

# Modeling of photovoltaic power generation and electric vehicles charging on city-scale: A review

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## Abstract

Photovoltaics (PV) and electric vehicles (EVs) are promising technologies for increasing energy efficiency and the share of renewable energy sources in power and transport systems. As regards the deployment, use and system integration of these technologies, spatio-temporal modeling of PV power production and EV charging is of importance for several purposes such as urban planning and power grid design and operation. There is an abundance of studies and reviews on modeling of PV power production and EV charging available in the literature. However, there is a lack of studies that review the opportunities for combined modeling of the power consumption and production associated with these technologies. This paper aims to fill this research gap by presenting a review of previous research regarding modeling of spatio-temporal PV power production and charging load of EVs. The paper provides a summary of previous work in both fields and the combination of the fields. Finally, research gaps that need to be further explored are identified.

This survey revealed some research gaps that need to be further addressed. Improving the accuracy of PV power production ramp-rate modeling in addition to quantifying the aggregate clear-sky index on city-scale are two priorities for the PV potential studies. For the EV charging load models, differences in model assumptions, such as charging locations, charging powers and charging profiles, need to be studied more extensively. Moreover, there is an imminent need for metering the load of charging stations. This is essential in developing accurate models and time series forecasting techniques. For studies exploring both the PV and EV impacts, local weak points in a spatial network need to be discovered, especially for the city-scale studies. Cooperation between eminent researchers in the PV and EV fields might propagate state-of-the-art models from the separate fields to the combined studies.

*Keywords:* Photovoltaics power production models, Electric vehicle charging models.

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## List of Abbreviations

<i>BEV</i>	Battery electric vehicle.	<i>HP</i>	Heat pump.
<i>BOS</i>	Balance of system.	<i>ICEV</i>	Internal combustion engine vehicle.
<i>CC</i>	Constant current.	<i>IEA</i>	International Energy Agency.
<i>CHP</i>	Combined heat power plant.	<i>LiDAR</i>	Light detection and ranging.
<i>CV</i>	Constant voltage.	<i>NREL</i>	National Renewable Energy Laboratory.
<i>DOD</i>	Depth of discharge.	<i>PHEV</i>	Plug-in hybrid electric vehicle.
<i>DSO</i>	Distribution system operator.	<i>PV</i>	Photovoltaics.
<i>EV</i>	Electric vehicle.	<i>RMSE</i>	Root mean square error.
<i>EVI</i>	Electric vehicles initiative.	<i>SOC</i>	State of charge.
<i>GHG</i>	Green house gases.	<i>TOU</i>	Time of use.
<i>GIS</i>	Geographical information system.	<i>V2G</i>	Vehicle to grid.
<i>HEV</i>	Hybrid electric vehicle.		

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## 1. Introduction

Since electricity generation and transportation accounted for 60% of all energy use in the world in 2013, renewable energy sources for electricity generation and electrification of transport provide a great potential for reducing fossil fuel use [1, 2]. In an ambitious set of targets the European Commission has setup a policy framework for 2030 which includes 40% reduced CO<sub>2</sub> emissions compared with the 1990 level [3]. This implies reducing energy use, increasing energy efficiency and increasing the percentage of energy demand met by renewable energy sources.

While electrification of transport presents a great possibility for reducing CO<sub>2</sub> emissions [4], a renewable energy source of the electrification, such as photovoltaics (PV) power production, presents an even stronger case [5]. This, however, is contingent on the use of plug-in vehicles. The number of electric or hybrid vehicles has risen rapidly in the world, with over 565,000 plug-in cars sold globally 2011-2015 [6]. In the year 2016, the global sales of plug-in cars exceeded 750,000 vehicles [7]. Electric vehicles (EVs) is a term applied to hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and battery electric vehicles (BEVs) [8]. In this paper, EVs refer only to PHEVs and BEVs.

As an example, a target of 20 million EVs and fuel cell vehicles, on the road was set by the Electric vehicle initiative (EVI) to be achieved in 2020 [9]. This target is expected to be surpassed if the 78% growth rate achieved in the year 2015 was maintained [10]. However in the year 2016, the annual growth rate of EV sales has fallen below 50% for the first time since 2010, and the annual growth rate of publicly available charging has increased by 72% [11]. The Electric and plug-in hybrid roadmap aims that EVs represent 50% of the sales of vehicles worldwide by 2050 [12]. This is to say that the current research is investigating penetration levels of EVs that are expected to take place within decades, which is likely going to affect the

household electricity consumption patterns. This change will make the current studies inaccurate in their representation of the grid load. Thus, continuous updating of modeling parameters is needed to cope with changing external factors.

Alongside the electrification of transport, the share of renewable energy has risen as well. In particular PV power capacity grew by 50 percent — or 75 GW — during 2016 [13, p.4], and a cumulative 303 GW was installed globally as of 2016 [13, p.7]. The growth of PV power production in the world is mainly due to falling prices on PV panels, balance of system (BOS), and installation costs, largely due to increases in production volume, and governmental subsidies [14, 15]. The price for PV systems have been more than halved from 2007–2015 [15]. However, in mature markets the PV power production installation rate rapidly decreased and the total installed capacity appears to stagnate below 10 percent of the installed electricity generation capacity [14, p.15]. Still, for these capacities, PV power production has potentially adverse effects on the local electricity grid, such as over-voltage and even component failure [16]. For these situations local self-consumption of PV power can reduce the risk of adverse effects by reducing the electricity that is fed into the grid. In this case there is potential for using PV power to charge EVs [2, 17–20].

Type of EV charging, as well as location and time of charging affects the synergy potential of combining PV power production and EV charging, where controlled charging generally has higher potential than uncontrolled charging [18]. Uncontrolled charging is here defined as opportunistic, as opposed to controlled charging, which can be based on some scheme. Estimates of opportunistic EV home-charging suggest that home-charging occurs mostly during late evening (from about 6 p.m.) and night-time [17, 21]. When combined with PV power production that is an increased self-consumption [17], but that it generates a larger mismatch overall [5, 17]. It should also be emphasized that the match between PV power production and EV charging is higher when aggregates of charging stations and PV power systems are considered [22]. It should also be mentioned that local battery storage can also improve this matching [23].

Multiple businesses in the electricity sector — like grid operators, power plants, electricity traders, and large consumers — rely heavily on accurate load models [24–27]. Even for city planning purposes and for design and operation of urban electricity distribution grids, models of future dispersed PV power production and EV charging patterns are important for, e.g., matching variability in PV supply and improving local self-consumption of PV production in EV charging [2, 16, 28–30]. Models that combine a realistic spatial distribution over a city or parts of a city with high time resolution are necessary for detailed system integration studies. However, there is a lack of data for EV charging on the city-scale [31], and the literature is even more scarce on the combination of EV charging and PV power production in cities. At the same time, recent research on solar irradiance has provided advances in modeling of dispersed and correlated high-resolution irradiance over small spatial scales, and there is an abundance of EV models that address different important aspects, including time-scales and driving patterns [2, 32]. There should be opportunities for a combined modeling approach based on existing models. A first step towards this is to map the current state-of-the-art in the PV and EV modeling fields.

The aim of this review paper is therefore to provide an overview of the fields of EV charging and PV power production modeling on city-scales to identify the main research and development gaps and the opportunities for combining modeling approaches for the two technologies. The paper provides a summary of previous work in both fields and the combination of the fields — which was not performed as extensively before — and identifies gaps that need to be further explored in future research. Reviewing time series forecasting techniques is beyond the scope of this paper because of the following reasons: (1) time series forecasting techniques for PV power production were reviewed before in [33, 34], and (2) EV charging load forecasting papers are scarce. This is a result of the scarcity of metered data measured at charging stations [31, 35]. Among Ref. [35–37] who developed forecasting techniques for EV charging load, only [36] used recorded load data. Ref. [35, 37] relied solely on exogenous variables — such as ambient temperature, traffic data, and driving behaviors — in their forecasting technique.

The authors read and analyzed previous research contributions in addition to the important former advancements in both fields individually and combined. The aim is to highlight the previous research results along with the currently unanswered questions so that forthcoming studies explore the open questions and avert the formerly explored ones.

The paper is structured as follows. Section 2 reviews recent advances in solar irradiance and PV power

production modeling that allow city-scale spatio-temporal models of dispersed PV systems to be developed. Section 3 reviews EV charging models, with a broad overview of available models and a special focus on controlled charging, which is generally believed to be necessary for a smooth integration into the existing infrastructure. Section 4 reviews the existing studies and models of combined EV charging and PV power production. Finally a concluding discussion, pointing out gaps in knowledge, data and model capabilities, is given in Section 5.

## 2. City-scale modeling of PV power generation

For modeling the power output from a large number of PV systems spatially distributed over time in a city, three main parts need to be included: (1) the solar irradiance distributed over the systems, taking varying cloudiness into account, (2) a method for identifying and efficiently representing a large number of building areas on which PV systems are mounted, and (3) suitable models for conversion of irradiance components between horizontal and tilted planes and for PV system output. In the following sections we summarize current state-of-the-art and common practice in these areas.

This section contains spatio-temporal modeling of solar irradiance, and excludes forecasting, since that is outside the scope of this paper. For overviews of solar irradiance and solar power forecasting, see, e.g., Ref. [33, 34].

### 2.1. Spatio-temporal solar irradiance modeling

Broadly speaking, a spatio-temporal model of solar irradiance describes how the irradiance simultaneously varies over both space and time. The output is typically irradiance time series [38], probability distributions for instantaneous irradiance [39] or some measure of variability [38] for a number of dispersed sites [38] or aggregated over a geographical area [40, 41]. Input data are typically meteorological parameters that characterize the weather at a certain location, either very generalized, such as the daily clear-sky index [39], or more detailed cloud cover parameters [39].

As many studies over the last years have shown, temporal variability of the solar irradiance over a set of sites can be considerably smoother than at a point location, with higher dispersion leading to lower total variability (for overviews, see e.g. Ref. [42, 43]). This is because cloudiness varies over dispersed sites, making high-resolution irradiance time series measured at different sites more or less correlated or uncorrelated depending on the distance between them. Knowledge about this distance-smoothing effect stems both from dense solar radiation networks [44–48] and from monitored PV plants [49–52] and is similar in character to that of other weather-dependent renewables, such as wind and wave power [43]. Common practice for solar irradiance is to study and model the clear-sky index, which is the ratio between global solar radiation and the corresponding clear-sky radiation, and essentially describes the non-systematic variability (cloudiness variability) in the solar irradiance.

Spatio-temporal irradiance models are often built around a correlation model. This is the case for the so-called wavelet variability model [41], in which a single-site time series is smoothed out to represent the profile of a set of distributed sites or a large PV plant. A correlation model also makes up the backbone of a recent analytical model for the irradiance variability continuously distributed over an area [53] and in several solar forecasting approaches [54–56]. Correlations between sites in terms of solar irradiance over short distances and high time resolutions were first studied and modeled in Ref. [47, 57–59]. Exponential decay models are the ones most commonly used to describe how the correlations depend on the distance between sites [42, 60], although there are indications that logarithmic modeling could be more accurate [53].

An important distinction to make is between isotropic and anisotropic correlation models. In the former, the correlation is assumed to be independent of the direction of cloud movement, while in the latter it depends on the cloud or wind direction. For ramp-rate correlations, empirical measurements have shown that the correlations are highly anisotropic for along-wind station pairs and cross-wind station pairs [48]. Anisotropic correlation models have subsequently been proposed [61, 62] and should be preferred for realistic spatio-temporal models.

A promising way to describe spatially distributed high-resolution solar irradiance is through probabilistic modeling. Early investigations of the clear-sky index at individual sites showed that it was bimodal or, at

least, that it displayed asymmetry with respect to the mean value [63–71]. Characterizations of probability distributions have since improved from daily and hourly resolution [72–75] to minutely or near-instantaneous resolution [76–79], and probability distribution models have been developed for characterizing the clear-sky index. Examples of distribution families for representing the clear-sky index include single Gamma [74], single Boltzmann [73], Bi-exponential [80], double Normal [78, 81], double Beta [82], double Boltzmann [79], Logistic combined with Weibull [83] and recently triple Normal [84]. Also a convolution-type model has been developed [85]. No clear preference for a single distribution family is indicated by the literature, which motivates further comparative studies.

Spatially correlated probability distributions can be modeled via a joint distribution function called a copula [86]. This methodology has been used for modeling of dispersed wind power plants [87], but has a yet largely unrealized potential of contributing to spatio-temporal solar irradiance modeling. Initial studies on using copula to model solar irradiance suggest that it can be used on city-scale [88], and possibly even regional scale, at least if applied to PV power generation [89].

## 2.2. Modeling of available building areas and PV systems

To go from spatially modeled clear-sky index to a full model of distributed PV systems within a city a number of steps are typically involved. First, to model sites for building-applied PV systems we must be able to identify available building areas. Second, clear-sky index data at these sites need to be converted to solar irradiance, for which a clear-sky irradiance model is required. Third, we must be able to convert solar irradiance on the horizontal plane to the tilted plane of the building-applied PV system. Finally, a PV model must be used to convert in-plane solar irradiance to PV power output. State-of-the art modeling within each of these steps is summarized below.

Methods for assessing areas available on buildings for PV systems were reviewed in Ref. [90], which divided methods into constant-value methods (using high-level statistics to make rough estimates in regions), manual selection methods (based on manual identification of rooftops from aerial photographs) and geographical information system (GIS)-based methods (applying algorithms to GIS-based building data for automatic detection of suitable areas). For spatio-temporal PV system modeling on city-scale, the last set of methods is clearly the most relevant. Most existing studies using the latter method have been used for determining the annual energy potential [91, 92], but there have been attempts at GIS-based spatio-temporal modeling with higher temporal resolution [93]. For studies of widespread PV dispersion in cities, there are recently developed methods that automatically construct low-complexity polygon models of buildings from light detection and ranging (LiDAR)-data [94–96].

For determining global radiation on building surfaces from clear-sky index data, several detailed and advanced clear-sky models are available. Models that estimate the solar irradiance in cloud-free skies for any time and location on Earth exist, such as the state-of-the-art models McClear [97] (for a thorough review see [98]) and National Renewable Energy Laboratory’s (NREL’s) Bird Clear-Sky Model [99]. These are fully physical models, including advanced atmospheric and radiative transfer models. For a survey of different models and model types see [100]. In general, the error of simpler models tends to vary over time more than that of more advanced models, even though the simpler models are only slightly less accurate than the more advanced ones given the same conditions [101]. Among the models compared in Ref. [101], the most accurate model, which was an advanced model, achieved a root mean square error (RMSE) of 4.7% while one of the simpler models achieved a RMSE of 6.3%.

For converting incident solar irradiance from the horizontal plane to the tilted plane, both the diffuse and beam components must be available. Since only global irradiance can be obtained by combining global clear sky irradiance with the clear-sky index, global radiation must first be split into beam and diffuse radiation. Several methods are available for this [102], with the Erbs model being commonly used due to its simplicity combined with a good performance [103]. Different models also exist for converting diffuse radiation to the tilted plane [104, 105]. Two of the most commonly used ones, both with good performance, are the Hay model [106] and the Perez model [107].

The last step in city-scale PV modeling is the model of the PV systems. Several PV performance models are available [108], with varying degrees of complexity. For city-scale modeling, it is reasonable to aim for

a less complex model which still reproduces the essential features of PV modules, such as [109, 110], and a reasonably simplified model of inverters, such as in [111].

The most common type of PV installation is grid-connected [15], which constitutes distributed generation of PV power production in the electricity distribution grid [16]. There are two main challenges with intermittent distributed generation: on the one hand, there is an increased need for power system balancing to keep the system frequency within limits; and on the other, the local distribution grid may experience new, reversed, power flows, voltage rise and component overloading [16]. Several studies explored PV impacts on the electricity grid [112–116]. Ref. [117] studied the approaches followed by several countries aiming to improve PV integration in the grid. The challenge for distributed generation thus regards the limits of the distribution grid. The term, ‘hosting capacity’ can be used to define the amount of distributed generation power for which the grid performance becomes unacceptable [118]. There are a number of possible ways to increase the hosting capacity though such as altering tap changer settings, curtailment, reactive power control and self-consumption [23, 118].

### 3. Modeling of EV charging load

The current research on EVs charging is based on the outcomes of the research in the previous century. Since 1913 benefits of off-peak charging have been perceived [119]. These benefits were further explored in Ref. [120]. Some models were based on mechanical estimation of the specific consumption (kWh/km) of the EVs [121] based on data including vehicle dynamics and the driving cycles of the drivers. Vehicle dynamics data contains data about aerodynamic drag, weight, and drivetrain efficiency of the vehicle. Driving cycle is the pattern according to which speed changes with time. The previous models were implemented on HEVs that cannot be connected to the grid. However, a recent model in 2011 followed the same approach on EVs [122]. In the year 1999, Ref. [123] developed a probabilistic model to estimate the charging load of 10000 EVs in an urban area. The daily driving distance as well as the charging start time were probabilistically distributed. Nowadays, probabilistic models are more often used to represent trip start and end times as well as daily driving distance distribution. Ref. [124] developed a deterministic model that estimated the charging load of EVs, the model used average driving distance as well as the specific consumption to estimate the impact of night time and fast charging on the grid. The impacts of EVs charging on the electricity grid were studied in Ref. [125, 126]. Controlled charging was explored in Ref. [127, 128].

#### 3.1. Overview of recent models

Nowadays, accurate EVs charging models are essential tools to predict the impacts of EVs on the electricity grid. The mathematical models developed in the literature are plentiful. They can be categorized based on their modeling technique to Markov chain models [21, 129, 130], queuing theory models [131–133], deterministic models [134], Bayesian inference model [135], Markov-modulated Poisson process [136], zero inflated Poisson [137], joint searching scheduling algorithm [138], fuzzy based model [139], Gaussian mixture model [140], and other stochastic models [141, 142]; or based on the simulation techniques to Monte Carlo [129, 135, 142–144], and fuzzy linear programming [145]; or based on the probability distribution to Poisson distribution [138, 144], Gaussian distribution [129, 142]. Overall, the accuracy of the model is not dependent on the modeling technique, rather it depends on the model assumptions. In general, stochastic models tend to cater for uncertainties of the charging vehicles. Hence, stochastic models tend to provide better security risk assessment for the system at hand [141, 142]. On the other hand, deterministic models tend to represent the worst case scenario in the grid [142].

Models can be also categorized depending on the input data of the model. The most basic models rely on measuring the charging load of a number of EVs, then this data is used to generate the demand profile of a large number of EVs as in Ref. [137, 146, 147]. Alternatively, the models presented in Ref. [129, 138, 146–154] relied on statistical data for vehicles driving in cities. In most of the cases, the statistical data was data for internal combustion engine vehicles (ICEVs) due to the abundance of statistics on this type of vehicles in comparison with the EVs. It is often assumed that the driving habits of EV owners will not be affected by the switch from ICEVs towards EVs [122, 151, 155]. On the other hand, some models

measure charging data from EV charging stations [133, 139, 142, 144, 156]. These models are not as wide spread as the previous ones due to the scarcity of charging stations in general. Moreover, few existing stations record data from charging sessions [31, 35]. Combining data from charging stations and driving statistics will result in a more accurate model. Data from driving statistics will calibrate the total daily charging needs of the vehicle, while data from public charging stations will calibrate tendency of vehicle owners to publicly charge their vehicles. This modeling strategy needs to be further implemented in the future studies, since the accessibility of public charging stations, which is an important step towards more sustainable transportation [157], is expected to significantly increase in the future. Consequently, owners of EVs will be able to charge their vehicles during the day in public charging stations and charge their vehicles at home in the evening.

With the expected increase in public charging stations, more models are expected to assume that the owners of EVs will have the ability to charge their vehicles in different locations during the day, for example at work and at home. In the literature, this assumption was studied in Ref. [129–131, 143, 146, 150]. Accurate predictions of the daily charging load in charging station is an important input to planning new charging stations. The daily load of the charging station is paramount in the selection of the station equipment. It is also vital in the assessment of the capability of the grid to withstand the station’s charging requirement. Models developed in Ref. [131, 141, 144, 156, 158] estimated the load of EV charging stations.

Most of the models in the literature assume a constant charging power during the whole charging session. This assumption is, however, not accurate [159]. On the other hand, constant power charging represents the worst case scenario for charging an EV. Batteries, however, have different charging stages, and charging power is not constant in the stages. Batteries are charged using various charging methods like: constant current (CC), constant voltage (CV), constant power, and taper charging [160]. The commonly applied method is a mixture of CC and CV charging [161]. As depicted in Figure 1, in this method the charging session starts with CC until a certain voltage is reached, after that the charger completes charging through reducing the current at CV [162]. Models developed in Ref. [137, 147, 159, 163] consider the dependence of charging power on the charging stages. The inaccuracy of assuming constant power charging on the modeling results has still not been explored.

Charging of EVs induce a stress on the electricity grid [153, 164, 165]. Since EVs consume large amounts of energy at high power, undesirable peaks can occur in the electrical system [165]. In the year 2014, the International Energy Agency (IEA) member states recorded an average final electricity consumption of 21.85 kWh/day/capita [166] which is smaller than many EVs batteries. Several papers studied the effect of EVs charging on grid voltages [141, 142, 144, 147, 153, 164, 165, 167, 168], power peaks [142, 144, 149], network losses [142, 144, 149, 152, 153, 165, 167], and components loading [141, 142, 144, 147, 151, 152, 164, 168]. Usually, studies that explore the impacts on the electricity grid propose a controlled charging strategy to reduce the impact on the grid [142, 151–153, 164, 169, 170].

Figure 1: The voltage and current variation during a charging session of a battery. In this diagram the CC-CV method is used for battery charging. This figure is inspired by Ref. [8, 159, 162].

### 3.2. Controlled charging

Regardless of model assumptions and grid topology, there is a consensus in the literature that uncontrolled charging of EVs stresses the electricity grid. Ref. [171] showed that the enhancements needed in the grid cost up to 19% of the network costs without EVs and 60–70% of these costs can be reduced through controlled charging. In order to alleviate this stress, controlled charging should be implemented. In addition to enhancement to the grid stability, controlled charging has other advantages, such as reducing charging costs for both EV owners and grid operators. Controlled charging is proposed in many research papers. However, the user acceptability of the controlled charging was not considered while modeling. The models assume that the users are going to adopt the controlled charging strategy precisely as designed which might not be the case. Based on a survey on 237 EV owners, Ref. [172] showed that the respondents were motivated to adopt controlled charging when it protects the grid and when it improves the integration of renewable

energy sources. Owners also showed little motivation towards monetary compensation. Besides that, they expressed an unwillingness towards sacrificing their flexible mobility for the sake of controlled charging.

Controlled charging strategies in the literature are divided into two categories: centralized and decentralized strategies. The decentralized strategies allow vehicle owners to schedule their charging. The centralized charging employs a controller that schedules the charging of multiple vehicles [173, 174]. The centralized controller can be placed in the charging station or, in some cases, can be a separate entity known as an aggregator. The controller is responsible for acquiring data about electricity prices, the grid situation as well as the state of charge (SOC) of the vehicles under control. The decentralized strategy can be easily scaled up to match the number of participating vehicles besides it is more tolerant to faults and requires less computational power and communication lines [173]. On the other hand, the centralized strategy ensures optimal charging of EVs and provides more services to the grid operator and the electricity market [174]. The business model of aggregators requires a large number of vehicles that can be controlled otherwise the model will not achieve the aimed outcomes [175]. Hence, high penetration of EVs is a prerequisite for an aggregator scale controlled charging. Table 1 provides an overview of the controlled charging strategies in the literature.

Table 1: Summary of literature investigating controlled charging.

#### 4. PV and EV synergies

The environmental impact of driving an EV is highly dependent on the primary energy source of the electricity grid used to charge the vehicle [176, 177], this dependence is decreasing as emission control in power plants is improving [176]. On the other hand, half of the life cycle environmental impact of EVs occurs during production [178]. For example, in the USA and China, an EV that is charged using 80% electricity from renewable energy sources could reduce green house gases (GHG) emissions by up to 85% compared with the current emissions [176]. EVs can emit more CO<sub>2</sub> and SO<sub>2</sub> compared with ICEVs in electricity grids that rely on a coal-natural gas mixture as the primary energy source [179]. Consequently, synergies between renewable energy sources like PV and EVs are paramount to increase sustainability in transportation [180]. A study made on the EU countries showed that the major benefits of switching from ICEVs to EVs is the reduction in local emissions [181]. Moreover, EVs are more efficient and dissipate less heat compared with ICEVs. As a result, the energy consumption for air conditioning in cities was reduced by 14.4 million kWh [182].

Charging EVs during both daytime and night-time increases the daily mileage driven by the same battery capacity compared with only night-time charging [18, 183, 184]. This finding demonstrates the possibility of reducing the EV battery size [18]. This scenario will only be feasible provided that owners have access to charging stations during the day. Moreover, increasing accessibility to charging stations is an important step towards more sustainable transportation [157]. Following Ref. [185], the literature studies exploring synergies between PV and EVs can be categorized based on the scale of the study into three categories: small, medium, and large scales. Small scale studies focus on the scale of parking lots and charging stations, while low voltage feeders and residential neighborhoods are studied in the medium scale studies. The large scale studies explore the synergies on the scale of a whole city. It is important to note that the scale of the study depended on the scale of the impact which the authors intended to investigate.

Ref. [29, 186–193] studied the energy balance between the local PV power generation and the EV charging load. Controlled charging benefits were explored in [18, 28, 194–197]. Grid optimization was studied in [198]. Financial and environmental benefits were explored in [193, 199]. Finally, several studies proposed operating strategies for smart charging stations that take into consideration the PV production and the electricity grid loading [200–208].

Solar panels installed above parking lots represent a great potential for charging EVs with the already available solar energy during the day. This locally produced energy will reduce the impact of EV midday charging on the electricity grid. The amount of impact reduction depends on the grid design, the penetration of the PV and EVs, the existence of battery storage systems and other model assumptions such as charging power. A study in New Jersey [186] estimated the yield from a horizontal PV panel installed above a parking lot of 15 m<sup>2</sup>. The results showed that the yield energy is enough to drive EV commuters to and from work given that they live within a radius of 24 km of their work. Another study in Switzerland [190] estimated the potentials of installing PV on parking lots. Only 29 stations out of the 40 studied were suitable for PV production. The annual energy produced was enough to supply 40% of the energy needed to drive light weight EVs. A similar study was made on three different locations in Italy [191]. This study simulated different charging scenarios as well as different initial SOCs for the batteries of the EVs. Energy from PV could supply from 1%–3% to 56%–72% of the needed energy to charge the EVs. In the Netherlands, a study [192] estimated the impacts of installing battery storage systems as well as PV on workplace charging station. The results proved that without having the battery storage installed PV can supply up to 60% of the energy needed for charging the EVs. It was also shown that a 10 kWh battery would reduce the energy imported from the grid by 25%. However, the utilization of the battery is not proportional to the battery capacity, and since 75% of the variations in solar insolation between days is less than 15 kWh, batteries with capacity less than 15 kWh were recommended by the authors. The authors in [199] studied the financial and environmental benefits from adopting a PV powered charging station for EVs compared with home-charging. This study was made on two US universities, one located in Ohio and the other located in California. The payback period of the PV was dependent on the parking fee and the size of the panels. Nonetheless, it ranged between 4–30 years.

A recent similar study compared the economic and environmental impacts of a university-located EV charging station using different orientations of PV panels in Sicily [193]. The authors observed that the east-oriented panels resulted in a higher self-consumption. In the same time, east-facing panels reduced the daily solar production in the winter by up to 20%. However, the south-oriented panels required energy storage to shift the afternoon solar production to the following day's early morning charging. The authors showed that orienting the PV panels to match the early morning charging — east orientation — will cost 77% of the south-directed panels and storage. This value was obtained when the authors oversized the east-oriented panels, compared with the south-oriented panels, to account for the 20% drop in daily production in the winter months. In Ref. [209], the authors developed an optimization algorithm to control the energy flow between a charging station connected to building where PV panels were installed on both the station and the building. The objective of the optimization was to minimize the operating cost. The authors studied combinations of different building types, different charging availability, and different initial SOC. Building types such as office, apartment, warehouse, etc. were included, and charging availability included daytime long duration, daytime short duration and night time charging. Unfortunately, the optimization algorithm did not adjust the orientation of the PV panels. The previous two papers revealed a research gap regarding the relation between the orientation of PV panels and the self-consumption of EVs for different charging behaviors like early morning and late afternoon charging.

In [194], the authors studied the possibility of controlling the voltage of a low voltage feeder that had high PV penetration level using an EV charging station that had a battery storage system. This study was performed on a 7 bus feeder supplying 33 residential customers with a 28% PV penetration level (measured as a percentage of total energy consumption). The results showed that EV charging stations can ensure that the feeder voltages remain within safe limits. Moreover, the capacity of the battery storage system decreased with the increase of the distance between the EV charging station and the transformer, 47 kWh for the furthest location compared with 12 kWh for the nearest location. Ref. [198] developed an optimization technique to optimally size and allocate solar parking lots for EVs located in a LV feeder. The objective of the technique was to reduce the costs and to ensure that the network is operating within safe limits. The technique reduced the energy loss in the grid by 49% and reduced the total costs by 39%. The authors in [195] proposed a coordination scheme between combined heat power plants (CHPs), PV, battery storages and EVs in an industrial micro-grid. The results showed a reduction in the overall costs of the industrial micro-grid, a reduction in EV charging costs and an enhancement in network security. Another similar

study was based in Belgium [210]; this study explored charging of EVs in an office building micro-grid that contained a CHP unit and PV. The percentage of self-consumption of the energy produced from the PV and the CHP increased with the increase in the number of EVs. The amount of increase varied based on the charging scenario, the charging power, and the number of EVs. The self-consumption increased up to 80.2% from 70% when no EVs were charged. The study also showed that controlled charging could reduce the impact on the grid. The conclusion is that workplace charging using PV will reduce the charging load on the grid. An extensive study [28] explored the implication of various levels of PV and EV penetration on a small test feeder. The PV penetration ranged from no PV to each customer installing 25 m<sup>2</sup> of PV panels, and the number of EVs varied from zero to one EV per household. Moreover, different EV charging strategies were simulated. Synergies between PV and EVs helped reduce the drawbacks of each. However, both technologies have opposite implications; consequently no ideal solution to all the problems was achieved. One limitation of the previous study arose from the fact that it tested a feeder with small impedances and short distances between nodes which may have affected the results of the simulation [211]. This indicates the necessity of further research in this area.

On the larger scale, Ref. [196] assessed the synergy between PV and EVs in a city in Northern Italy. Two modes of EV charging were modelled: controlled and uncontrolled charging. The controlled charging increased the maximum EV penetration by 64% compared with the uncontrolled charging. Moreover, the penetration level of PV increased from 218% to 249% when implementing controlled charging. Ref. [29] estimated the electricity demand profile of the city of Toyonaka in Japan in the year 2030. Various scenarios were proposed for EVs and PV penetration in the grid. This study revealed that PV reduced the total electricity load by 19.7% and using vehicle to grid (V2G) cut peaks by 37.3%. The authors in [212] modeled actual households' consumption and PV data in an urban region in Brazil. The aim of the study was to use V2G to stabilize the network and achieve financial profit to the owners of the EVs. In this study, the feeder was able to handle all the energy generated from the PV panels. Financial profit up to \$1000 was possible with only 40% allowable depth of discharge (DOD) for the V2G to operate within. A study made on Kansai area in Japan [197], an area which has 8 million households and 7.76 million cars, integrated PV, EVs, and heat pumps (HPs) at various penetration levels. High levels of PV penetration could be achieved through charging EVs and operating HPs during off-peak hours and during high PV production. During peak hours, EVs could supply electricity to the grid and HPs could go on standby mode. In Texas, a study [18] performed on a grid supplying 23 million customers explored the benefits of combining both PV and EVs. The study assumed that EVs constitute 50% of the transportation sector. Two charging strategies were explored; controlled and uncontrolled. Uncontrolled charging assumed that the vehicle is charged whenever parked. Controlled charging was similar to the uncontrolled charging strategy but it stopped charging during peak hours from 3 p.m. to 9 p.m. provided that the vehicle would be fully charged at 7 a.m. The results showed that the synergy between PV and EVs reduced the demand peaks and decreased the curtailed PV energy during times of high solar production and low demand.

It was shown that the population density is inversely correlated with both the energy used for transportation and the solar production, both measured per capita [187–189]. This is to say that the solar yield from PV installed above a certain roof and the energy used for transport by the inhabitants who live under the same roof both decrease as the population density increases. A study made on the city of Toronto, Canada, explored the relationship between the energy use per capita and population density [187]. The study included the households' energy use, transportation energy use, and solar energy generation. The authors showed that the net yearly energy use per capita is lower in densely populated regions compared with the sparsely populated ones. They also showed that this trend was reversed if highly efficient solar panels in addition to strict-efficiency measures were adopted at homes which included shifting to EVs. In this study, the authors assumed that the roofs were horizontal. In addition, they also included the solar yield from facade mounted PV panels. In Ref. [188], the authors evaluated the solar rooftop potential in the city of San Francisco and compared this to the vehicle energy use. The authors compared the electricity produced by a certain rooftop and the electricity consumed by the vehicles owned by the people living under this roof, the results were compared in kWh/capita. The results showed that the yearly yield of the PV panels is higher than the charging load of the vehicles — both in kWh/capita — if BEVs replaced conventional ICEVs. This result was valid for all population densities. However, when spatially presented,

415 few regions had a higher BEV charging load compared with PV production. Unfortunately, the authors did  
not comment on this finding. One limitation for this study was that they calculated the solar production of  
one fourth of the rooftop areas — including the north facing sections of tilted roofs. In [189], the authors  
calculated the energy generated from the potential PV installations on rooftops and facades of buildings in  
the city of Auckland in New Zealand. They included only the most efficient facades and roofs — above 95%  
420 — depending on the tilt and orientation of the PV panel. Unfortunately, they did not describe the method-  
ology used to evaluate the efficiency of the roofs and facades. The authors showed that the persons share  
of PV production could accommodate for the EV charging load regardless of the population density. The  
previous three studies used deterministic assumptions for the EV models. The use of stochastic assumptions  
is preferred over deterministic assumptions [213].

## 425 5. Concluding discussion

The current rate of uptake of PV and EVs indicates that these technologies are going to have significant  
impacts on the electricity grid in the future. The impacts include both challenges, like increase in grid  
losses, and potentials, like balancing the intermittence of the generation and the load. A careful assessment  
of the impacts is paramount to ensure successful adoption of both technologies. In this paper, a review  
430 of the current research related to modeling the power use and production for both technologies has been  
presented. Even though the amount of research that was done on these topics is plentiful, there are some  
gaps that need to be explored.

First regarding PV power production modeling, improved modeling of variability of the clear-sky index  
over space and time is of interest. That is, improved accuracy for estimating PV power production ramp-  
435 rate can assist future smart grids more accurately match power supply with demand. Also, quantifying  
the aggregate clear-sky index and subsequent PV power production on a city-scale, is interesting. Here  
high resolution solar irradiance data on city-scale for various regions is scarce, and more metering networks  
such as NREL’s radiometer array [214] at Oahu, Hawaii, USA, could be useful. Improved modeling of solar  
irradiance for single or multiple locations might also assist in improving the models for PV power production  
440 forecasting.

As regards EV charging models, there is a need to introduce more variability in the model assumptions.  
That is, multiple charging powers, charging locations, and battery capacities need to be modeled in the same  
paper. This strategy will ensure a more accurate model that reflects the different requirements of different  
EVs. Moreover, there are few papers that model the charging spatially over a complete city. Spatial models  
445 excel at predicting the impacts of charging in multiple locations in the grid and during different times of  
the day. Future research on V2G and controlled charging is expected to find a compromise between the  
needs of vehicles owners and grid stability. Further research needs to explore the impact of the high PV and  
EV penetration on the electricity tariffs and electricity market. Moreover, the reaction of vehicle owners  
to aggregator requirements needs to be further explored. Comparative studies that estimate the costs of  
450 grid enhancements compared with the costs of controlled charging need to be further explored. Also, more  
detailed data on EV charging could be beneficial for narrowing down the vast number of EV models and  
free parameters, potentially giving more accurate predictions.

Finally, as regards the combination of modeling PV power production and EV charging, there is a need for  
improved modeling on the variability of the combined power use and production in the local distribution grid.  
455 In particular, for various profiles of charging, such as home-charging, work charging and public charging.  
In similarity with the research gaps identified for both PV power production modeling and EV charging  
modeling, there is a gap in the understanding of the variability of the combination of this for large scales,  
such as city-scale. City-scale studies lag behind the former advancements reached in the separate fields.  
In other words, advanced spatial models for the solar yield and the charging load of EVs for the different  
460 profiles of charging are still missing. Collaborations between researchers in both fields are encouraged. The  
next step of that is to estimate electricity grid-impacts, and to identify the spots of critical power production  
or consumption in the grid, and to quantify the potential and need for controlled charging.

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Table 1: Summary of literature investigating controlled charging.

Author and reference	Notes on simulation method	Scale of controller	Aims of study	Notes
Ma et al. [1, 2], Zhu et al. [3]	Mean field game theory	Vehicle	Reduce charging costs and fill the load valley	The strategy was designed so that all vehicles receive charging load goal from a system operator, then, the vehicles schedule their charging aiming to reduce charging costs, after that the system operator resends the goals with the charging strategies of all vehicles. The vehicles then have to re-schedule their charging based on the new inputs. This process had to be repeated until the optimal schedule is achieved by all vehicles.
Kim and Rahimi [4]	–	Vehicle	Reduce charging peaks	This study estimated the load profile and the green house gases (GHG) emissions of a fleet of EVs in Los Angeles in the years 2020 and 2030. Several controlled charging strategies were proposed, strategies vary in charging time and charging location, some of the strategies charge at home and work, others charge only at home. Controlled charging reduces peaks and fills the load valley, however, the GHG emissions associated with controlled charging are higher than that of the uncontrolled charging.
Rotering and Ilic [5]	Classical dynamic programming	Vehicle	Reduce charging cost	This model compared two controlled charging strategies. The first strategy aimed at reducing the costs. The second strategy added grid support on the aims of the first strategy. The study also made a financial analysis of the proposed solution. The profitability of the strategy with grid support is higher than that of the first strategy, this is reflected in \$4000 reduction in the net present value.
Paevere et al. [6]	–	Vehicle	Reduce power peaks of households	In controlled charging, the charging load was shifted to off-peak hours, thus the charging power increased due to the reduction of the charging duration. On average, the daily charging peak is 0.66 kW/vehicle and 0.93 kW/vehicle for uncontrolled charging and controlled charging respectively. This translates to 40.9% increase in peaks due to controlled charging.

Falahati et al. [7, 8]	Fuzzy logic control	Charging station	Control the frequency of the grid	The proposed method uses fuzzy logic to respond to signals containing the frequency deviation of the grid as well as the state of charge (SOC) of the EVs. This model was tested on 35 bus system and resulted in 59–73% reduction in frequency deviation in comparison with uncontrolled charging method. The method also showed that load shedding is needed to control the frequency of the grid in case of sudden increase in the load.
Kim et al. [9]	Flexible poisson with hidden Markov chain	Charging station	Stabilize the voltage of the grid	Using the voltage constraints in the grid, an estimation of the maximum power that the charging station can draw was made. This power is then distributed on the charging vehicles based on one of two compared methods: first in first served or processor sharing.
O’Connell et al. [10]	Rolling optimization method	LV feeder scale	Reduce charging costs	The model reduces charging costs while satisfying the voltage constraints of the grid and capacity constraints of the transformer and cables. The cost of charging was reduced by 50%.
Kara et al. [11]	–	Aggregator	Reduce charging costs	The model shifts the load from the high cost period to low cost period based on the time of use (TOU) tariff structure. The model ensures 37% reduction in the load peaks and 24.8% reduction in monthly bill costs.
Esmaili and Rajabi [12]	Non-linear program	Aggregator	Reduce charging costs	The model controls charging of EVs while maintaining grid operating constraints concerning voltages and thermal loading. The model was tested on the modified IEEE 31-bus system, and the results show that the thermal stresses are easier to fulfill compared with the voltage constraints. The energy loss increased from 10.7% to 12.1% from the total delivered energy due to the increase of power supplied to both EVs and households.

Kristoffersen et al. [13]	Quadratic program	Aggregator	Reduce grid congestion and charging costs	The costs of battery degradation are high, therefore it is uneconomical to sell electricity to the grid. The vehicles rarely charge during the day due to cheaper night time charging. Only long distance drivers charge during the day. The model prevents electricity prices from reaching zero in cases of high renewable generation.
Sundstrom and Binding [14]	Quadratic program	Aggregator	Trade electricity in the electricity market	Similar to Ref. [13] adding analyses of the impacts on the grid. The results show that controlled charging reduces overloading and voltage drop.
Ansari et al. [15]	Monte Carlo	Aggregator	Satisfy the needs of the network operator and the market expectations	The model simulates three modes of driving: working drivers, retired drivers and drivers of company owned vehicles. Controlled charging flattens the load curve and reduces peaks by 63% in case of 50% EV penetration. It also alleviates the voltage drop in the residential zones during charging peaks. The system loading is maintained below 100%.
Lopes et al. [16]	–	Aggregator	Maintain safe network operation	The model communicates with the distribution system operator (DSO) to know the grid loading and if necessary schedule the charging of EVs. The penetration limit of the grid increased from 10% up to 52%. Grid enhancement are needed in case of higher penetration of EVs.
García-Villalobos et al. [17]	Weighted and fuzzy control	Aggregator and EVcontroller	Mitigate voltage unbalance and reduces charging costs	Four different charging strategies were simulated in this model: uncontrolled, smart charging, smart charging with voltage unbalance reduction, and the previous strategy with vehicle to grid (V2G). The model was tested on a small LV grid with 14 nodes and 43 houses. Smart charging without voltage unbalance reduction causes voltages to go below safe limits, however, a reduction in peaks and charging costs is ensured.

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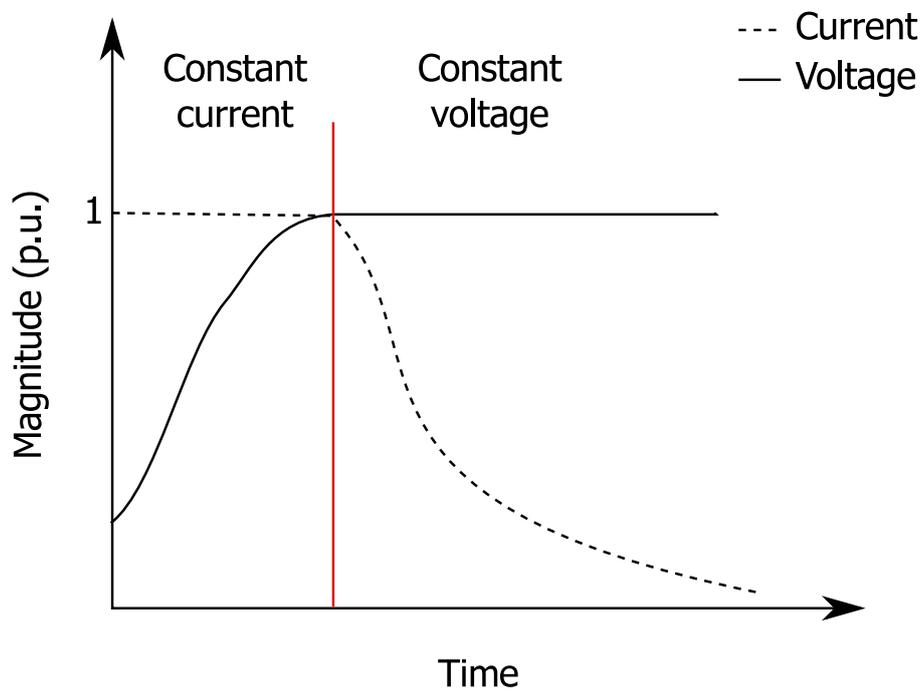


Figure 1: The voltage and current variation during a charging session of a battery. In this diagram the CC-CV method is used for battery charging. This figure is inspired by Ref. [1-3].

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