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1 Estimating the spatiotemporal potential of self-consuming photovoltaic energy to 2 charge electric vehicles in rural and urban Nordic areas

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The penetration of electric vehicles (EVs) and photovoltaic (PV) systems has increased globally in the last decade. For planning purposes, the spatiotemporal variability of distributed PV power generation and EV charging needs to be quantified for urban and rural areas. This study introduces a state-of-the-art, open and generally applicable model framework for assessing the spatiotemporal mismatch between EV load and PV generation for urban or rural areas. The model is applied to a rural and an urban area, both 16 km × 16 km and located in Sweden, and is evaluated for the extreme months of January and July. Results show an energy deficit of at most 86% and up to ten times surplus took place in January and July, respectively. A high self-consumption (SC) of 77% was observed for January, and a high self-sufficiency (SS) of 69% for July. This is to say that during July, PV can fulfill 69% of the EV charging load. Moreover, there were no observed correlations between the PV-EV temporal matching scores (the SS and the SC) and the dominant type of charging, e.g., workplace charging in each grid cell (1 km × 1 km) of the areas. This can be partially attributed to the wide distribution of the rooftop orientations in both areas. This challenges the assumption of low PV-EV temporal matching in residential parts of the city. Applying the proposed methodology to other regions is incentivized.

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10 I. INTRODUCTION

11 A. Literature overview

12 Electric vehicles (EVs) have recently been promoted to increase sustainability in the trans-
13 portation sector¹. The carbon footprint of EVs can be further reduced if they are charged using
14 electricity from renewable energy sources (RES)². Photovoltaic (PV) panels provide a unique po-
15 tential to locally produce clean electricity to charge EVs. The suitability of PV — when compared
16 with other RES — lies in the fact that PV can be installed on rooftops close to where EV charging
17 is expected to take place³.

18 The electricity grid connects the electricity producers to the consumers. The more the produc-
19 tion and consumption match spatially and temporally, the lower the dependence on the electricity
20 grid is^{4,5}. This translates to lower grid investments^{4,5}. Additionally, the self-consumed electrical
21 energy can be cheaper than the retail price of electricity which further motivates increasing the
22 self-consumption (SC)⁵. High SC can also alleviate the grid costs and taxes from PV prosumers⁵.

23 The temporal matching between midday PV power production and EV non-residential charg-
24 ing motivated researchers as early as 1997 to investigate the potential for synergy between PV and
25 EVs⁶. Synergies between the two technologies were recently modeled on the scale of a few build-
26 ings^{7–11}, a residential neighborhood^{12,13}, a university microgrid¹⁴, a city^{15–18}, and on regional
27 and national scales^{19,20}. As regards the types of the buildings, residential buildings¹¹, workplace
28 buildings^{8,10}, a university⁹, and a hotel⁷ were simulated.

29 The results indicate that this synergy introduces benefits such as decreasing the curtailment of
30 PV²⁰, the dependency on the grid⁷, and the peak load¹². Furthermore, it increases SC — defined
31 as the ratio between the self-consumed electricity to the total produced electricity²¹ — of PV^{12,17},
32 the renewable energy ratio⁸, and the maximum possible penetration of both technologies²².

33 In addition to these benefits, some challenges have been identified, e.g., an increase in the
34 variability of the load of the households¹⁵, along with a regional¹⁹ and a seasonal¹⁶ mismatch
35 of the SC. Another important challenge is the need for smart charging and control strategies to
36 achieve some of these benefits^{7,8,12,23}. These strategies had numerous objectives such as increasing
37 the SC of PV^{8,12}, reducing grid losses²³, and achieving a net zero energy building (NZEB)⁷.

38 Regarding the spatial limitations, PV power production and EV electricity consumption cannot
39 be spatially matched if the EVs are parked away from the PV panels, e.g., residential PV cannot

40 directly charge the EVs at workplaces. To the best of the authors knowledge, only Cao⁸ proposed
41 to control the charging of the EVs even if they were parked far from the studied building. In
42 effect, the author created a virtual connection between the locations of the EVs and the studied
43 building, i.e, grid limitations were neglected. In contrast, Lazzeroni *et al.*²³ proposed to implement
44 a residential PV-EV synergy model, using smart charging, only on the EVs that are not strictly
45 used for work-home trips. Another potential solution to the spatial problem is to optimize the
46 orientation of the PV panels to match the local load profile^{9,24}; for instance, afternoon residential
47 EV charging can benefit from west oriented PV panels.

48 B. Contribution

49 From the previous summary a few research gaps have been identified. Firstly, there is a lack
50 of high-resolution spatiotemporal studies estimating the potential synergy between PV generation
51 and opportunistic, or non-smart, EV charging. Secondly, many studies have proposed smart charg-
52 ing schemes for EVs, which might not be realistic²⁵, nor accepted by the owners of the EVs — es-
53 pecially if it restricts their flexibility²⁶. This paper addresses these gaps by simulating the synergy
54 using 10-min resolution generation and charging data and presenting the results in a 1 km×1 km
55 spatial grid. Furthermore, this paper improves upon a recent study¹⁷ by adopting a more realistic
56 opportunistic charging profile which is based on geographical information system (GIS) data; and
57 goes further than two other recent studies^{16,19} by using higher spatial and temporal resolutions.
58 Thus, this study makes a more realistic and detailed analysis and provides a deeper understanding
59 of the synergy between the two technologies at the challenging high-latitude locations.

60 For this paper, the spatiotemporal power yield from rooftop PV and the opportunistic EV charg-
61 ing load were simulated for one urban and one rural area in Sweden using recently developed
62 state-of-the-art models. Two months were simulated, January and July, reflecting the seasonal
63 extremes in mismatch between PV electricity production and EV charging load in Sweden and
64 similar high latitude countries. The self-sufficiency (SS) and SC were calculated to evaluate the
65 temporal matching, and the results are presented in the paper. The SS represents the ratio between
66 the self-consumed electricity and the total EV charging load²¹. While the case studies focuses on
67 high latitudes, the methodology is applicable to any region, and the PV-EV synergy could thus be
68 investigated for different climates and traffic situations.

69 This paper is organized as follows. The proposed modeling method is described in Section II.

The results are presented in Section III. Finally, conclusions are drawn in Section IV.

II. METHODS

A. Study overview

In this study, three previously validated models were combined to investigate the PV-EV synergy potential: the first is the Bright model used to generate synthetic high resolution irradiance data (Section II B), the second is the PV model used to evaluate rooftop PV power production (Section II C), and the third is the EV model employed to estimate consumption in parking lots (Section II D). A diagram representing the models, the needed data, and the generated results is presented in Fig. 1.

FIG. 1. A diagram representing the employed models in purple, the data needed by the models in pink, and the generated data in blue.

In order to test the synergy potential, the authors selected two areas in Sweden. The areas were defined by a $16\text{ km} \times 16\text{ km}$ square enclosing a rural municipality and an urban city, respectively. The rural area was chosen in the proximity of the municipality of Herrljunga (N58.04, E13.02, $\approx 9'000$ inhabitants²⁷), while the urban area confined the city of Uppsala (N59.86, E17.64, $\approx 170'000$ inhabitants²⁸). The coordinates of the lower-left vertex for the rural and the urban areas are (N57.97, E12.92) and (N59.77, E17.51), respectively.

In this study, two months were simulated: January and July. The two months were chosen to reflect the two seasonal extremes of both the PV power generation and the electricity consumption of EVs in Sweden and similar high latitude countries. Furthermore, to present the results, we

88 divided each area into 1 km $\times$ 1 km squared grid cells, i.e., 256 in total, and the results were
89 presented for each grid cell. Presenting the results on a gridded format occurs frequently in RES-
90 related work^{29–32}.

91 **B. Bright model**

92 Irradiance data of high resolution (sub-hourly) with high spatial distribution are rare and there-
93 fore 10-min synthetic irradiance data were used in this paper. These data were stochastically gen-
94 erated using the Bright model^{33,34}, which was validated at Lerwick BSRN station (LER, 60.1389°
95 latitude, -1.1847° longitude) proving its suitability to high latitudes³⁴.

96 The model relies on historical local climatic data (pressure, wind speed, cloud height and
97 okta³⁵) to train Markov chains. These chains were then used to stochastically generate spatiotem-
98 porally correlated time series of global horizontal irradiance (GHI) and direct normal irradiance
99 (DNI) data for several neighboring locations. In this study, the locations were represented using
100 a 16 km $\times$ 16 km grid, equally spaced by 1 km. Due to limited access to all the required climatic
101 data, a weather station in Norrköping, Sweden (N58.59, E16.18), was used as the basis for the
102 data generation, being located between Uppsala (160 km) and Herrljunga (190 km).

103 **C. PV model**

104 The PV model, that computes the potential PV power generation on building envelopes, was
105 developed in Ref. 36 and cross-validated in Ref. 37.

106 The model essentially takes three types of input data to quantify the site-specific solar irradiance
107 on the building surface. These data are (i) light detection and ranging (LiDAR), which are used
108 to define the shape of the building roofs, but also to determine the shading of a building from
109 surrounding features, (ii) building footprints, which are used to mask the LiDAR data in order to
110 distinguish data points representing buildings from other data points, and finally (iii) GHI and DNI
111 from the Bright model.

112 LiDAR and building footprint data were provided by the Swedish Land Survey^{38,39}. The roof
113 shape of each building was determined by comparing a linear regression of the LiDAR data points
114 to a set of common roof archetypes³⁶. Due to the low resolution of the LiDAR data (0.5-1 pts/m²),
115 nearby buildings of similar shape were co-classed, i.e., data points were overlayed from two or

more buildings to increase the resolution and thereby increasing the chance of identifying the correct roof shape. Features that might shade a building and thereby reduce the incident solar irradiance, were represented as a triangulated irregular network (TIN), with zones of different resolution depending on the distance from the building under evaluation (see Ref. 36 for details). The building shapes and the LiDAR data were used to estimate the tilt and the orientation of the potential PV panel. The approximated rooftop area in the grid cells of the rural and urban areas are presented in Figs. 2a and 2d, respectively. The distributions of the orientations of the rooftops — weighted by the rooftop area — in both areas are presented in Figs. 2b and 2e. Note that the cross shapes of the distributions are due to the large number of Gable roofs, and similar triangular shaped roofs, in both areas.

Only rooftops with yearly insolation of 1000 kWh/m² or higher were considered suitable for PV installations. The underlying assumption is that the roofs with highest potential will be first populated by PV panels. The distributions of the orientations of the PV panels — weighted by the area of the panels — in the rural and urban areas are presented in Figs. 2c and 2f, respectively. The tilts of the PV panels ranged between 0°–80° in the rural area and between 0°–84° in the urban area.

D. EV model

The EV charging load was estimated using the EV model developed in Ref. 40. The model assumes that the charging profile in the publicly accessible parking lots depends on the nearby buildings. The same property map that was used to mask the LiDAR data was used³⁹, along with parking lot maps from Ref. 41. The assumption is that users of a parking lot visit the nearby buildings. The nearby buildings, here, were defined as the buildings within 100 m air-distance from the parking lot. An elaborate discussion regarding the air-distance is available in Ref. 40.

Three distinct charging profiles were assumed: Home, Work, and Other — similar to Ref. 42. The former two profiles represented the charging load of visitors of residential and workplace buildings, respectively. The *Other* profile represented the charging profile associated with shopping and leisure-activity buildings. Workplaces were considered to be buildings such as universities, schools, hospitals, industrial and governmental buildings. Residential buildings included only multi-story residential buildings, since single-family houses were assumed to have their own private parking spots. Finally, Other buildings represented buildings such as shopping malls and

FIG. 2. Approximated areas of the footprints of buildings in each grid cell, using the PV model in for (a) and (d). The area-weighted probability density function of the orientation of the rooftops in (b) and (e), and the PV panels in (c) and (f). The rural area is presented in (a)–(c) and the urban area in (d)–(f).

146 sport- and leisure-related buildings. Buildings with unspecified usage types were excluded from
147 the EV model. Figure 3 presents the ratio of the usage profiles estimated from the ground-floor
148 area of the buildings intersecting each grid cell. This figure shows the extent of concentration of
149 different usage profiles in each grid cell and in both areas.

150 As proposed in Ref. 40, the area of each parking lot was divided between the charging profiles.
151 The division was made proportional to the ground-floor area of the nearby building types; Home,
152 Work and Other⁴⁰. In other words, the parking lot was assumed to be proportionally used by the
153 users of the nearby buildings, and this proportionality was evaluated using the ground-floor area.
154 The usage of ground-floor area is motivated by the lack of information about the number of floors
155 of each building.

156 After estimating the usage profiles of the parking lots, a Markov model was used to simulate
157 the mobility of EVs between parking lots. Data from the Swedish mobility survey were used

FIG. 3. The percentage of the ground-floor area of the buildings belonging to each charging profile in each grid cell in the rural area in (a), and in the urban area in (b). The color legend is provided as a ternary plot in (c). White grid cells are grid cells that lacked buildings that contributed to the EV model, e.g., buildings with unspecified usage. Note that the center of this color triangle is gray in color with RGB code of (1/3, 1/3, 1/3), i.e., equal proportions of the three profiles.

to train the Markov chain⁴³. The specific electricity consumption of EVs was assumed to be 0.25 kWh/km during January and 0.15 kWh/km during July¹⁶. In addition, the EVs were assumed to have sufficiently large battery capacities to satisfy their charging demand, i.e., range limitations were not modeled. All the parking lots were assumed to contain a charging port with 6.9 kW charging power, i.e., 3-phase 10 A⁴⁴. The EVs were assumed to charge opportunistically upon arrival, i.e., smart charging was not considered in this paper. The parking capacity of each parking lot was estimated based on the area assumption of 28 m² per car — including the maneuvering lanes⁴⁰. To the best of the authors knowledge, there are no data regarding the number of cars per single-family house. Following the motivation in Ref. 40, each single-family house was assumed to have two EV chargers.

In total, 3'939 and 69'574 EVs were simulated for the rural and the urban areas, respectively⁴⁵. The results of the EV model were in minute resolution, which was then averaged to 10-min resolution to match the resolution of the modelled PV power generation.

171 E. Temporal matching metrics

172 The temporal matching between the PV power production P_t (kW) at each time-step t and the
173 EV power consumption E_t (kW) was evaluated using both the SS and SC. Both metrics were

174 evaluated using 10-min resolution data. The self-consumed power M_t (kW) can be calculated as²¹

$$175 \quad M_t = \min(P_t, E_t). \quad (1)$$

176 The SS (%) evaluates the ratio between the self-consumed power and the EV charging power²¹:

$$177 \quad SS = \frac{\int M_t dt}{\int E_t dt} \times 100. \quad (2)$$

178 The SC (%), on the other hand, evaluates the amount of self-consumed power as percentage of the
179 total PV power production²¹:

$$180 \quad SC = \frac{\int M_t dt}{\int P_t dt} \times 100. \quad (3)$$

181 A situation where both the SS and the SC are close to 100% is ideal, since $SS = 100\%$ implies that
182 the generated electricity fully and instantaneously supplies the EV charging load²¹. In addition,
183 $SC = 100\%$ indicates that there is no surplus production of PV, i.e., all the PV produced electricity
184 is instantaneously self-consumed²¹.

185 III. RESULTS

186 This chapter presents the main results of the study. In Section III A the aggregated results of
187 both the rural and urban areas are outlined, while Sections III B and III C explores the spatial and
188 temporal correlations between the PV power generation and the EV charging load, respectively.

189 A. Aggregate results

190 The results of the energy balance and the temporal matching metrics in both the urban and
191 rural settings are presented in Table I. The energy yield from PV was sufficient to supply the
192 energy needed for charging the EVs in both areas in July. In fact, there was a 4.59 and 40.26 GWh
193 surplus of PV yield in July in the rural and urban areas, respectively. In January there was a deficit
194 of 0.5 and 15.9 GWh in the rural and urban areas, respectively.

195 Figure 4 presents the the EV charging load during one winter and one summer weeks. The two
196 daily peaks — on weekdays — correspond to the profiles Work and Home, and are dependent on
197 the travel survey data as discussed in Ref. 40.

198 The SS was lower than 16% in January in both locations. On the other hand, in July, the SS
199 exceeded 60% in both locations.

FIG. 4. The EV charging load during a winter week and a summer week in the rural area in (a) and the urban area in (b).

The SC was at most 77% in the urban area in January. Hence, more than 23% of the PV yield could not be self-consumed to charge the EVs in either of the areas. Furthermore, the SC decreased from January to July by 38 percentage points and 64 percentage points in the rural and urban areas, respectively. This decrease can be explained by the large net production in July as compared with January when the charging load is more than the solar yield. It is important, nonetheless, to note that this study did not include the load in the buildings, which may either improve or worsen both the SC and the SS, depending on the season. The load of the buildings was not included in this study since these data are not publicly available.

The lower SC in the rural area compared with the urban area might be explained by the number of EVs per rooftop area. In the rural area, there were 41.9 EVs per hectare of approximated building area (see Section II C), while in the urban area there were 69.4 EVs per hectare, i.e., in the urban area there were more EVs per rooftop area.

TABLE I. Summary of the aggregate results for both areas in January and July.

	January				July			
	EV	PV	SS	SC	EV	PV	SS	SC
	(GWh)	(GWh)	(%)	(%)	(GWh)	(GWh)	(%)	(%)
Rural	0.77	0.27	16	44	0.45	5.04	69	6
Urban	18.43	2.53	11	77	10.62	50.88	60	13

212 B. Spatial matching

213 For the spatial analysis, each area was divided into 1 km×1 km square grid cells. The areas
214 contained 256 grid squares each. In contrast, Litjens *et al.*¹⁷ presented the spatial results by
215 dividing their study area into neighborhoods, and Li *et al.*²⁹ presented their EV charging results
216 on a 8.9 km×8.9 km grid.

217 The PV energy yield in each grid cell in both areas and months is presented in Figs. 5a, 5d, 5g
218 and 5j. In the rural area, if excluding grid cells with no generation, the median production was
219 0.4 and 7.3 MWh in January and July, respectively. The production was concentrated in populated
220 areas. In fact, 8 grid cells (from 176 grid cells with PV production) contributed with nearly half,
221 50% in January and 51% in July, of the PV generation in the whole area.

222 In the urban area, the median production from the producing grid cells was 2 and 37 MWh for
223 January and July, respectively. Nearly half, 50% January and 49% in July, of the PV generation in
224 the whole area was generated in only 19 grid cells. In the urban area, there were 220 grid cells with
225 PV production. Since the urban area is more evenly populated, see Fig. 2d, the generation is also
226 more evenly distributed than in the rural area. In the urban area, however, the highest producing
227 grid cells in January were not the highest producing grid cells in July. This is likely due to the
228 seasonal variation of shading patterns specific to the urban area.

229 The electricity consumption of the EVs in both areas is dependent on the locations of the
230 parking lots and the detached houses — where private chargers can be installed in the grid. The
231 spatial EV load in the grid in both areas is presented in Figs. 5b, 5e, 5h and 5k. In the rural area,
232 around half, 52%, of the electricity consumption in the whole area in both January and July took
233 place in only 7 grid cells from the 182 grid cells with EV load.

234 In the urban area, half of the electricity consumption took place in 25 grid cells from the 222
235 grid cells with EV load. This shows that in the urban area the charging was more spatially dis-
236 tributed. On the other hand, in the rural area the concentration of workplaces, shopping and leisure
237 locations in a few grid cells resulted in a more concentrated charging demand.

238 As shown in Table I, the net energy yield in both areas was negative in January and positive
239 in July. This pattern was not maintained on the spatial level; few grid cells violated it, as shown
240 in Figs. 5c, 5f, 5i and 5l. These grid cells had low net positive or negative yields when compared
241 with the largest cell in the area. At most the absolute net yield value in the exception grid cell
242 represented 12% of that in the largest grid cell in the area in the respective months. This was the

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FIG. 5. The PV energy yield is presented in (a), (d), (g), and (j); the electricity consumption of the EVs is presented in (b), (e), (h), and (k); and the net energy yield is presented in (c), (f), (i), and (l). The rural area is presented in (a)–(f), and in the urban area is presented in (g)–(l). January is presented in (a)–(c) and (g)–(i); and July is presented in (d)–(f) and (j)–(l). White grid cells are grid cells without consumption or generation. Please note the different scales of the colorbars.

case in the rural area in January, where the largest cell with net positive yield represented only 12% of the deficit in the cell with the highest net deficit.

C. Temporal matching

As stated in the introduction, spatial matching — or net positive yield — does not imply temporal matching. Consequently, two metrics were evaluated, the SS and the SC, spatially presented in Figs. 6 to 9. Both metrics are formally defined in Section II E.

As shown in Figs. 6a, 7a, 8a and 9a, the SS was low in January and high in July in both areas. In contrast, the SC was high in January and low in July in both areas, as depicted in Figs. 6c, 7c, 8c and 9c. During January, days in Sweden are short (≈ 7 h), and the afternoon EV charging cannot be covered by the predominant midday PV power production. On the other hand, the long days of July result in a better matching between generation and charging.

As shown before in Table I, the SS scores were higher in the rural area than in the urban area, and the opposite was true for the SC scores. On the spatial level, these patterns were not clearly observed. For example, the median SS scores were 1% and 48% in the rural area during January and July, respectively. The same scores in the urban area were 1% and 52%.

As regards the SC, it was observed that the the median score in the rural area was small and it increased from 4% in January to 5% in July. On the other hand in the urban grid, the median score decreased from 11% in January to 7% in July.

The SS and SC equations are not associative (see Eqs. 1 to 3). This explains the lack of consistent patterns regarding the SC and SS on the grid cell resolution as compared with the whole area. To further clarify this, assume an area with 100% SS and SC scores. Assume that this area consists of only two grid cells. In one grid cell, EV load exists yet no PV yield exists; while on the other grid cell, PV yield exists yet no EV load exists. Even though in the whole area the SC and SS scores equal 100% both grid cells have SS and SC scores equal 0%.

In order to depict the relations between the temporal matching and the building types in each grid cell, Figs. 6b, 6d, 7b, 7d, 8b, 8d, 9b and 9d are presented. The figures depict ternary plots between both the SS and the SC, and the percentage of the ground-floor area of buildings belonging to each charging type in each grid cell. The three charging profiles assumed here are Work, Home, and Other representing charging at workplace, residential, and shopping/leisure locations, respectively.

FIG. 6. The SS, in (a) and (b), and the SC in (c) and (d) in the rural area in January. Ternary plots for (a) and (c) are presented in (b) and (d), respectively. The ternary plots depict the relation between the SS/SC and the percentage of buildings belonging to each charging profile in the grid cells, presented in Fig. 3.

273 The ternary plots show that neither the SS nor the SC were strongly correlated with the housing
 274 types in the grid cells. These results were unexpected as grid cells dominated by residential houses
 275 (late afternoon charging) were expected to have lower SC compared with grids dominated by
 276 workplaces (midday charging).

277 Two explanations can be proposed for these surprising results. Firstly, the majority of the
 278 grid cells are dominated by residential buildings (see the red colored grid cells in Fig. 3). These

FIG. 7. The SS, in (a) and (b), and the SC in (c) and (d) in the rural area in July. Ternary plots for (a) and (c) are presented in (b) and (d), respectively. The ternary plots depict the relation between the SS/SC and the percentage of buildings belonging to each charging profile in the grid cells, presented in Fig. 3.

grid cells might, nonetheless, have disproportionately large — when compared to the ground-floor areas of buildings in the grid cell — parking lots that are connected to workplaces or leisure buildings, and the EV charging load in these parking lots are affecting the SS and SC results in the grid cell. In other words, the PV yield in residential buildings might be consumed by the EVs charging in the large parking lot of a workplace, for example, in the same grid cell.

As an example for this first explanation, a cell from the urban area was chosen. This cell

FIG. 8. The SS, in (a) and (b), and the SC in (c) and (d) in the urban area in January. Ternary plots for (a) and (c) are presented in (b) and (d), respectively. The ternary plots depict the relation between the SS/SC and the percentage of buildings belonging to each charging profile in the grid cells, presented in Fig. 3.

has (x,y) indices of (2,8) measured from the lower left corner, and had an SC score of 96.1% in January. The distribution of the building footprint areas — as shown in Fig. 3b — was (92.0%, 2.6%, 5.4%) for the profiles (Home, Work, Other), i.e., predominantly residential area. However, due to the existence of large parking lots belonging to the profiles Work and Other, the distribution of the charging ports belonging to the respective profiles in this cell was (43.4%, 46.7%, 9.9%).

The second explanation can be attributed to the orientation of the roofs and the shading patterns

FIG. 9. The SS, in (a) and (b), and the SC in (c) and (d) in the urban area in July. Ternary plots for (a) and (c) are presented in (b) and (d), respectively. The ternary plots depict the relation between the SS/SC and the percentage of buildings belonging to each charging profile in the grid cells, presented in Fig. 3.

in the grid cells. The orientation of the roofs in the grid cells might — due to the nature of the surrounding natural barriers and landscape — result in an afternoon PV power production in residential areas, see e.g., Refs. 24 and 46. This afternoon production can temporally match afternoon EV charging in residential areas. Similarly, the orientation of the roofs in workplace areas will also impact the temporal matching with the morning EV charging in workplace areas. In fact, Miceli and Viola⁹ proposed installing an east oriented PV panel to charge EVs in a university

297 campus. The distribution of the orientation of the roofs and PV panels — weighted using the
 298 areas — in both studied areas is presented in Figs. 2b, 2c, 2e and 2f. The figures depict a broad
 299 distribution for the orientations of the roofs and PV panels in both areas.

300 To further elaborate on the impact of PV orientations on the temporal matching scores, another
 301 cell was chosen from the urban area. This cell has (x,y) indices of (11,4) measured from the lower
 302 left corner, and had an SC score of 89.4% in January. The distribution of the building footprint
 303 areas — as shown in Fig. 3b — was (96.3%, 3.7%, 0.0%) for the profiles (Home, Work, Other), i.e.,
 304 predominantly residential and no buildings belonged to the profile Other. Unlike the previously
 305 discussed example cell, the distribution of the charging ports belonging to the respective profiles
 306 in this cell was (96.2%, 3.8% 0.0%) which closely reflected the buildings. However, unlike the
 307 previous example cell, there were westwards PV panels in this grid cell, see Fig. 10.

308 The estimate of the contribution of each explanation on the correlation between the temporal
 309 matching scores, i.e., the SC and the SS, and the building types in the grid cells is beyond the
 310 scope of this paper. This contribution might vary from city to city based on the landscape and
 311 natural barriers. Thus, it can better be left for dedicated future studies.

FIG. 10. The area-weighted probability density function of the orientation of the installed PV panels in the
 cells with (x,y) indices (2,8) in (a), and (11,4) in (b) in the urban area. The indices of the cells are measured
 from the lower left corner of the area.

314 IV. CONCLUSION

315 This work evaluates the spatiotemporal mismatch between PV power generation and EV charg-
316 ing in two Nordic areas, one urban and one rural. Two months were simulated representing the
317 two seasonal extremes in Sweden and similar high latitude countries.

318 The aggregate results indicated that in both areas there was a PV-EV energy deficit in January
319 and an energy surplus in July. The deficit amounted to 65% and 86% of the EV load in January in
320 the rural and urban areas, respectively. The surplus, on the other hand, equalled 10 and 4 times the
321 EV charging load in the rural and urban areas, respectively, in July.

322 Regarding the temporal matching between the PV power generation and the EV charging, it
323 was found that the SC was high in January ($SC \leq 77\%$), and lower in July ($SC \leq 13\%$). The July
324 results mean that most of the PV power, more than 87%, was not instantaneously consumed by the
325 EVs in July. That being said, the SS was as high as 69% in July. In January, however, the SS was
326 as low as 11%.

327 Even though there were energy surplus in July, at most 69% of the EV charging load could be
328 supplied by the PV yield, i.e., temporally matched.

329 It was also found that there were no observable correlations between the type of buildings in
330 the grid cell ($1\text{ km} \times 1\text{ km}$ square) and either the SC nor the SS. Grid cells dominated by residential
331 buildings did not necessarily have low SC.

332 As a result, grid operators should not take a low SC of PV to charge EVs in city zones domi-
333 nated by residential buildings for granted. The rooftop orientations in the city and the existence of
334 workplaces close to residential buildings can affect the spatiotemporal mismatch between the PV
335 power production and the EV charging. In addition, strategically located battery storage systems
336 and smart charging can be employed to improve this mismatch. This is, however, left for future
337 studies to explore.

338 To summarize, this provisional investigation demonstrates that the scenario of an all EV fleet
339 more than 60% supplied by PV is very plausible at high latitudes during summer, however it will
340 need additional electricity generation during winter months.

341 Future works can investigate the impact of choosing sub-optimal roofs, i.e., roofs with insola-
342 tion $< 1000\text{ kWh/m}^2$, on the temporal matching scores. On the one hand, the SC might decrease
343 due to the increase in the surplus; but on the other hand, the SC might increase due to improved
344 load matching when installing more PV with east/west orientations. The SS can either increase or

345 remain constant when installing more PV.

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353 AUTHOR CONTRIBUTIONS

354 M.S. developed the EV model and conducted the analysis of the results. D.L. developed the
355 PV model and simulated the PV power generation. M.S. and D.L. co-wrote the manuscript. J.W.
356 participated in the study design and edited the manuscript. J.M.B. developed the Bright model and
357 edited the manuscript. J.M. participated in the study design and edited the manuscript.

358 DATA AVAILABILITY STATEMENT

359 The data that support the findings of this study are available from the corresponding author
360 upon reasonable request.

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