ancillary services discussed in this paper is 3 hours, the BC3 will not be considered in further analysis.
 437 Fig. 17 shows the flexibility of BC1 and BC2 with the uncertainty coefficient of $\gamma = 0$. In BC1, the flexibility
 438 algorithm reaches to prolong the potential interval of BC1 from 5 hours up to 10.5 hours. In BC2, the
 439 flexibility reaches 8 hours.

440 The flexible interval (fi) of each BC will be used for service assessment in the next section. The availability
 441 uncertainty is considered with $\gamma = 0.1$ in the further analysis. This value is estimated for the PEV fleet in
 442 Niort.

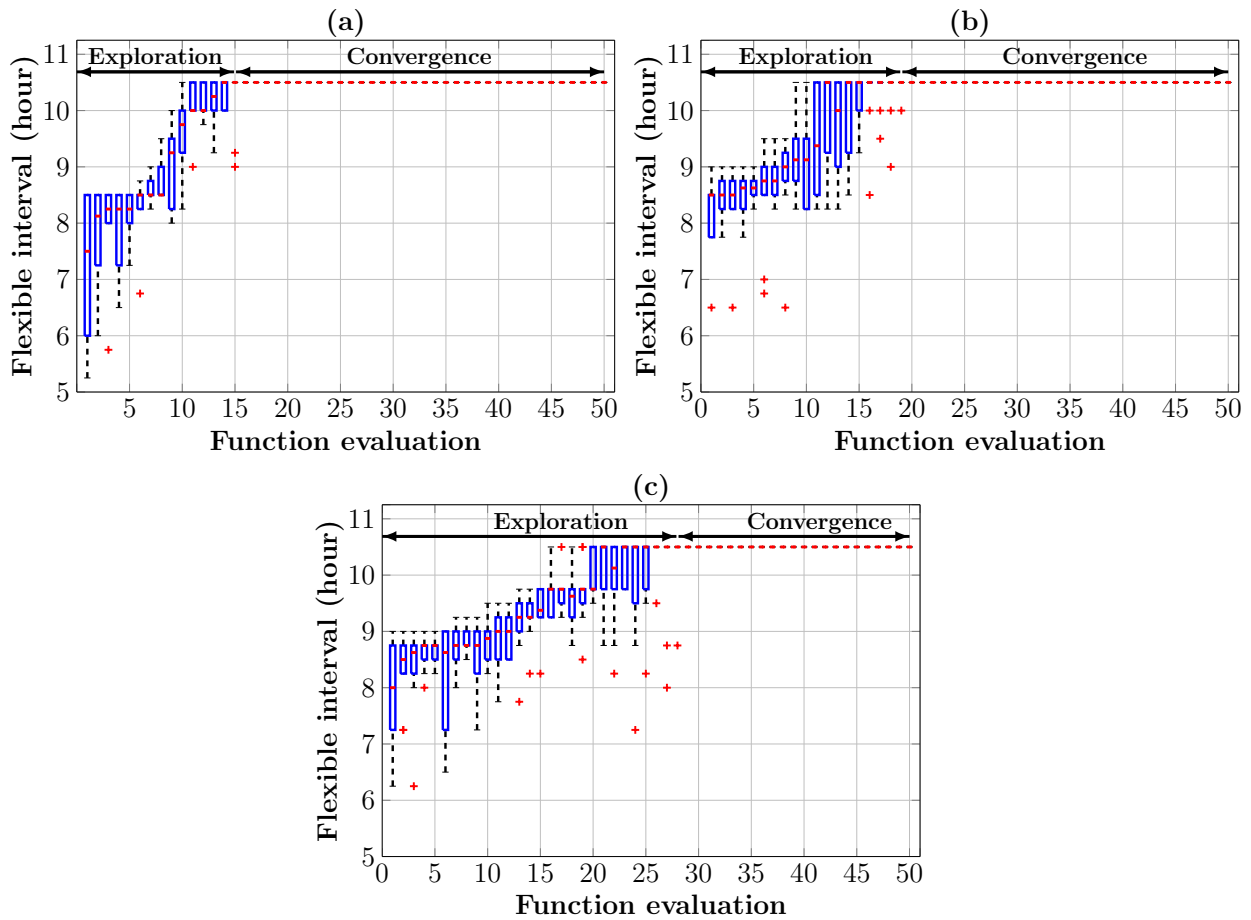


Fig. 15: Function evaluation (Individuals' boxplot per evaluation) for, (a) 50 PEVs fleet, (b) 200 PEVs fleet and (c) 500 PEVs fleet.

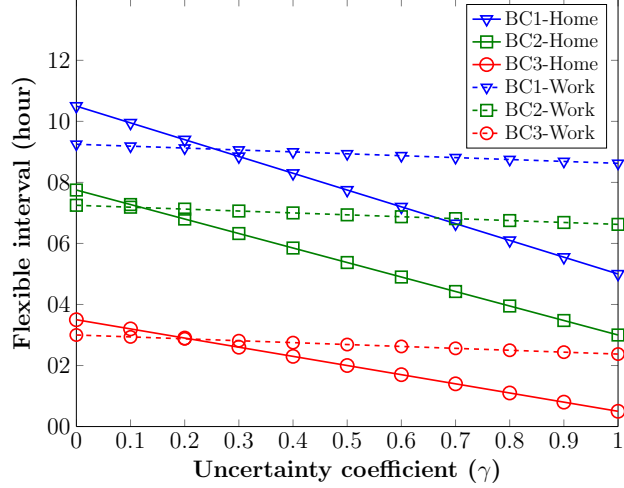


Fig. 16: Bidding flexibility vs. uncertainty for both scenarios.

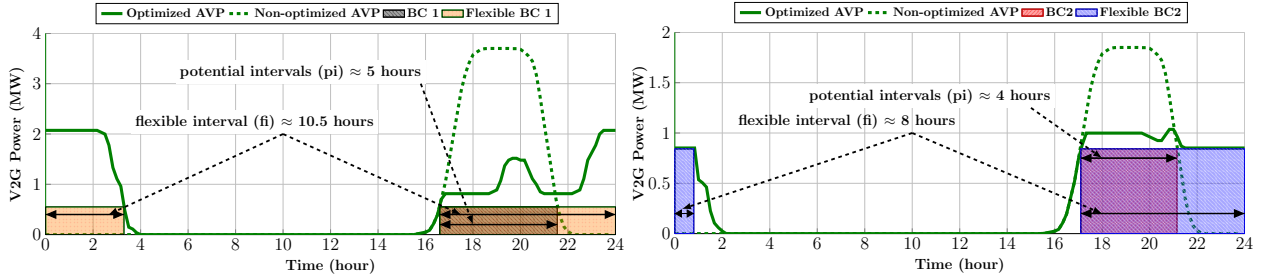


Fig. 17: Left plot: BC1 flexible interval, Right plot: BC2 flexible interval.

443 9. Ancillary service assessment

444 9.1. Ancillary services

445 In [27], a possible list of ancillary services for storage systems at the distribution grid level under the
 446 confirmation of main French DSOs is proposed. These services' feasibilities are analyzed also for PEVs in
 447 previous work of the authors [47]. In this paper, these services are evaluated for PEVs under an aggregation
 448 contract considering each service constraints. The active power based services presented in Table. 7 are
 449 chosen for this study. The first constraint for each service is the minimum amount of power, and minimum
 450 required time interval. These limits are used in order to design the fuzzy inference system for each service.
 451 Thanks to a service/localization matrix available in [27], the localization limitation of each service is also
 452 taken into account as another constraint. The utilization frequencies of the services, which depends on the
 453 nature of the service and the activation signals, are considered as the last constraint. In this study, three
 454 activation signals in form of a probability function are considered (Fig. 18). Annual averaged daily load
 455 profile (DLP) is considered as probability function for services sensitive to DLP variations. Annual averaged
 456 daily frequency *regulation up* signal is used for regulation services and finally, annual averaged daily balancing
 457 mechanism (BM) demand is chosen for BM service assessment. In the Table 8, the analyzed services in this

458 study are introduced.

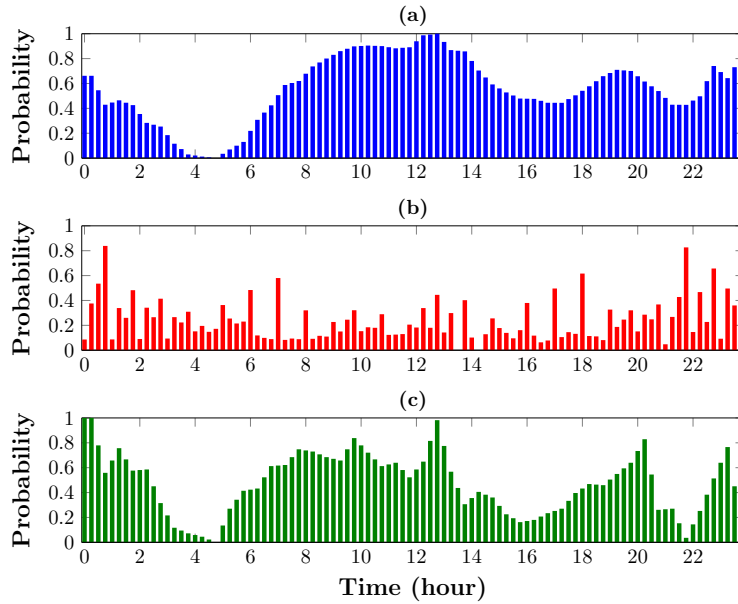


Fig. 18: Probability of activation signals for, (a) Daily load profile (DLP), (b) Frequency regulation up (RU), (c) Balancing mechanism up (BM).

Table 7: Ancillary services requirements for distribution grid [27, 48].

Service	Loc. limit	Min. Power (kW)	Max. Power (kW)	Min. time(h)	Activation signal
PPSMV	A	500	2000	3	DLP
PPSLV	C	100	500	3	DLP
VRMV	B,D	500	2000	3	DLP
VRLV	C	50	500	3	DLP
LM	A	100	2000	3	DLP
ETCM	A	2000	5000	3	DLP
FR	A	1000	5000	3	RU
BM	A	10000	15000	3	BM

459 *9.2. Distribution grid service/localization limitation*

460 At the distribution grid level, the effective potential place for each type of ancillary service is different.
 461 Reference [27], under the consultation of major French DSOs, proposes the different candidate locations for
 462 installing energy storage systems. These places are considered as the limit for the aggregated number of
 463 PEVs in order to assess the service potential. In this study, based on the chosen services, 4 candidate points
 464 are considered as the limits for each type of service (Fig. 19). **Point A** is at the topmost level of distribution
 465 grid in border of distribution and transmission grid. This point is considered as a HV/MV substation for

Table 8: Ancillary services characteristics for distribution grid.

Service	Characteristics
PPS	Peak Power Shaving is evaluated at both MV and LV grid. PEVs are charged during off-peak hours and discharged via V2G at peak hours. It provides economic interests for PEV owners, aggregators and DSO.
VR	Maintaining voltage in acceptable contractual/regulatory boundaries [49]. At MV feeder a few % of regulations needs at least 500 kW to 2 MW [48]. It is based on typical value of MV feeder impedance in French distribution grid. This study is only focused on the active power contribution on voltage regulation.
LM	Peak load should be avoided to minimize the losses. The line length, active and reactive power of the connected consumers are important for dimensioning the storage units.
ETCM	The DSO has to pay to TSO an annual bill related to energy transmission. Minimizing the bill with local produced renewable energy consumption and PEV charging coordination can be possible [38].
FR	Primary frequency regulation for French grid is 600 MW. A Minimum of 1 MW at the distribution grid level is required [50].
BM	Balancing Mechanism is a part of tertiary frequency control. The French producers and consumers having 10 MW available Power can participate in BM market [50]

466 the range of 63 to 225 kV for HV side and 15 to 20 kV for MV side. **Point B** is considered as the MV
467 feeder level for feeders with 15 or 20 kV voltage level. **Point C** is considered as the LV bus bar inside the
468 MV/LV substation for the range of 400 V in LV side. Finally, for industrial/professional customers possessing
469 a private MV/LV substation, **Point D** is considered, which will be the case for office charging scenarios.

470 In fact, for each service, based on its localization limitation mentioned in the Table. 7 the aggregated
471 number of PEVs fleet will be evaluated at that limit.

472 For our case study in Niort, a statistical analysis is done in order to discover the distribution of residential
473 customers inside the distribution grid and for the 4 candidate locations. In point A, the possible number
474 of PEVs for home scenarios are brought in Table. 9. For office scenario, 2841 PEVs can be aggregated up
475 to the point A. The possible number of PEVs in Niort for each provision scenario are distributed between
476 all MV/LV substations based on the residential consumers' distribution, inside the MV/LV substation (Fig.
477 20.a). Distributions of PEVs at the level of MV feeder for home scenario are brought in Fig. 20.b. The
478 residential consumers are considered as the charging locations at home and for office scenario, the professional
479 consumers are taken into account. For both scenarios, the maximum number of PEVs at each level of the
480 grid are calculated considering the actual subscribed power for each consumer. It means that the capacities
481 of the grid for hosting the PEVs are taken into consideration as constraints. For both evolution scenarios
482 at home scenario, there is no case exceeding the subscription limitation. For office scenario, the maximum
483 possible number of PEV before limitation violation are considered for study, as there is no evidence to justify

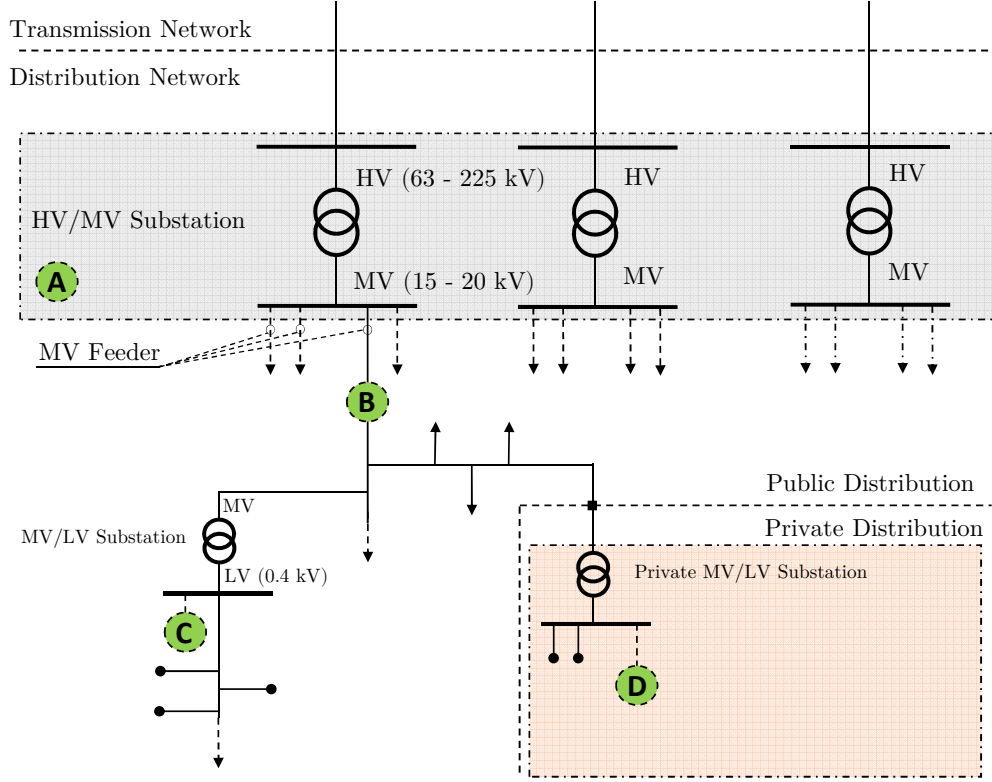


Fig. 19: Distribution grid schematic with location limitation for ancillary services.

484 the exact number of PEVs for office scenarios. It is due to the combination of traffic flow between Niort and
 485 its neighbor cities during the day. Their distribution at point B, C and D are brought in Fig. 20.c along with
 486 mean values considered in potential calculation.

Table 9: Aggregated number of PEVs up to HV/MV substation (point A) for home scenario.

Evolution horizon	2020	2025	2030
Low Scenario	681	1446	2127
High Scenario	1702	4680	7657

487 9.3. Fuzzy inference system service assessment

488 In order to assess the potential of PEV fleets for V2G ancillary services, a methodology is proposed.
 489 This method considers the bidding capacities characteristics of each fleet and compares it with potential
 490 probability of each service. A fuzzy inference reasoning system is designed to quantify the potential of each
 491 fleet and each bidding capacity for each particular ancillary service. As the services' requirements are defined
 492 by power and time in form of an interval, the assessment procedure seems to be in a fuzzy form as the exact
 493 evaluation also needs accurate requirement. For each service, minimum and maximum power need and time
 494 are identified in Table. 7. Two inputs are considered for this system. The first one is dedicated to time

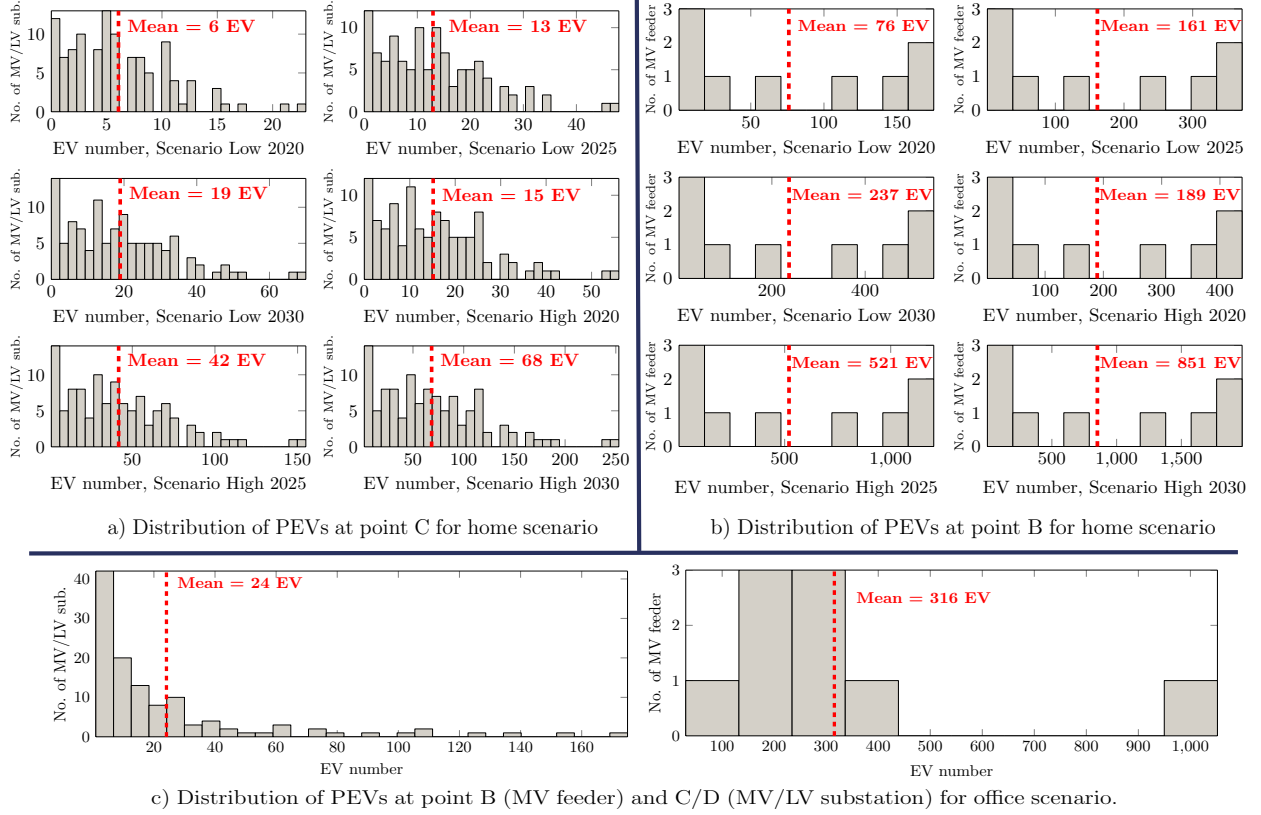


Fig. 20: Distribution of PEVs at different points for home/office scenarios.

495 interval of each service that can be provided by that particular bidding capacity of the fleet. By considering
 496 the probability of the service as $ST(t)$ and probability of bidding capacity as $FT(t)$ the first input is defined
 497 as:

$$DUR = \sum_{t=1}^{24} FT(t) \times ST(t) \quad (34)$$

498 Probability of bidding is a vector with value 1 during the flexible interval (fi) of each bidding and 0 for
 499 other intervals of the day.

$$FT(t) = \begin{cases} 1, & BS_z \leq t \leq BS_z + fi_z \\ 0, & elsewhere \end{cases} \quad (35)$$

500 This input is normalized using g factor as, $g = 1/\sum_{t=1}^{24} ST(t)$. The second input is the power that should
 501 be provided for each service. The membership function of this input will be made based on minimum and
 502 maximum required power for each service provided in the Table. 7. The example of inputs and output for
 503 service PPSMV is brought in Fig. 21.

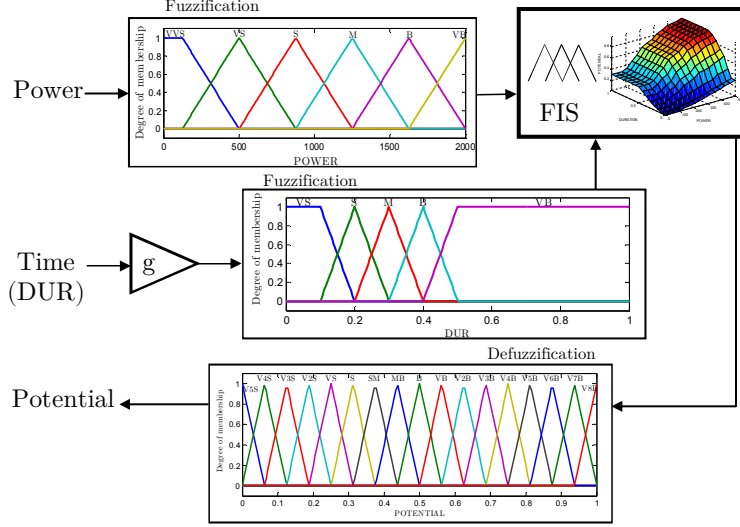


Fig. 21: FIS algorithm, inputs and output example for service PPSMV.

504 **10. Results and discussion**

505 A graphical indicator is designed for potential comparison of different services and bidding capacities
 506 represented in Fig. 22 for home and Fig. 23 for office scenarios. For each BC a minimum potential factor
 507 called *BC limit* is calculated using minimum power of the services and flexible interval of the BC. This factor
 508 is considered as minimum requirement for each BC of the services and is represented in form of a dotted-
 509 dashed line with filled upward area. Based on this indicator, every fleet evolution scenario should be inside
 510 the BC filled area in order to be competitive for that service. Afterwards, the potential of the different fleets'
 511 evolution scenarios is assessed using their provided power associated with their aggregated number of PEVs
 512 at each service's candidate point.

513 For home scenario, the services PPSLV and BM are not competitive up to 2030 horizon unless for high
 514 scenario of BC2. However, the services PPSMV, LM and FR are mostly well adapted with the provisions.
 515 In FR service, the low scenario BC1 can be possible from 2030. For PPSMV, the low scenario BC1 is also
 516 possible from 2025. In ETCM service, low scenario BC1 is not at all competitive up to 2030. This is the
 517 same case for low scenarios BC1 and BC2 in VRLV and VRMV services.

518 For office scenario in Fig. 23, the services PPSLV, VRMV and BM are impossible. The services FR, LM
 519 and PPSMV are inside the area, so they can be competitive for the office fleet. The actual study shows that
 520 for BC1 the services VRLV and ETCM cannot be competitive. It should be taken into account that in this
 521 study, the numbers of PEVs at work are estimated based on actual grid capacity, and the studied volume
 522 availability is not at all guaranteed.

523 The results for both scenarios show that the services in the low voltage grid have not enough potential due
 524 to the non-sufficient number of aggregated PEVs at LV grid, i.e. mostly less than 30 PEVs in all provision
 525 scenarios. In addition, for service BM, due to its huge power capacity requirement, the fleets' provisions are

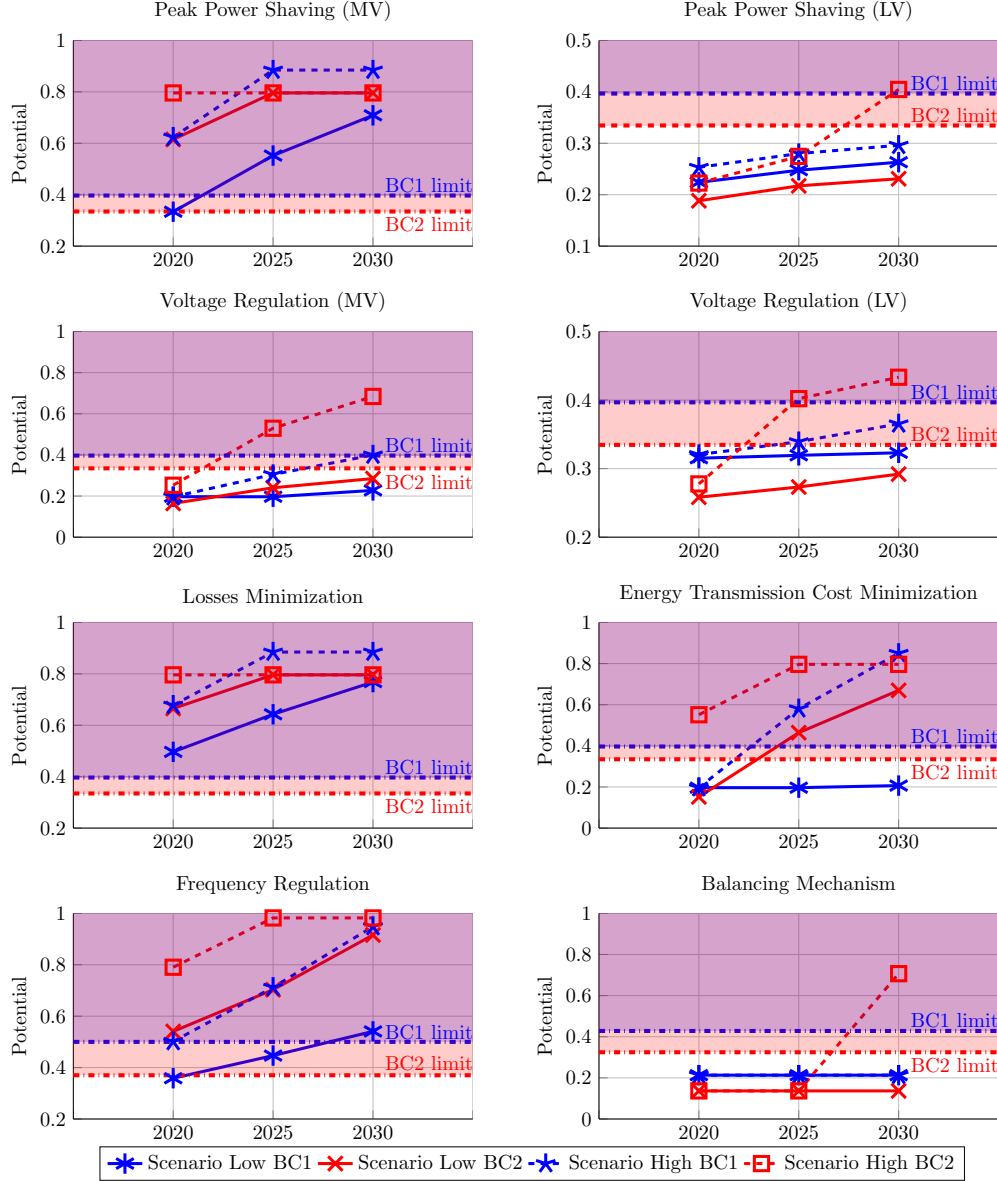


Fig. 22: Potential evaluation for home scenario under all evolution scenarios.

526 mostly not competitive as the available aggregated number of PEVs at point A cannot cover the BM service
 527 power capacity requirement.

528 The proposed approach provides the potential evaluation of V2G ancillary services for distribution grids.
 529 This approach is useful in V2G energy management modeling by concentrating on the main requirements
 530 and limitations of each particular case study. By utilizing the proposed approach, the V2G management
 531 system will be efficient and scalable to that specific case study. Furthermore, the real potential services can
 532 be listed based on their priorities, which would be practical in the energy management scheming's step. By
 533 knowing the flexible capacity of each V2G fleet, in the context of renewable energies' intermittent mitigation,
 534 the management systems can be efficiently dimensioned to the real capacity of the V2G fleet as well. The

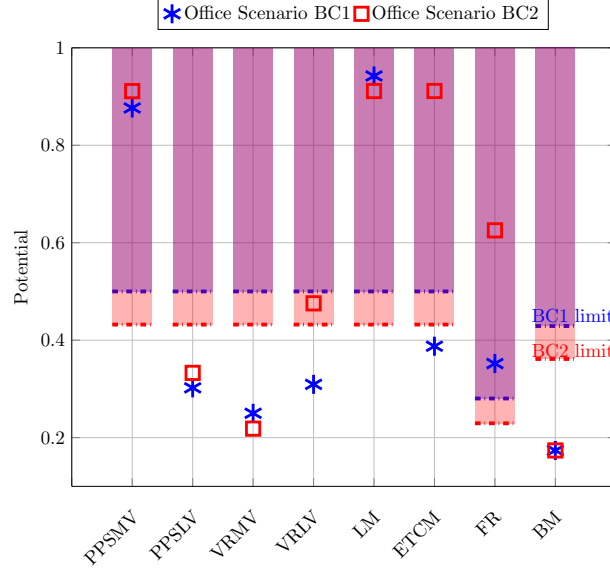


Fig. 23: Potential evaluation for office scenario with PEV number estimated up to the grid capacity (subscribed power limit).

535 proposed approach facilitates the choice of the proper ancillary services for V2G energy management and
 536 also increases the benefits from the services' mutualization for the aggregators.

537 11. Conclusion

538 V2G ancillary services potential assessment was discussed in this paper. The available V2G power of
 539 the PEV fleets doing daily home-work commuting was modeled. This modeling is based on stochastic data
 540 such as arrival/departure time and driving distance and averaged data, containing vehicle's characteristics.
 541 The interdependency of stochastic variables was analyzed using copula function. Two rarely discussed im-
 542 portant factors affecting the AVP were also modeled and their impacts on AVP were identified. Availability
 543 uncertainty of the PEVs during their plug-in interval was modeled using only daily trips percentage and
 544 its decomposition thanks to the Gaussian mixture model. Secondly, the service localization limitation was
 545 considered in the procedure of V2G service assessment of the PEVs fleet.

546 The impacts of availability uncertainty were studied on three potential bidding capacities for both home
 547 and work scenario. The results indicated that the biddings in work places are more reliable than biddings
 548 at home as the probability of uncertainty has less concentration during the work plug-in time compared to
 549 the one at home. The flexibility of each bidding capacity was calculated using a robust global optimization
 550 technic. The impacts of uncertainty also showed linearly drops on flexibility intervals and generally fewer
 551 negative impacts on work biddings' flexibility intervals compared to home scenario. Using the obtained
 552 flexible interval for each bidding capacity and V2G power of each PEV fleet, the potential of ancillary service
 553 participation of the fleets was studied thanks to a fuzzy inference system. The fuzzy system lets to quantify
 554 the potential of each fleet considering the requirement of the services such as minimum power and time and

555 localization limitation of the services inside the different point of distribution grid. This methodology, using
556 the statistical mobility data of Niort, a city in west of France, was applied and possible services for this city
557 were identified.

558 This study showed that based on the actual provision of PEV evolution in France, the services peak power
559 shaving in MV grid, frequency regulation, losses minimization and energy transmission cost minimization are
560 more competitive compared to balancing mechanism, voltage regulation and peak power shaving in LV grid.
561 It should be taken into account that, the impact of V2G infrastructure development and availability of V2G
562 per individual vehicle are also another important factor that may affect the presented results. The general
563 approach presented in this paper is sufficiently discussed, and it has potential to be applied on other similar
564 case studies.

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