Renewable and Sustainable Energy Reviews 89 (2018) 61–71

Contents lists available at ScienceDirect

Renewable and Sustainable Energy Reviews

journal homepage: www.elsevier.com/locate/rser

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

Mahmoud Shepero[a,*], Joakim Munkhammar[a], Joakim Widén[a], Justin D.K. Bishop[b,c], Tobias Boström[d]

[a] Department of Engineering Sciences, Uppsala University, P.O. Box 534, SE-751 21 Uppsala, Sweden
[b] Arup, 13 Fitzroy Street, London W1T 4BQ, United Kingdom
[c] Centre for Sustainable Road Freight, University of Cambridge, Department of Engineering, Trumpington Street, Cambridge CB21PZ, United Kingdom
[d] Energy and Climate Group, Department of Physics and Technology, UiT The Arctic University of Norway, NO-9037 Tromsø, Norway

A R T I C L E I N F O

Keywords:
Photovoltaics power production models
Electric vehicle charging models

A B S T R A C T

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.

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_2 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_2 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

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

* Corresponding author.
E-mail addresses: mahmoud.shepero@angstrom.uu.se (M. Shepero), joakim.munkhammar@angstrom.uu.se (J. Munkhammar), joakim.widen@angstrom.uu.se (J. Widén), jdkb2@cam.ac.uk (J.D.K. Bishop), tobias.bostrom@uit.no (T. Boström).

https://doi.org/10.1016/j.rser.2018.02.034
Received 16 December 2016; Received in revised form 21 December 2017; Accepted 27 February 2018

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% — 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 to 2015 [15]. However, in mature markets the PV power production installation rate rapidly decreased and the total installed capacity appears to stagnate below 10% 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 [17,2,18–20].

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 [21,17]. When combined with PV power production that is an increased self-consumption [17], but that it generates a larger mismatch overall [17,5]. 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 [16,28,2,29,30]. 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 [35,31]. Among Ref. [36,35,37] 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