EV STOCHASTIC SAMPLING: ADDRESSING LIMITED GEOGRAPHIC AREAS

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ABSTRACT

The anticipated mass roll-out of electric vehicles in Europe and the continuously increasing number of distributed energy resources are posing major challenges to Europe's distribution system operators with regard to ensuring a secure and reliable energy supply and network operation. The work in this paper describes a method for representing the behaviour of electric vehicles in a novel grid planning tool. The method uses Markov chains and data sampling for creating individual day plans for every individual of the vehicle population. This agent-based approach provides the necessary flexibility to be used during the grid planning optimization process. Since this method works on the basis of statistical data, the possibility for adaptions according to local data is provided, whilst requirements on calculation resources and simulation time are kept to a minimum.

INTRODUCTION

Assessing impacts of Electric Vehicles (EV) on power systems is challenging, as EVs are new loads and planning of distribution systems is strongly impacted by the accurate forecast of future load scenarios. First, it is necessary to define charging methodologies that depend on multiple variables such as future business scenarios and EV owners' behaviour. Next, it is crucial to identify driving and parking (determines availability for charging) patterns to be able to determine energy consumption needs in time and in space, as EVs are mobile loads. This paper focuses on this last aspect.

Different approaches can be found in the literature. The goals vary from focusing more on the vehicle and its movement [1][2] to simply appearing as an interface to the power grid [3]. Due to the lack of data it is not possible to forecast EV consumption based on historical patterns and so general mobility data is used, based on current vehicle fleets.

This work proposes a generic approach to develop a mobility pattern generator to be used for drafting EV load scenarios for simulations within distribution systems operation and planning. The study of a distribution system is typically conducted for a part of the whole system, a Medium Voltage (MV) or Low Voltage (LV) network, which means that EVs may circulate among the network nodes or even enter and leave the chosen subsystem for a while. The proposed method is able to capture these dynamics allowing the development of more accurate and realistic EV future scenarios.

INPUT DATA

Since this method aims at being applicable across the different European countries it is important to depend on as little data as possible for staying functional in data rich as well as data poor areas. Whilst information regarding the network (grid data) and charging infrastructure are essential, the usage of local mobility data is optional and default values are provided.

Grid data

Grid data and related information is expected to be provided by the grid planner. For the method described in this work, especially two types of data are relevant:

- Network type
- Charging infrastructure

Regarding the network type information is needed on whether the grid is located in a rural or an urban area. Additionally, each of the Charging Points (CPs) of the defined charging infrastructure has to be allocated to one of the following locations categories:

- Home (H) – CPs at households
- Work (W) – CPs at working and industrial places
- Shop (S) – CPs at commercial places
- Else (E) – CPs elsewhere

These charging locations match with the trip purposes of the KONTIV design [4][5][6] and allow mapping these two types of data. Figure 1 illustrates the definition of charging infrastructure in a distribution grid and the allocation of each CP to an allocated charging location.

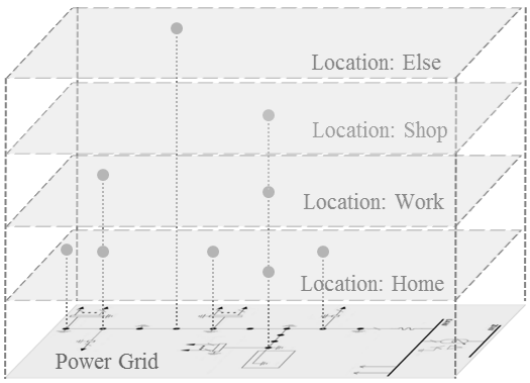

Figure 1 - Definition of the charging infrastructure and allocation to aggregated charging locations

Charging infrastructure located outside the investigated electricity network can be defined as one aggregated charging point, since charging outside the covered area has no direct effect on the local grid.

Mobility data

For the calibration of the method statistical mobility data in the form of the commonly used KONTIV design is used. This kind of data is collected through surveys and distinguishes between mobility groups and trip purposes. Figure 2 shows Austrian example data [7] for the distribution of departure times of vehicles per trip purpose.

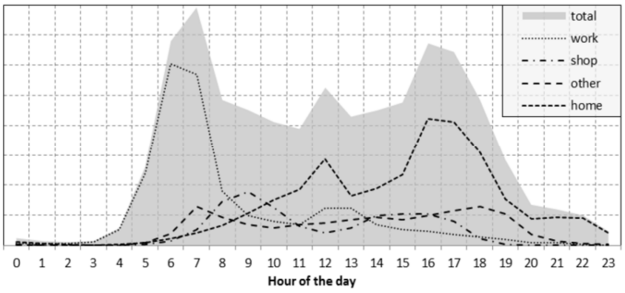

Figure 2 - Example of a distribution of departure times of vehicles per trip purpose

Electricity networks always cover a limited geographical area which is not a closed system independent from bordering areas. Figure 3 shows a simplified scheme of the two types of population affecting a specific (network) area and the different commuter types. The grey area contains the local population which consist of intra-commuters (which are only travelling within the local area) and out-commuters (leaving the local area). From the inbound population only the in-commuters to the local area are of interest and are affecting the local grid.

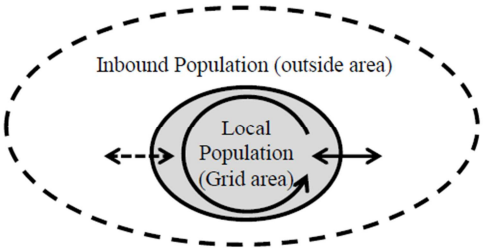

Figure 3 – Definition of population and commuters

Generally, rural and urban areas show different commuter behavior. Whilst urban areas usually attract more in-commuters, rural areas host a larger share of out-commuters.

METHOD

Three steps are used in this method, as depicted in Figure 4. The generation of the population of EVs situated within the grid area is based on the number of charging points at households. Based on the number of the local EV population and statistical information of the ratio of in-, intra- and out-commuters an inbound EV population is defined (in-commuters). Markov Chains [8] including state transitions matrices (individually for rural and urban areas as well as for local and inbound population) are used for creating individual travel chains for every agent (EV).

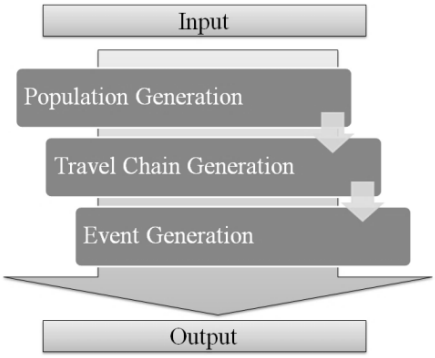

Figure 4 – Three-step method

Travel chains address the defined travel purposes. For each EV within the total population, an individual travel chain addressing none or several of the defined locations is generated. The initial state of the EVs is defined as absorptive. As soon as travel chains are addressing the initial state again the chain ends at this state, simulating a daily return to "base/home". Figure 5 shows a graphical overview of the different charging locations and areas. The individual probabilities for each transition from one state to another are directly linked to the distribution of departing vehicles per travel purpose from statistical or historical input data. EVs address per time step, according to their current travel purpose, one of the state locations.

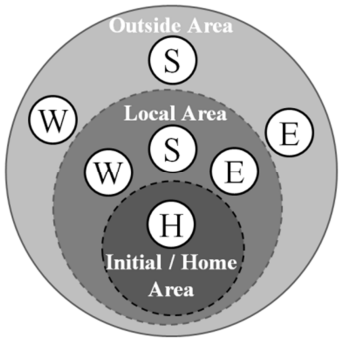

Figure 5 - Overview of possible interconnections of charging locations for creating travel chains

Population Generation

As mentioned in the Input Data section, the total population consists of a local and an inbound population. The local population derives from the number of charging stations at households (Location type "Home") defined within the grid area. Equation (1) shows the mathematical formulation of the local (intra-grid) population EV_L generation.

$$EV_L = \sum_{i=1}^{CP_H} i \qquad (1)$$

Next to the population inside the grid area, an outside population has to be added for covering activities of in-commuters which are also frequenting local charging infrastructure. This calculation is based on the following information:

- Ratio of in- to out-commuters
- Local grid population (EV_L)

The inbound share value derives directly from local commuter data and describes the ratio of the local population (consisting of intra- EV_{intra} and out-commuters EV_{out}) to in-commuters EV_{in} and is considered through equation (2):

$$Inbound_{Share} = \frac{\sum EV_{intra} + \sum EV_{out}}{\sum EV_{in}} \quad (2)$$

The inbound population EV_I is calculated by equation (3) below:

$$EV_I = EV_L \cdot Inbound_{Share} \quad (3)$$

Travel Chain generation

After the definition of a population during step one of this method, individual travel chains for every agent of the population can be generated. A travel chain consists of 3 states at the minimum, where the initial and final states are always at the home location (either local or external, depending on the population type). Figure 5 shows the three different areas (initial/home, local and outside) and the charging locations per area. Table 1 shows the structure of the transition matrix for creating the travel chains with Markov chains. The individual probabilities for each state derive directly from the mobility data and type of network (rural or urban). The abbreviations "L" and "O" indicate the area of the charging location (local or outside). State 8 ($H_{L/O}$) is defined as absorptive (probability of p_{hh} is 1,0), which means that a chain reaching this state, will end here and no further states can be reached. Whilst the probabilities for the locations W, S and E are based on the same data from the origin/destination matrix, the values differ due to inclusion of the commuter shares. This also leads to the need of individual transition matrices for the local and inbound population.

Since the creation of travel chains is based on probability, there is a chance running into disproportional long or endless chains for individual day plans. To avoid this and to meet existing statistical average values for travel chain lengths (e.g. 3,3 trips per day in Upper-Austria in 2012 [7]), a maximum value for generated travel chains is introduced.

Event Generation

After generating the population and creating individual travel chains for each agent, time discrete events can be added for each day plan. The following abbreviations are used for event generation process:

T_I	Initial time
T_A	Arrival time
T_T	Travel time
T_D	Departure time
R	Distance driven
v	Average travel speed

Figure 6 provides a schematic overview of the event generation process based on an example of a travel chain containing six states in total. The x-axis displays a 24-hour day and the y-axis indicates the different states and charging locations. The day plan for the agent starts with the initial time (T_I) at 00:00 and ends at 23:59.

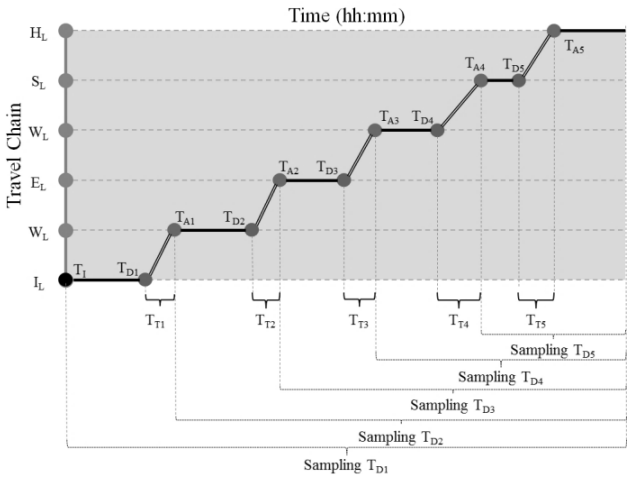

Figure 6 - Event generation process on the basis of an example travel chain

Table 1 – Eight-state transition matrix for generating travel chains

		State 1	State 2	State 3	State 4	State 5	State 6	State 7	State 8
		$I_{L/O}$	W_L	S_L	E_L	W_O	S_O	E_O	$H_{L/O}$
State 1	$I_{L/O}$	p_{ii}	p_{iwl}	p_{isl}	p_{iel}	p_{iwo}	p_{iso}	p_{ieo}	p_{ih}
State 2	W_L	p_{wli}	p_{wlwl}	p_{wlsl}	p_{wlel}	p_{wlwo}	p_{wlso}	p_{wleo}	p_{wlh}
State 3	S_L	p_{sli}	p_{slwl}	p_{slsl}	p_{slel}	p_{slwo}	p_{slso}	p_{sleo}	p_{slh}
State 4	E_L	p_{eli}	p_{elwl}	p_{elsl}	p_{elel}	p_{elwo}	p_{elso}	p_{eleo}	p_{elh}
State 5	W_O	p_{woil}	p_{wowl}	p_{wosl}	p_{woel}	p_{wowo}	p_{woso}	p_{woeo}	p_{woh}
State 6	S_O	p_{soi}	p_{sowl}	p_{sosl}	p_{soel}	p_{sowo}	p_{soso}	p_{soeo}	p_{soh}
State 7	E_O	p_{eoi}	p_{eowl}	p_{eosl}	p_{eoel}	p_{eowo}	p_{eoso}	p_{eoeo}	p_{eoh}
State 8	$H_{L/O}$	p_{hli}	p_{hwl}	p_{hsl}	p_{hel}	p_{hwo}	p_{hso}	p_{heo}	p_{hh}

After each sampling of a departure time and a distance driven out of a data base or corresponding distribution function, the travel time is calculated to obtain a specific arrival time. Equation (4) explains the calculation of the arrival time T_A, based on the departure time T_D, average travel speed v and driven distance R.

$$T_A = T_D + \frac{R}{v} \tag{4}$$

Based on the calculated arrival time, the available time frame for sampling the departure time of a follow-up trip is limited. Figure 6 visualizes the sampling process, which is also summarized in the following paragraphs.

For the sampling of the first value of departing times T_{D1}, the first link of the travel chain, the equation (5) is used, where P represents the probability based on a distribution fx of values (departure times).

$$T_{D1} \rightarrow P(x = x_1) = fx(x_1) \tag{5}$$

For the second link, equation (6) below describes the necessity of limiting the time frame for selecting the second value. This ensures that the individual events are in chronological order.

$$T_{D2} \rightarrow P(x = x_2 | x_2 > T_{A1}) = gx(x_2, T_{A1}) \tag{6}$$

Equation (6) can be generalized to describe further sampling steps, including step 2 (see equation (7)).

$$T_{Dm} \rightarrow P(x = x_n | x_n > T_{Am}) = hx(x_n, T_{Am}) \tag{7}$$

As displayed in Figure 2, different distribution curves per trip purpose are available, which allows to sample departure times from the corresponding database in dependency of the trip purpose (state).

CASE STUDY AND RESULTS

This section and the following test case illustrate the workability of the method and are based on mobility data from Upper-Austria [7]. The following assumptions had to be taken for this use-case:

Table 2 - Assumptions for the use-case

Grid Type	Area Type	Inbound Share	Population		Ø Travel Speed
			Local	Inbound	
MV	Rural	50 %	574	287	60 km/h

The inbound share for this case is set to 50 %. This means that per two local EVs one in commuting EV is to be expected. The inbound share value depends on the location type (rural or urban) and derives from statistical survey data. The average travel speed (necessary to be able to calculate the arrival time) is set to 60 km/h. Because the area type was assumed to be rural, a corresponding transition matrix was calculated based on data from several rural areas from [7].

Figure 7 shows the number of total travel chains per population and the average value for a single EV. Since the focus of the investigation is on the local area, results displayed in the following figures from outside locations are aggregated to one location called OUTSIDE.

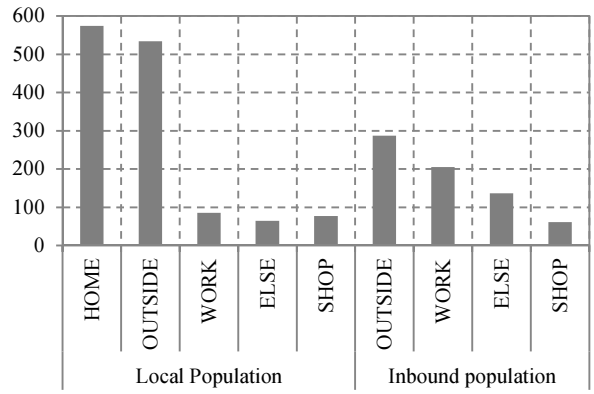

Figure 7 - Travel chains per population type

Time series of arrival and departure times from different sources are analysed and compared to the output of this method. Figure 8 shows the distribution of departure times of vehicles of the local population.

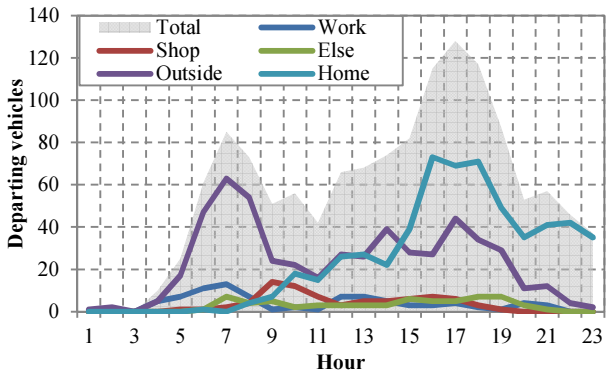

Figure 8 - Distribution of departure times of the local population

Figure 9 shows the distribution of departure times of vehicles of the inbound population.

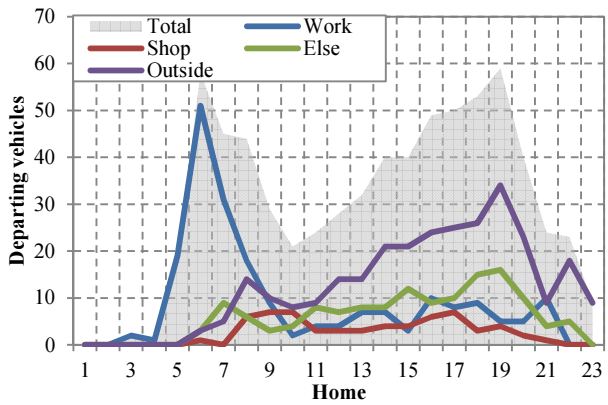

Figure 9 - Distribution of departure times of the inbound population

Figure 10 shows the distribution of arrival times of vehicles at the local (grid) location and takes vehicles of local and inbound population into account. It has to be noted, that these characteristics are just representing the arrival of EVs at locations within the grid area. The EVs merely have the option to charge, which depends on whether or not charging infrastructure is available. In the case no charging poles are defined or all stations are occupied, the vehicle cannot be charged and is only parking.

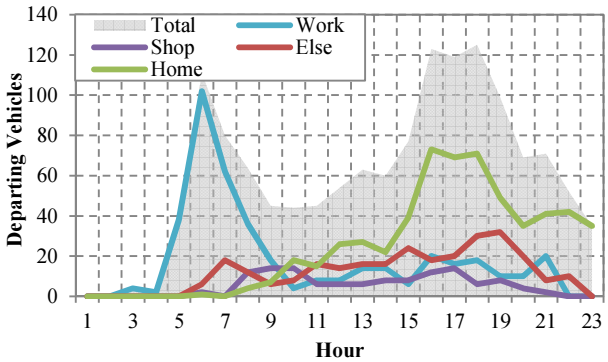

Figure 10 - Distribution of arrival times at the local area

Table 3 shows the number of total travel chains per population and the average value for a single EV. The average number of trips per EV is highly influenced by the value which defines the max. length for travel chains.

Table 3 - Travel chain results

Grid Type	Local population	Inbound population
Nr. of travel chains	1336	690
Ø trips per EV	2,32	2,4

CONCLUSIONS AND OUTLOOK

The work presented in this paper proposes a method for generating a population of EVs based on network data for network planning purposes. This method allows combining the advantages of two different approaches: i) to provide the flexibility and degrees of freedom of agent-based simulations and ii) the improved performance and modifiability of statistical methods. By using statistical mobility data, the method provides a high degree of adaptability to local data (if available). However, it also offers the possibility to perform simulations in data-poor areas by using a set of default values. From the grid planner perspective, only the definition and classification of the charging infrastructure is required. Regarding addressing limited geographical areas, this method takes neighbouring areas into account by simulating commuters coming into and going out of a specific area. This is especially relevant as rural and urban areas show distinct commuter behaviour which also affects the expected impact on the distribution grid.

In future work, further validation of results is to be provided. The validation process covers the following aspects:

- Distribution of departure/arrival times
- Distribution of trip purposes
- Distribution of travel distances
- Distribution of travel chains
- Types and length of travel chains

The validation will compare identical use-cases, based on the same data, simulated with state-of-the-art methods and the method described in this paper.

ACKNOWLEDGMENTS

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