Modelling City Scale Spatio-temporal Solar Energy Generation and Electric Vehicle Charging Load

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Abstract—**This study presents a model for estimating building-applied photovoltaic (PV) energy yield and electric vehicle (EV) charging temporally over time and spatially on a city scale. The model enables transient assessment of the synergy between EV and PV, thus is called the EV-PV Synergy Model. Spatio-temporal data on solar irradiance is used in combination with Light Detection and Ranging (LiDAR) data to generate realistic spatio-temporal solar power generation profiles. The spatio-temporal EV charging profiles are produced with a stochastic Markov chain model trained on a large Swedish data set of travel patterns combined with OpenStreetMap (OSM) for deterministically identifying parking spaces in cities.**

The modelled estimates of solar power generation and EV charging are combined to determine the magnitude and correlation between PV power generation and EV charging over time on city scale for Uppsala, Sweden. Two months (January and July) were simulated to represent Sweden's climate extremes. The EV penetration level was assumed to be 100% and all the roofs with yearly irradiation higher than 1000 kWh/m^2 were assumed to have PV panels.

The results showed that, even in January with the lowest solar power generation and maximum EV load, there can be a positive net-generation (defined as the integration of PV generation minus EV charging load over time) in some locations within the city. Central locations exhibited a positive temporal correlation between EV charging load and PV generation. Negative temporal correlations were observed in the outskirts of the city, where typically night time home-charging was prevalent. In the highest PV power generation month (July) the solar generation was 16 times higher than the EV charging load. Spatially, the net-generation was positive in almost the entire city. However, the time-series correlation between the EV charging load and the PV generation reached more extreme positive and negative values in comparison with January. This was a result of the higher variability in irradiance during July in comparison with January. In summary, we find that there is a favorable synergy of EV-PV technology within the city center with assumptions of workplace charging behaviors for both winter and summer months. An unfavorable synergy with suburban areas where typically nighttime charging behaviors negatively correlate to PV generation. This suggests that distributed PV should be targeted around city center/workplace EV charging stations.

I. Introduction

The number of plug-in electric vehicles (EVs) increases rapidly around the world; the rate of uptake is expected to continue increasing over the coming years [1]. EV charging affects the performance, efficiency, and required capacity of the grid, particularly when uncontrolled [2]. Therefore, estimations of charging patterns over time and space are important for grid and charging infrastructure design [3]. Simultaneously, there is an expansion in the installed capacity of grid-connected distributed photovoltaic (PV) power generation alongside increasing EV uptake [4]. Grid-connected PV is widely reported to cause detrimental impacts to conventional grid infrastructure due to irradiance, and subsequently PV power, variability [5]–[7]. The use of PV power generation for EV charging demand is widely stated as a potential solution [8]–[10]. However, the synergistic alignment of EV demand and PV supply may vary significantly across a city. This alignment is expressed in terms the spatial correlation, e.g., for residential and commercial districts, and in terms of the temporal alignment, e.g., EV charging overnight and PV generation through the day. This PV-EV synergy needs to be further investigated [3], [11].

There is a great abundance of models for EV charging and PV power generation in the literature, while combinations are more scarce [3]. Models combining EV charging and PV power generation include models for single locations [12], [13], but also on aggregate or city-scale [10], [11], [14]–[19] and even regional or country scale, see e.g., [20], [21]. These studies generally point to matching challenges between EV charging and PV power generation.

Particularly interesting are the high resolution spatio-temporal studies. Ko et al. [16] used Geographic Information System (GIS) and Light Detection and Ranging (LiDAR) data to estimate the PV power generation and the vehicle energy use—including EVs—for the city of San Francisco, USA. In the study, the spatial net-demand, in kWh/capita, of isolate districts were presented in relation to population density. The net-demand was shown to be negative for all population densities if internal combustion engine vehicles (ICEVs) were used. This is to say that for all population densities the ICEVs consume more energy per capita than the PV yield per capita. However, if EVs replaced ICEVs the net-demand was shown to be positive for all population densities.

Byrd et al. [17] developed a model using "meshblocks" to quantify PV power generation and combined it with EV charging load on city scale from central business districts to suburbs; it was applied to the city of Auckland, New Zealand. The study indicated that there is a surplus of PV electricity, even when used for EV charging and to offset household electricity use during daytime with the assumption of current travel patterns.

PV power generation profiles as used in EV-PV synergy models are typically sampled from a library of stored profiles, produced from probabilistic models (e.g., [15]), or applied the same to all sites with the assumption that there is full correlation across a city (e.g., [16], [17]). These PV power profile generation methodologies typically ignore the geographic smoothing effect [22] and natural spatial decorrelation [7] of solar irradiance in the temporal and spatial domains, which are fundamental to a EV-PV synergy analyses. Thus, realistic test scenarios of PV power profiles interacting with EV charging loads are absent from the literature.

Overall, there is a need to combine stochastic spatio-temporal models for EV charging and PV power generation on city scale, in particular to identify local weak points in spatial networks as stated by the literature [3].

This study presents a model that combines spatio-temporal modelling of solar energy on rooftops based on LiDAR data with a Markov chain model of EV charging distributed on available parking spaces, determined from OpenStreetMap (OSM). The presented model is general and geographically unrestricted, but applied in this study to Uppsala, Sweden. The aims are to (1) improve the state-of-the-art spatio-temporal modelling of EV charging and PV power generation on city scale, (2) develop a geographically-flexible model capable of analysing PV-EV synergy, which (3) includes the best available solar irradiance methodology that incorporates realistic geographic smoothing in the spatial dimension to facilitate realistic city-scale case study applications.

The paper is structured as follows: In Section II the methodology of the study is outlined, including the EV charging model and PV model.

In this paper, we refer to the 'EV-PV Synergy Model' as a catchall term for the full model presented in this paper. We use the terms 'EV Model' and 'PV Model' to distinguish between each major component of the EV-PV Synergy Model. The EV Model has two parts: a deterministic component described in Section II-A, and a stochastic component described in Section II-B. The PV model is presented in Section II-C. In Section III the conditions for the case study are presented. Section IV presents the results of the study and in Section V a concluding discussion is made.

II. EV-PV Synergy Model Methodology

A. Spatial EV charging stations

The EV Model's deterministic component is based on the extraction of parking lot locations and their neighboring buildings from GIS maps. Parking lots here means publicly accessible parking lots.

In a large city, drivers are assumed to park close to their destinations [23], [24], thus, the parking behavior at parking lots is assumed to be influenced by the nearby building types, e.g., early morning commuter arrival at parking lots close to workplaces. In this paper, buildings from GIS maps, are categorized into three categories: workplaces, residential, and other. Next, three corresponding parking behaviors are assigned: Work, Home, and Other, respectively. These three parking profiles were previously observed in [25], [26].

Nearby buildings are defined as buildings that are located within a buffer zone surrounding the parking lot. This buffer zone represents the maximum walking distance from the parking lot to the visited buildings. The buffer zone can be understood as the air-distance surrounding the borders of the parking lot such that this air-distance represents the maximum walking distance, see previous usage in e.g., [27]. In other words, buildings intersecting this buffer zone are assumed to be visited by the people parking in the parking lot. The authors assumed that all these buildings are equally visited by the users of the parking lot. The parking lot is then assumed to have a corresponding parking behavior to the building classifications of buildings intersecting the buffer zone. If multiple building categories are close to a parking lot, the parking lot is assumed to have a directly proportional mixture of parking behaviors reflecting the close building categories [28]. For example, if both workplace and residential buildings are located within the buffer zone of a parking lot, the parking lot is assumed to have a mixture profile of Work-Home. This is to say that this parking lot is used by visitors of both workplace and residential buildings. The ratio of unique charging profiles found within a parking lot is assumed to be directly proportional to the ratio of nearby building categories, defined in terms of ground floor area.

B. Markov chain EV charging model

The EV Model has a stochastic component that produces spatio-temporal charging profiles. A non-homogeneous first order Markov chain is used to model the spatio-temporal mobility of EVs in the city. A Markov chain $\{Y_t\}_{t=0}^{\infty}$ is a memoryless process in time t where the probability of the next state Y_{t+1} depends only on the current state Y_t, the transitional probability is discreet and is derived from an observational dataset [29]:

$$P(Y_{t+1}|Y_t, ..., Y_1, Y_0) = P(Y_{t+1}|Y_t). \tag{1}$$

The Markov chain can be characterized by the transition matrix T:

$$T = \begin{pmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{pmatrix}, \tag{2}$$

where p_{ij} is the probability of changing from state i to state j where both belong to the state space $\{1, 2, 3\}$. In our model, the Markov states represent the three parking profiles {Home, Work, Other}.

The previously defined Markov chain is a homogeneous Markov chain, whose transition probabilities are time-independent. In the problem of modelling the spatial mobility of cars in a city, the transition probabilities between states are expected to depend on the transition time, e.g., early morning and late evening mobility patterns are not equal [30], [31]. Consequently, in the proposed model a non-homogeneous Markov chain is defined such that the transition probabilities depend on the time of transition δ, i.e., $T(\delta)$. The time of transition, δ, reflects the minute during the day when transition occurs (1440 minutes) and whether the day is a weekday or a weekend (2 cases). In other words, 2,880 transition matrices are used to model the spatio-temporal mobility of EVs.

EVs are assumed to move between parking lots. In each time-step, the Markov chain model estimates the parking state of each EV. If an EV changes its parking state, a new parking location is sampled from the set of parking lots belonging to the same state as the new state of the EV. This assumption means that the same EV would likely park at different place each time it transitioned to home. The impact is accepted at this stage of scoping the EV-PV Synergy Model and development of more sophisticated charging station locations is reserved for future work.

The depleted battery capacity E (kWh) of the EV i can be defined as

$$E_t^i = \begin{cases} E_{t-1}^i + C_i^n \Delta t, & \text{if charging at station } n \\ E_{t-1}^i + d\eta, & \text{if driving} \\ E_{t-1}^i, & \text{else} \end{cases} \tag{3}$$

where the C_i^n is the charging power (kW) in station n, d is the driving distance (km), and η is the specific consumption of the EV (kWh/km) [32].

The total energy demand at each parking lot n at time t is then defined for I number of EVs currently charging as

$$E_t^n = \sum_{i=1}^{I} C_i^n. \tag{4}$$

C. PV model

The PV Model also h as two main features. Firstly, there is a PV location potential model that decides where PV installations could occur. Secondly, irradiance is derived inclusive of meteorology and simulated at each location then converted to power.

The model used here to simulate the PV power generation on rooftops is described in [33] and validated in [34]. In short it takes building footprints to mask LiDAR data, which is used to determine the roof topology of each building in the studied area. Since LiDAR data of relatively low resolution (0.5-1 pts/m^2) are available for almost all of Sweden [35], the model was developed with a co-classing routine, initially proposed in [36], in which LiDAR data from similar buildings of a neighborhood are blended in order to increase the resolution. Thereby the chance of finding the correct roof shape was shown to improve [33], [36]. Next, the solar irradiance on the roof surfaces is computed, considering shading from surrounding objects, such as trees and other buildings, represented in the same LiDAR dataset. PV modules are then placed virtually on parts of the roofs that have an annual irradiation exceeding a user-defined threshold. In this study this threshold was set to 1000 kWh/m^2,yr, for which the installation of PV can be motivated financially in a Swedish context [37]. Finally the PV power is computed in a simplistic manner as

$$P_{\mathrm{PV}} = G_t \eta_{\mathrm{PV}} \eta_{\mathrm{con}} (1 - L_{\mathrm{obs}}), \tag{5}$$

where G_{t} is the global irradiance on the tilted plane (i.e., the roof), $\eta_{\mathrm{PV}} = 20\%$ is the Pv module efficiency, $\eta_{\mathrm{con}} = 95\%$ is the conversion efficiency and $L_{\mathrm{obs}} = 20\%$ is a conservatively assumed reduction of the roof area, identified as good for PV, due to obstacles such as bay windows and chimneys [38]. Therefore, we have a realistic estimate of the PV potential for the city of Uppsala, Sweden.

The solar irradiance required for this study require high spatial resolution due to the high PV distribution from the LiDAR PV potential model. Furthermore, the fluctuations in EV charging happen on high temporal resolutions, and so irradiance data must have at least 10 min resolution. Such spatially distributed and high temporal resolution data are not available for Uppsala, nor are they regularly available freely around the world. As an aim of this paper is to develop a geographically flexible EV-PV Synergy Model, synthetic irradiance data must be used.

There are very few synthetic solar irradiance generators that have a spatial dimension to capture the geographic smoothing and naturally decorrelating relationship of solar irradiance [22]. Options exist to produce spatial synthetic profiles derived from an input irradiance time series [39], however, high resolution irradiance data inputs does not satisfy data availability for a generally applicable model. One option enables synthetic data production that mimic the fluctuation in solar irradiance over time and across a city using the Bright Solar Model, described in [7], [40]–[42].

It takes historical data on cloud base height, cloud index (or Okta numbers), pressure and wind speed (at 10 m above ground) to train seasonal, pressure dependent and diurnal Markov chains that can reproduce stochastic time series of the atmospheric conditions for a single geography that represents the meteorology of a wider area (estimated up to 20km radius). Cloud fields are produced defined by the cloud speed, direction and cloud index that are then moved across the spatial domain to produce a binary clear or cloudy time series for each location within the study, thus capturing spatial decorrelation and geographic smoothing. From binary cloud cover, the transmission of the sky can be determined from distinct statistical distributions of the clear-sky index to the cloud index [43]. A synthetic global irradiance time-series is then derived from a clear-sky model linearly reduced by the clear-sky index. Finally, the global irradiance is decomposed into its subcomponents. Hence, the irradiance profiles of different locations of the city are not identical, but still correlated to some extent. Without this spatial decorrelation, grid impacts can be overestimated [7].

III. Case study

The city of Uppsala, Sweden, was chosen for a case study. Uppsala is a medium sized city with 156,000 inhabitants. Building footprint data of around 50,000 buildings were extracted from the Swedish land survey maps [44]. However, these data lack information about the parking lots. Consequently, the parking lot data were obtained from OSM [45]. The city was divided into grid cells of 1×1 km. The total building footprint area for each grid cell and locations of parking lots (blue) are presented in Fig. 1.

For the deterministic component of the EV Model, buildings such as workplaces, universities, schools, industrial and governmental buildings were assumed to belong to the Workplace category. Buildings that are cultural or sport related

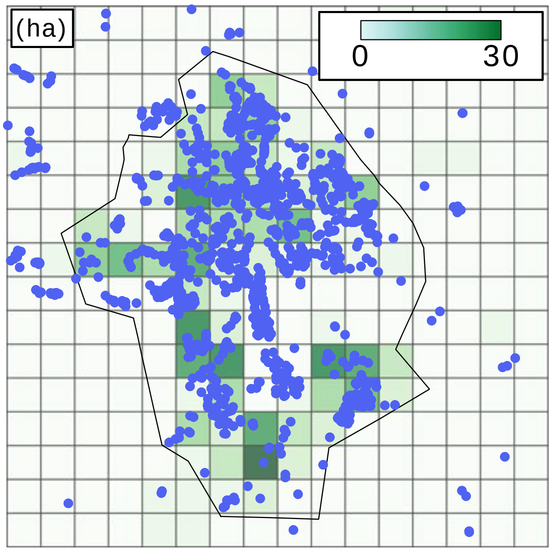

Fig. 1. Total building footprint area, in hectare (ha), for each grid cell (1 × 1 km) across the city of Uppsala, Sweden. The blue dots represents parking lots.

and the unspecified buildings were assumed to belong to the Other building category. The maximum walking distance, buffer distance, was assumed to be 100 m [46]. Charging was assumed to take place upon parking regardless of the parking location, i.e., spatio-temporally opportunistic. Residences were assumed to have 2 parking spaces, and each of these spaces was assumed to have an EV charger. The parking lots—obtained from OSM—were assumed to have parking spaces based on the parking lot's area, and each of these spaces was assumed to have an EV charger. The authors assumed that the area needed to park a car in a parking lot to be 28 m^2/car including the maneuvering lanes, see the parking lot design examples in [47]. All EV chargers were assumed to have a 3.7 kW capacity. In total, we simulated 44,192 EVs representing a 100% EV penetration case.

For the stochastic component of the EV Model, the Swedish mobility survey data record trip distances, departure/arrival times, and departure/arrival locations [48]. These data were used to train the Markov chains, i.e. to learn the transition matrix $T(\delta)$. The training process is described in detail in [49]. In addition, the distances d were sampled from the survey distances for the recorded trips between similar origin/destination parking locations. Trip distances longer than 200 km, 0.44% of the recorded trips, were excluded from this study as the authors assumed that theses long trips will need fast highway chargers and will not charge in the city. Two months were simulated, a winter and a summer month (January and July). The EV consumption η was assumed to be 0.25 kWh/km as a worst case scenario for January and 0.15 kWh/km for July, see [50]. The change in the EV specific consumption mainly reflects the need for heating during winter [50]. The battery capacity of the EVs was assumed to be large enough to satisfy the drivers' daily needs. This assumption was motivated by the short average daily driving distance in Sweden of 22 km/day [51], and by the findings in [52] where the authors showed that the current range of EVs can satisfy 80% of the daily needs of Swedish and German drivers.

For the PV Model, atmospheric data from Norrköping, Sweden, since not all necessary data existed for Uppsala. However, this was considered to be of minor concern since irradiance data would in either case be synthetic yet representative of the meteorology of Uppsala, just as the data from the EV model are. The Bright Solar Model then produces synthetic, spatially decorrelated irradiance time series for each location in the study, which is then translated to PV power according to Eq. 5. LiDAR data from the Swedish land survey were used [35] to create the 2.5D representation of the buildings and to analyze shading on the roof surfaces [53]. 2.5D here refers to the inability of the LiDAR survey method to capture overhangs, such as carports, which would be needed for a full 3D representation. As with the EV load, two months of corresponding PV generation were also generated (January and July). The EV-PV Synergy Model is then complete.

IV. Results

It is important to point out that this model is transient, in that the total EV load and PV generation are calculated for each time step, and not as an overall difference, such that

$$E^{\mathrm{net}} = \int_{t=1}^{T} (E_n^{\mathrm{PV}} - E_n^{\mathrm{EV}})dt, \tag{6}$$

where E_n^{PV} is the PV power generation at site n, E_n^{PV} is the EV charging at site n. T is the minutes of simulation within the month selected. Hence, E_n^{net} represents transient analysis.

Fig. 2 presents the main results from this study, i.e., the EV charging load, the PV electricity generation and the net-generation (PV minus EV) for January and July, respectively. The simulations resulted in a total EV load of 7.1 GWh and 4.2 GWh in the city in January and July, respectively. For the same months, January and July, the PV generation amounted to 6.3 GWh and 67 GWh in the city. At most, the yearly charging load of EVs can reach an approximated 85.2 GWh (7.1 GWh×12), and the yearly PV generation can be approximated to be 394.1 GWh (by assuming that July represents 17% of the yearly solar irradiation, as it was for the Norrköping data described Section III). For comparison, the annual load in 2016 for the city of Uppsala was 953 GWh [54].

As shown in Fig. 2, the spatial load of EVs has a similar spatial distribution as the distribution of the parking lots in the city presented before in Fig. 1. Moreover, the difference between the winter load and the summer load of EVs relates only to the energy consumed during the month, since the mobility patterns of EVs were not assumed to vary seasonally and only the EV specific consumption η (kWh/km) was.

The PV Model simulation resulted in a total installed capacity of 420 MW$_\mathrm{p}$, which may be compared to the local goal of reaching 100 MW$_\mathrm{p}$ by 2030 within the municipality (i.e., including the rural areas surrounding Uppsala that are not part of this study) [55]. The total PV generated electricity for January and July, respectively, are presented in the center column of Fig. 2. Naturally for these high latitudes, the electricity yield is much higher in the summer compared with

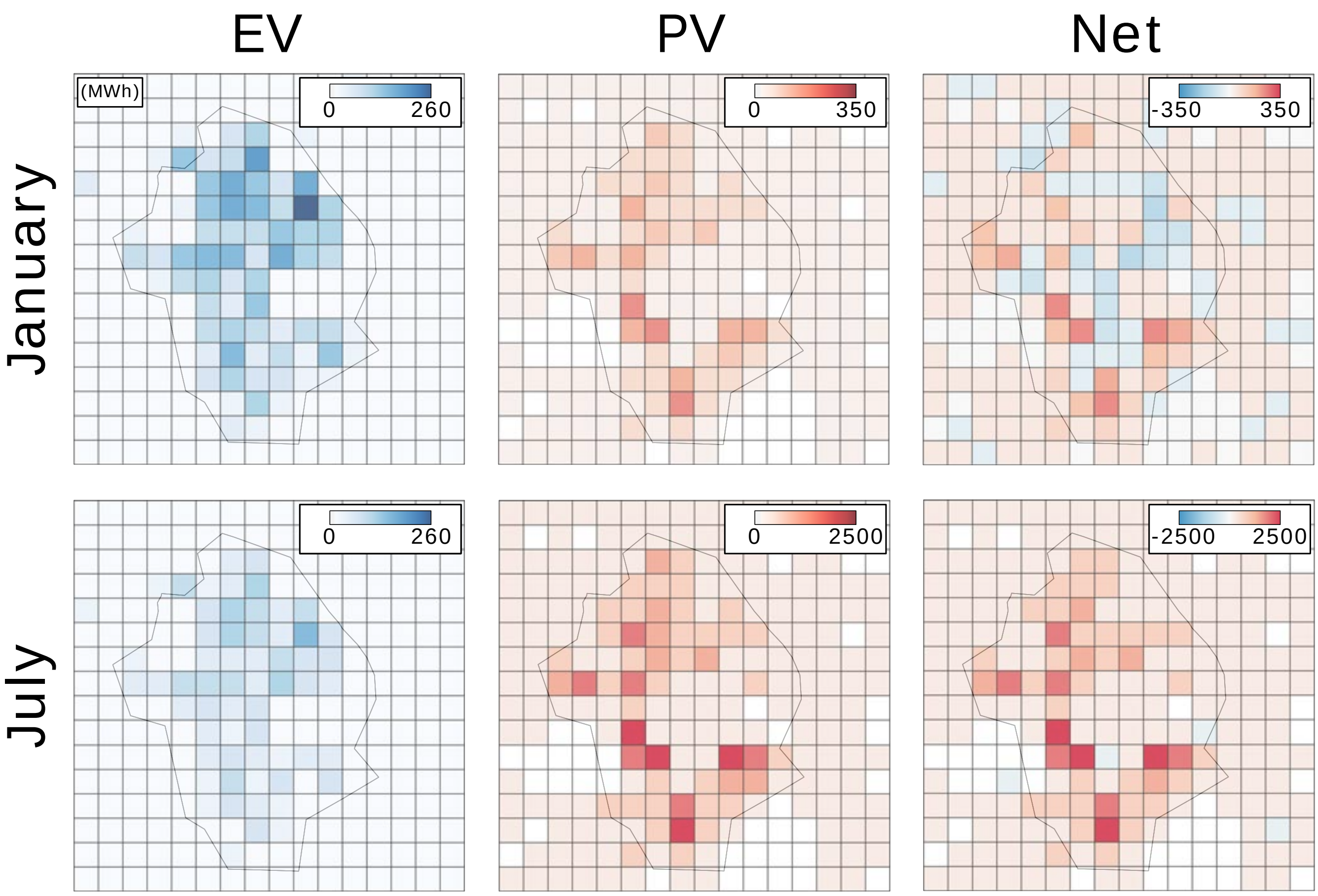

Fig. 2. Total monthly EV charging load (EV), PV electricity generation (PV) and net load (see 6) for January and July, respectively, presented in a 1×1 km resolution grid across Uppsala, Sweden. All values are presented in MWh. Note the difference in scale between the subfigures.

the winter, leading to an over-production; see the different scales for the results of the winter and the summer months.

The bias of the EV load towards winter, and the bias of the PV production towards summer is more obvious in the net-generation. During January, the net-generation was negative in many (predominantly residential) grid cells in Fig. 2. Home charging demanded more energy than Work and Other charging because the travel survey trips ending at residential locations had a longer driving distances. Moreover, there is small number of Work charging events on weekends. On the other hand, the summer month provided a positive net-generation in all the grid cells, where buildings and parking lots exist, as illustrated in the bottom right subplot of Fig. 2. We have not explored whether this excess power is usable in building demand. What it does show, however, is that EV charging has good synergy with PV generation.

In Fig. 3 the correlation between the EV and the PV time-series in each grid cell are presented. It is clear that the correlation tend to be positive near the city center, and negative in the outskirts for both months. This is due to the poor matching between home-charging and PV power generation, which has been reported in previous studies [10], [56]. Comparing January (Fig. 3a) and July (Fig. 3b) one can see that the correlation is more extreme in July, in terms of both positive and negative correlation, which has to do with more extreme fluctuations in the irradiance during the summer.

V. Concluding discussion

In this paper, the authors presented a spatio-temporal model to evaluate the synergy of both the charging load due to electric vehicles (EVs) in cities and the photovoltaic (PV) generation in cities. This was achieved through the development of the EV-PV Synergy Model — a hybrid of an EV Model and PV model.

The EV Model uses GIS data to deterministically extract information about the locations and sizes of parking lots. This information is used to stochastically estimate the charging load in the charging stations located in these parking lots as EVs move between Home, Work or Other throughout the day. The PV Model uses a spatio-temporal solar irradiance generator combined with using LiDAR data that evaluates the potential of PV locations within the domain. This is decided by roof topology and shading of buildings. Combining these results in PV yield from the building roofs in the city. The EV-PV Synergy Model then performs transient analysis of EV load and PV generation imbalance around the city.

A case study was made on the city of Uppsala, Sweden, a city with approximately 50,000 buildings and 44,000 cars. We simulated two months (January and July) representing climatic extremes of the winter and the summer seasons. The case study assumed a 100% EV penetration and a charging power of 3.7 kW. As regards PV, the roofs with yearly irradiation higher than 1000 kWh/m^2 were assumed to have PV panels.

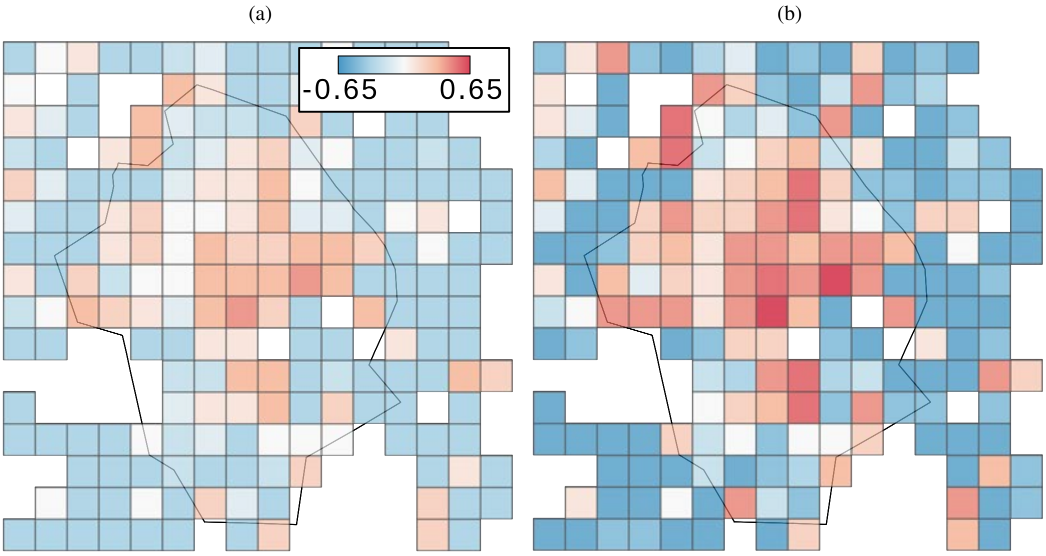

Fig. 3. Correlation between EV charging and PV power generation time-series (10 min) for (a) January and (b) July, respectively.

The results show, as expected, that the charging load of EVs is highest during winter, and that the PV generation is highest during summer. Even though the PV power production in January was approximately 10% of that of July, the net generation calculated as the total imbalance of EV demand minus PV generation at each minute of simulation resulted in excess generation in January for some parts of the city. In July, the net generation was positive for almost all the parts of the city including the residential parts.

The results also showed higher—positive—time-series correlations between the EV charging load and the PV generation in the city center than in the outskirts. This was expected as workplace charging occurs during daytime when PV generation is prevalent and workplace charging is the dominant type of charging in the city center.

Overall, the annual EV charging load was estimated to be approximately 85 GWh, and the annual PV generation was estimated to be 400 GWh. In comparison, the annual energy use in Uppsala municipality was estimated to be 953 GWh in 2016 [54].

We have demonstrated high synergy between EV and PV, such that we believe that rapid uptake in both technologies will be mutually beneficial. However, to fully understand the impact of a high penetration scenario for both EVs and PV on city scale, one would need to study the local power grid, e.g. by performing parallel transient power-flow simulations in which corresponding building load, EV charging load and PV power generation would be included together. This would enable researchers to assess what the impact of said EV-PV scenario would have on the electricity grid. However, without any further information on the power system infrastructure, this is not possible. Regardless, the method presented demonstrates an interesting synergy between two technologies experiencing rapid uptake. We can still offer insight to urban planners and utilities on what parts of the city that can be expected to experience the most extreme, both positive and negative, net power demand in a future power system.

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