Annual hourly E-Mobility modelling and assessment in climate neutral Positive Energy Districts

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***Abstract*— This paper presents a full-year hourly district e-mobility model and its integration into a Positive Energy District simulation and assessment model including building operation, use and embodied energy and emissions. The aim of this work is to model the operation and energy flexibility potential of an EV fleet in a district through mono- and bi-directional charging and enable its assessment in terms of self-utilization of local and volatile regional RES surpluses. Results of example residential, office, school and supermarket use cases show an increase in self-utilization of local PV of up to 30% due to EV inclusion, even if PV installation size exceeds legal building code requirements by a factor of two to four. Bi-Directional charging can cut annual grid electricity by up to 30% but require an increase in battery full equivalent cycles of 20%.**

Keywords—electric mobility, positive energy districts, multimodal energy systems

I. Introduction

As outlined in the definition of Positive energy districts (PED) and the balance calculation in [1], including mobility as a service into the energy assessment of PEDs has several advantages:

- Local energy surpluses can be passed on to mobility of residents and even passer-bys [2].
- Assessability of sustainable mobility solutions as part of the building/district assessment promotes such measures in the planning and implementation of buildings and districts [3,10].
- The impact of district location on induced trips of everyday motorized individual mobility (MIM) can be quantified and assessed.
- Concrete measures to reduce everyday mobility or the emissions caused by it, such as mobility sharing offers, charging infrastructure for e-cars, etc., should be quantitatively assessable. [3]
- Synergies of e-mobility charging infrastructure through the dynamic consideration of actual charging times and PV surpluses in the district and the advantages of energy-flexible districts can thus be mapped [9].
- Utilization of bidirectional EV charging to provide battery services to the district and building energy systems, reducing grid interaction and feed-in of PV surpluses.

But there are several challenges to the inclusion of mobility in an hourly full-year energy simulation of buildings and districts:

- Lack of data and methods to reliably determine the energy balances and emissions of transport without great effort and uncertainty [4].
- Difficult to abstract aggregate district flexibility and storage effects of E-Mobility based on individual EV models and patterns [5].
- Modelling individual mobility agents as part of a PED multi-Energy system is infeasible due to size and performance constraints of the assessment model [11].

We propose a model for these three problems as part of our PED modelling and assessment framework [6] that include:

- Full-year flexible e-mobility model including hourly location, energy demand and state-of-charge of EVs
- Flexible mono- and bi-directional charging logic based on DSM signals from onsite and offsite regional volatile Renewable Energy Systems (RES, i.e. PV and Wind)

The following questions are addressed here:

- How much mobility demand can be expected from a district at a given location? Both annually and translated into hourly mileage profiles.
- What logic governs mono- and bi-directional charging strategies?
- How can district EVs be modelled collectively instead of individual agents?
- What effects on the multi-energy system (MES) can be observed from flexible (bi-)directional charging strategies for example districts of different usages?

This approach focuses solely on modelling everyday motorized individual mobility (MIM), other forms of everyday mobility are accounted for outside the PED system boundary in a national balancing approach described in [1], so is delivery and holiday trips.

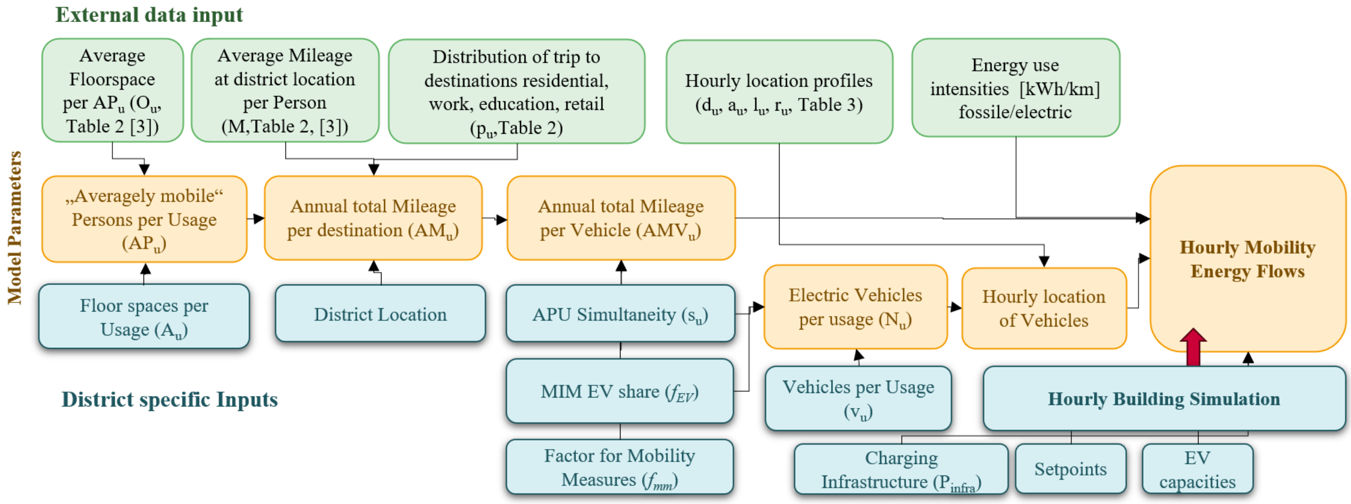

Figure 1: Mobility Method modelling overview

TABLE I. NOMENCLATURE

Variable	Description	Unit
u	District floor usage type, can be (res)idential, (com)mercial, (edu)cation, (ret)ail	
A_u	Useable Floor Area of Usage type *u*	m²
O_u	Average Floor Space of Usage type *u* per AP_u	m²/Pers
AP_u	Number of averagely mobile Persons per Usage u	
AM_u	Annual total mileage per destination u	km/APu/a
s_u	Simultaneity factor: ratio between averagely mobile Persons of a given usage u and real Persons	%
f_{ev}	EV share of MIM vehicles	%
f_{mm}	Scaling factor of AM_u based on onsite mobility measures	%
N_u	Expected total number of unique EVs originating and visiting the district usage u	
v_u	Vehicle density per 100m² floor area of usage u	1/100m²
$d_u(t)$	Share of EVs of usage u being **onsite** at the district at hour t	%
$a_u(t)$	Share of EVs of usage u being **offsite**, not at the district, at hour t	%
$l_u(t)$	Share of EVs of usage u leaving the district at hour t	%
$r_u(t)$	Share of EVs of usage u returning to the district at hour t	%
m(t)	Share of EVs travelling at hour t	%
$SoC_{x,u}$	Average battery State-of-Charge of EVs of usage u (x=d…at district, onsite or a…away, offsite)	%
c	Specific battery capacity of EVs	kWh
$E_{s,u}(t)$	Hourly Energy demand for driving	Wh/m²
$E_{Cmin,u}(t)$	Hourly Energy demand for charging onsite EVs to minimum SoC	Wh/m²
$E_{Cflex,u}(t)$	Hourly Energy demand for charging onsite EVs to maximum SoC	Wh/m²
$E_{Cext,u}(t)$	Hourly Energy demand for charging offsite EVs to minimum offsite SoC	Wh/m²
$E_{D,u}(t)$	Hourly Energy supply from discharging onsite EVs to the district down to a minimum SoC	Wh/m²

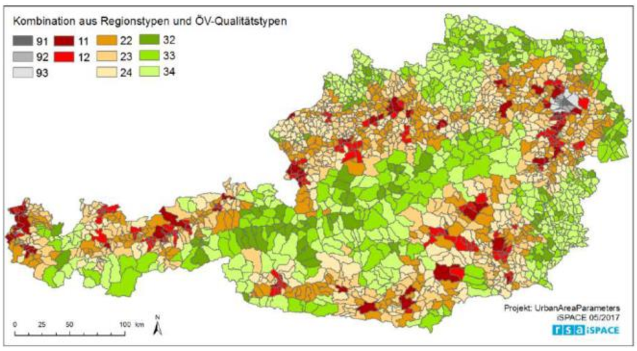

Figure 2: Average Annual Mileage *M* per *region* per Person from [7]

II. Methods and Data

A. Annual travellers, trips and mileages

The model estimates expected travelers and travels for each usage type: residential, work and shopping and calculates their annual mileage (i.e. length of all trips) through these steps: First, for each usage in the district, the expected number of “averagely mobile” users (“APu”, i.e. residents, workers, shoppers) are estimated based on census data of average floorspace per usage (Table II):

$$AP_u = A_u O_u^{-1} \tag{1}$$

TABLE II. MOBILITY CENSUS DATA [7]

Region	*Average MIM Mileage per Person (km/P/a)*	Destination			
		Residential	*Work*	*Education*	*Retail*
11	5 527	51%	19%	2%	28%
12	6 456	50%	17%	3%	31%
22	7 810	48%	23%	3%	27%
23	7 846	47%	22%	3%	27%
24	11 831	49%	25%	2%	24%
32	7 204	55%	18%	3%	25%
33	8 038	47%	25%	2%	26%
34	9 125	49%	22%	3%	26%
91	4 062	52%	21%	2%	25%
92	3 414	48%	18%	4%	30%
93	4 291	50%	17%	3%	29%
Average Floorspace per AP_u (m²/APu)		41.7	5.9	2.5	10.7
AP_U Simultaneity (s_u)		100%	80%	15%	100%

The associated annual total MIM Mileage driven to these destinations ("AMu") is selected from literature of annual mileage per location based on district location [7](as shown in Figure 2 and Table II):

$$\mathrm{AM_u} = \mathrm{AP_u} p_u M(region) \tag{2}$$

The annual total mileage per vehicle of each usage (AMVu) is then determined factoring in EV share of MIM, a factor based on mobility measures in the district reducing MIM mileage, and a simultaneity factor for the ratio of real people to APUs (mainly for education, as the annual statistical mileage of 100 APUs contain 5% trips to education which in reality are concentrated on just 15 real Students (i.e. 15% simultaneity of the base population), each making 30% of trips there.

$$\mathrm{AMV_u} = \mathrm{AM_u} s_u f_{mm} f_{EV} \tag{3}$$

B. How many EVs are at the district at each hour?

The expected total number of unique EVs originating and visiting the district is dependent on location specifics such as parking lot availability, the specific vehicle intensity must be provided as district input:

$$\mathrm{N_u} = v_u s_u f_{EV} \tag{4}$$

C. EV locations per hour: onsite or offsite

Vehicle location is tracked in aggregate, one for each usage types residential, work and retail. They represent the share of EVs currently onsite at the district, or offsite, i.e. driving or parked at other uses outside the district. Only onsite EVs may be bidirectionally charged, driving only happens with offsite EVs. The location of an average vehicle at any hour of the year is determined by weekly profiles from [8], given its relative probability of being onsite or offsite as shown in Figure 3. A vehicle is considered "present" at the district, if its location matches its originating usage, e.g. if an inhabitant's car is "at home" or a shopper's car is "at the shops". Otherwise, a vehicle associated with district usage u is considered "away" and cannot be charged/discharged at the district:

$$\mathrm{a_u(t)} = 1 - \mathrm{d_u(t)} \tag{5}$$

The total number of vehicles at the district $N_{d,u}$ or offsite $N_{a,u}$ is obtained by multiplying the above probabilities with the total EVu in the district. The share of vehicles of usage u **leaving from** or **returning to** the district at any given hour t is the difference of present vehicles between hours plus a time-depending exchange rate representing the fraction of onsite cars leaving just as others arrive:

$$\mathrm{l_u(t)} = \left(\mathrm{d_u(t)} - \big(1 + \mathrm{x(t)}\big)\mathrm{d_u(t+1)}\right)^{+} \tag{6}$$

$$\mathrm{r_u(t)} = \left(\big(1 + \mathrm{x(t)}\big)\mathrm{d_u(t+1)} - \mathrm{d_u(t)}\right)^{+} \tag{7}$$

For destinations with typically diurnal stays such as residential and work, the turnaround per hour is low (5-10%), but for retail and shopping it is high (75% to 100%) effectively decreasing the average shopping stay at the district to one or two hours. This does not account for vehicles leaving twice an hour, whose stay would be too short to have a significant impact on annual charging and discharging in the district.

All vehicles not at any location are considered in transit:

$$\mathrm{m(t)} = 1 - \textstyle\sum_{\mathrm{u}} \mathrm{d_u(t)} \tag{8}$$

D. Hourly Vehicle SoC changes

Vehicle battery state-of-charge (SoC) is also tracked in two aggregates per usage: (1) vehicles present at the district $\mathrm{N_{d,u}}$ and all vehicles currently away $\mathrm{N_{a,u}}$, their respective $\mathrm{SoC_{d,u}(t)}$ and $\mathrm{SoC_{a,u}(t)}$ are:

$$\mathrm{SoC_{d,u}(t)} = \varepsilon \mathrm{SoC_{d,u}(t-1)} + (\mathrm{E_{Cmin,u}} + \mathrm{E_{Cflex,u}} - \mathrm{E_{D,u}} + \mathrm{E_{r,u}} - \mathrm{E_{l,u}})\mathrm{c^{-1}N_{d,u}^{-1}} \tag{9}$$

$$\mathrm{SoC_{a,u}(t)} = \varepsilon \mathrm{SoC_{a,u}(t-1)} - (\mathrm{E_{S,u}} + \mathrm{E_{Cext,u}} - \mathrm{E_{r,u}} + \mathrm{E_{l,u}})\mathrm{c^{-1}N_{d,u}^{-1}} \tag{10}$$

With the following hourly changes: **(1) battery self-discharge** of all vehicles proportional to their current SoC, given by an hourly charge retention rate ε,

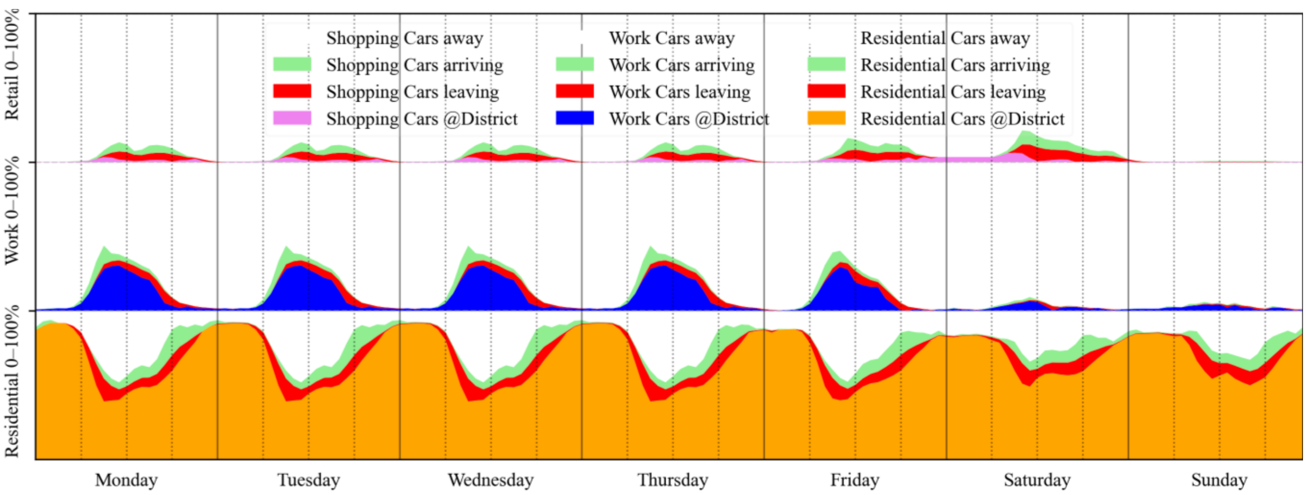

Figure 3: Onsite/Offsite Probability of vehicle of usage residential (orange, bottom), work (blue, middle) or retail/shopping (top, purple). Vehicles "leaving" (red) are considered onsite, switching to offsite at the end of the hour but can still be charged before, "returning" are offsite and arrive at the end of the current hour

(2) drive discharge, which is evenly distributed from the annual mileage assuming constant mileage per moving vehicle per hour:

$$E_{S,u}(t) = \eta AMV_u \frac{m(t)}{\sum_t m(t)} \tag{11}$$

(3) charging at the district is limited by the number of cars and charging stations onsite and the maximum charging power per EV and per charging station occurs in and occurs in two steps: (a) to reach the given minimum SoC per usage

$$E_{Cmin,u}(t) = \min\left(P_{infra}, cN_{d,u}(t)\min\left(P_{ev}, SoC_{min,u} - SoC_{d,u}(t-1)\right)\right) \tag{12}$$

Energy dispatch is used from these sources in order if available: local PV, local BESS, volatile offsite renewables and finally from the grid, as shown in the dispatch sequence in Figure 4. If additional local PV or offsite renewables are available, they are used to charge EV battery to full capacity, given the remaining power after charging to minimum SoC:

$$E_{Cflex,u}(t) = \min\left(P_{infra} - \sum_u E_{Cmin,u}, cN_{d,u}P_{ev,remaining}, cN_{d,u}\left(1 - SoC_{d,u}(t-1)\right)\right) \tag{13}$$

(4) discharging vehicles to the district occurs **only for residential usage**, and then **only** if (a) the $\mathbf{SoC_{d,res}}$ is greater than the given minimum SoC, (b) there is uncovered electricity demand in the district for user plug loads or HVAC operation:

$$E_D(t) = \min\left(E_{D,pot}, E_{ev>pl} + E_{ev>hvac}\right) \tag{14}$$

(5) External vehicle charging away from the district occurs if the average SoC of offsite EVs drops below a given point:

$$E_{Cext,u}(t) = cN_{a,u}\min\left(P_{EV}, \left(SoC_{min,ext} - SoC_{a,u}(t-1)\right)^{+}\right) \tag{15}$$

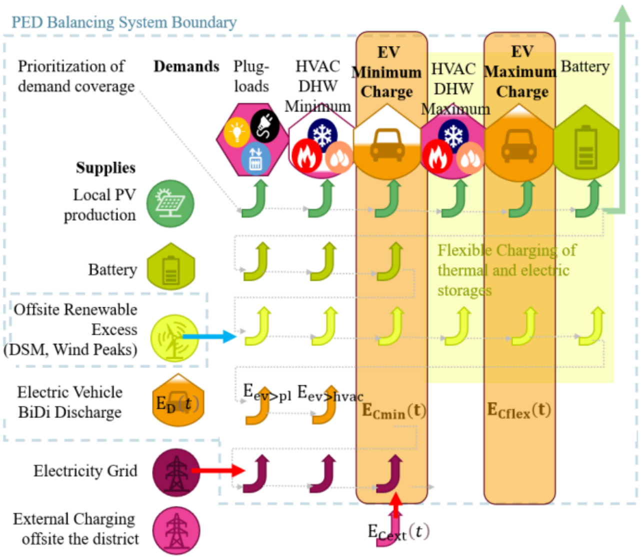

Figure 4: Energy dispatch sequence in the district.

(6) Change due to **SoC carried by the vehicles** leaving from (El) and returning (Cr) to the district, given as

$$E_{l,u}(t) = cN_d l_u SoC_{d,u}(t-1) \tag{16}$$

$$E_{r,u}(t) = cN_a r_u SoC_{a,u}(t-1) \tag{17}$$

E. Example Use Cases

Mobility energy flows are assessed for four different district usages of the same size: A group of ten single family detached houses, an office, a school and a supermarket. All example buildings feature similar HVAC systems with heat pumps and similar properties of modern buildings constructed to code (thermal hull, etc.), key model parameters are summarized in Table III.

TABLE III. EXAMPLE BUILDING PARAMETERS

Variable	10 SFHs	Office	School	Super-market
Net floor area (m²)	10x 240 =2 400	2 400	2 400	2 400
Unique visiting EVs	19	115	58	408
Vehicles per Area (1/100m²)	1	10	10	20
EV Share	100%	100%	30%	100%
Hourly EV Simultaneity	73%	10.1%	10.1%	3.4%
Min/Average /Max EVs per hour	9/14/18	0/12/40	0/5.8/58	0/14/49
Averagely mobile People	46	305	768	191
Annual EV Mileage (mio km)	0.44	2.97	0.9	1.74
PV (kWp) =100kWh/m²NFA	200	200	200	200
Flexible Grid use (up to x kW)	0	96	96	96

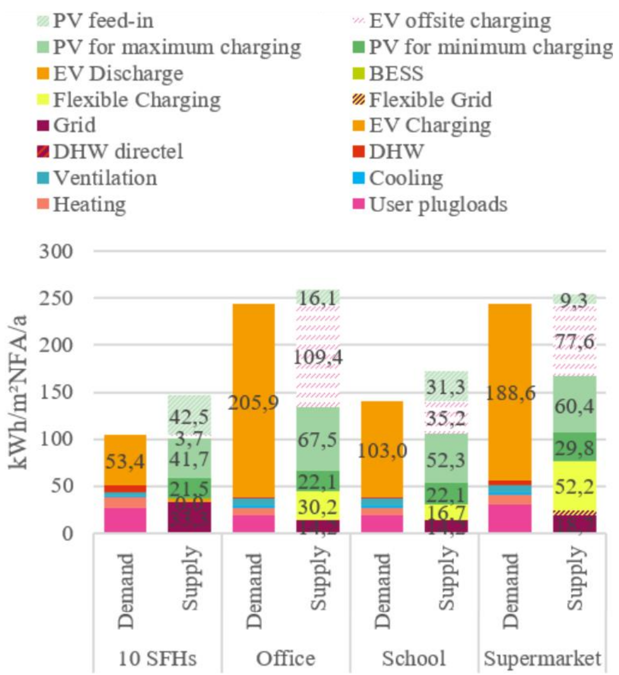

Figure 5: Annual electricity demand and supply for four 4 example usages (residential, work, education and retail)

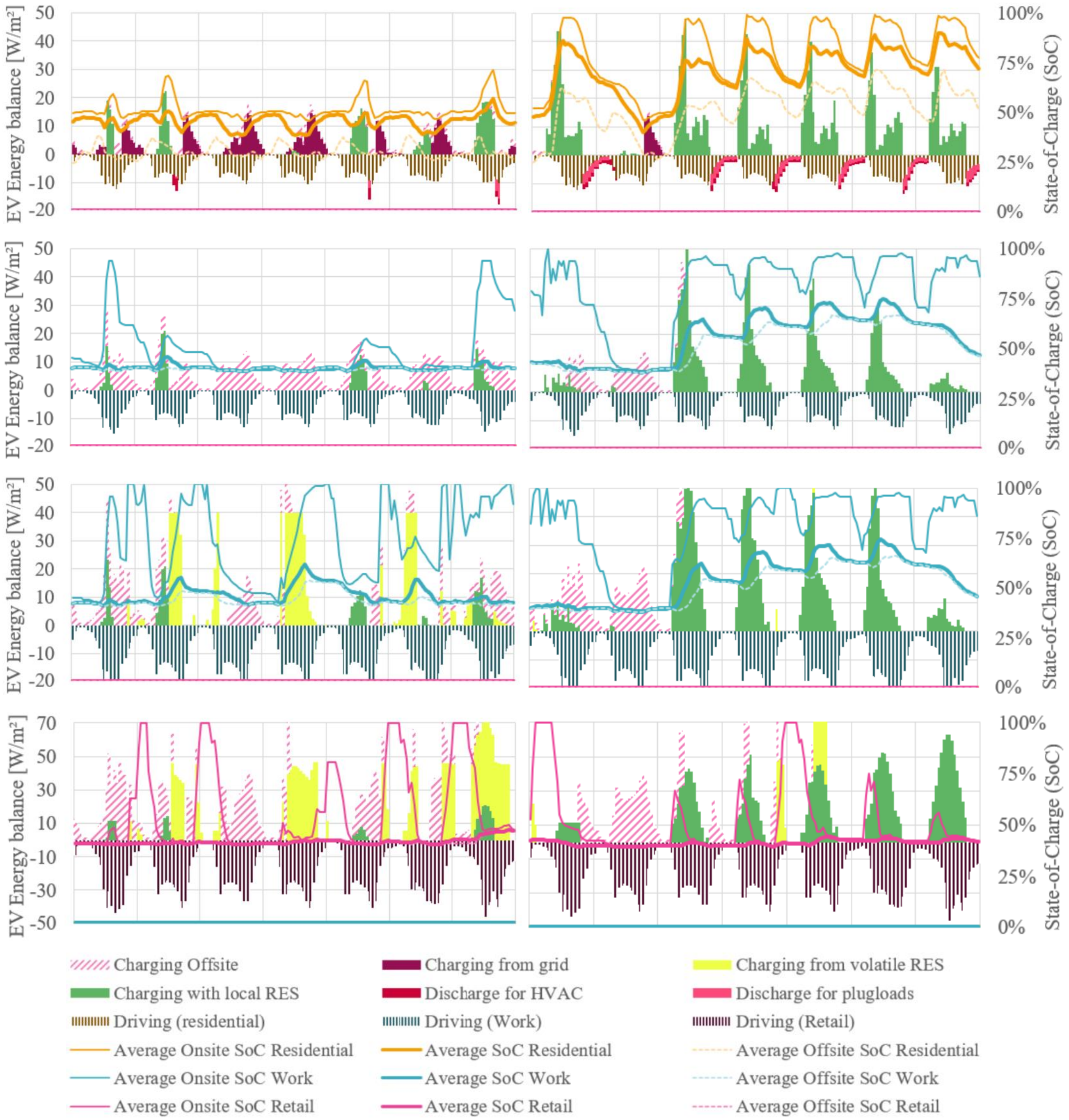

Figure 6 Hourly mobility energy balance (left axis) and EV SoC (right axis) for four example usages residential (top, orange), office (second, blue), school (second to last, blue), supermarket (bottom, pink) for a week in winter (28.January.-3.February., left) and summer (8.-15.July, left)

III. Results

Figure 5 shows the resulting electricity balance for the four example usages, highlighting the energy demand for EV mobility ranging from 53 to 205 kWh/m² to cover MIM through EVs, which occurs for residential almost exclusively onsite, 50% offsite for office and retail, and 34% for educational use which only has 30% EV share.

This annual energy balances shown in Figure 5 highlight the potential for EV MIM inclusion to enable larger economic PV integration by pushing PV self-utilization much higher than just for building operation: Residential self-utilization of 60% appears low but is actually very high for specific PV yields of 100 kWh/m²NFA, which dwarf typical installation sizes by a factor two to four. With 100% EV integration, the supermarket and office buildings support a PV installation 10 times the size required by the building code (1kWp per 100m² Gross Floor Area) with a self-utilization rate of 90%.

In this example, non-residential uses also feature flexible dispatch through hourly flexibility signals from volatile regional RES, which occur predominantly in the winter due to wind power peak events and enable an increase in use of charging infrastructure by 30% for office, and almost 50% for supermarkets uses. The limiting factor here is the fractional time of EVs spent onsite charging: Even though onsite RES are sufficient to fully charge onsite vehicles, they represent ever only a fraction of all EVs visiting the district, having little effect on their average SoCs.

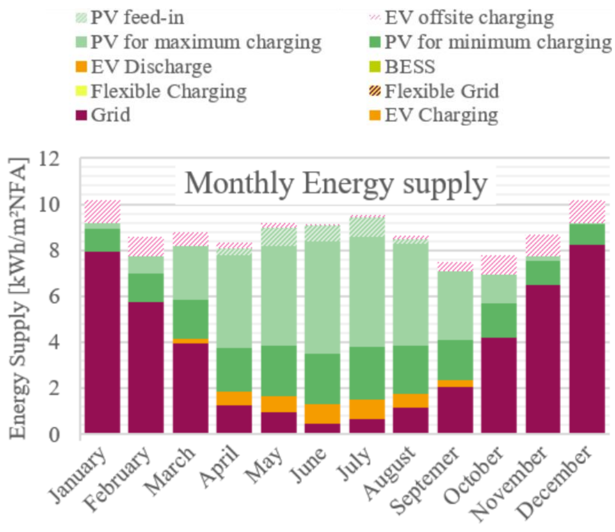

Figure 7: Monthly electricity supply for 10 Single family houses with bidirectional EV charging and 100 kWp PV system.

Using bi-directional charging for residential uses down to an average minimum SoC of 60% can reduce annual grid demand for heating and plug-loads by 28% from 29,3 to 21,3 kWh/m²NFA, at the cost of increasing annual full equivalent cycles (FEC) by 20% from 189 to 229 facilitating local utilization of large PV systems. This flexible discharge predominantly happens in the summer months after sunny days as can be seen in Figure 5 on the top right (in pink).

Figure 7 shows how the bidirectional EV integration into the same group of single-family houses with a smaller PV installation of 4 kWp per 100m² NFA (52kWh/m²NFAa) acts like a BESS, effectively increasing annual PV self-utilization from 37% without EV integration to 95% and reducing grid electricity demand in summer months to 5% of total electricity demand.

IV. Discussion and Conclusion

The method is very broad and has great uncertainties making it infeasible for concrete planning. In particular, the use of aggregate SoCs rather than tracking individual EV agents might oversimplify key constraints such as hourly charging potential based on actual SoCs. However, it delivers an effective method for quickly assessing bidirectional EV operation over a wide range of use cases and a multitude of effects:

- Influence of Location and mobility measures increasing or reducing overall mileage
- Effect of EV penetration and motorization
- Effects of charging infrastructure and if it can be expected to be under- or oversized
- Combination of BESS, EVs and DSM flexibilities.

This method is particularly interesting for non-residential and mixed usages, where the number of occupants and users is not well defined, do not align with typical residential vehicle use patterns and can vary greatly.

Modelling residential – and to a certain degree work related – mobility patterns is relatively straightforward due to immediate correspondence between floor area, vehicle usage and location. The same cannot be said for education and shopping-related mobility: Actual educational mobility patterns differ from statistical patterns, with only 15% of the population regularly visiting an educational facility, reducing the number of vehicles visiting accordingly. For shopping, the effect is reversed, as people travel to different shops during the week, the number of chargeable vehicles – and their corresponding charging potential – is significantly higher from the perspective of the shop location than just the average vehicles per shop. This is important for larger mixed-use districts, which typically curtail PV installation to self-consumption levels: Adding a supermarket to an energy community of low-density residential housing can increase the self-consumption of PV 70% to 85%.

V. Acknowledgements

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VI. References

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