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Forecasting residential solar photovoltaic deployment in California

Changgui Dong [a,b,c,*], Benjamin Sigrin [b], Gregory Brinkman [b]

[a] Renmin University of China, Beijing, China
[b] National Renewable Energy Laboratory, Golden, United States
[c] RUC National Academy of Development and Strategy, Beijing, China

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ABSTRACT

Residential distributed photovoltaic (PV) deployment in the United States has experienced robust growth, and policy changes impacting the value of solar are likely to occur at the federal and state levels. To establish a credible baseline and evaluate impacts of potential new policies, this analysis employs multiple methods to forecast residential PV deployment in California, including a time-series forecasting model, a threshold heterogeneity diffusion model, a Bass diffusion model, and National Renewable Energy Laboratory's dSolar model. As a baseline, the residential PV market in California is modeled to peak in the early 2020s, with a peak annual installation of 1.5–2 GW across models. We then use the baseline results from the dSolar model and the threshold model to gauge the impact of the recent federal investment tax credit (ITC) extension, the newly approved California net energy metering (NEM) policy, and a hypothetical value-of-solar (VOS) compensation scheme. We find that the recent ITC extension may increase annual PV installations by 12%–18% (roughly 500 MW) for the California residential sector in 2019–2020. The new NEM policy only has a negligible effect in California due to the relatively small new charges (<100 MW in 2019–2020). Furthermore, impacts of the VOS compensation scheme ($0.12 per kilowatt-hour) are larger, reducing annual PV adoption by 32% (or 900–1300 MW) in 2019–2020.

1. Introduction

Renewable energy for electricity generation, led by wind and solar, is key to the global climate-change mitigation strategy (IPCC, 2014). In the United States, renewable energy now accounts for the biggest source of increase in generation capacity. In 2015, the country saw over 2.3 GW_{dc} of distributed-generation photovoltaics (DGPV)[1] connected to the grid, which corresponds to almost 200,000 installations (GTM/SEIA, 2014). In California, even after the California Solar Initiative (CSI) ended in 2014, the DGPV market remains viable (BNEF, 2015a; GTM/SEIA, 2015). The DGPV installations are determined by individual customers and installed by solar companies, which are often beyond the control of utility companies. However, such high DGPV growth has important implications on utility planning processes, especially in terms of future infrastructure needed, system cost minimization, and reliable operation of the electric system.

The rapid DGPV deployment has spurred policy debates and policy changes in many ways. Various studies have been conducted to understand the benefits and costs of DGPV to the grid (Blackburn et al., 2014; Denholm et al., 2014; RMI, 2013), how to adjust policy-support schemes (CPUC, 2015b; Rábago et al., 2012; Randazzo, 2015), and the implication on utility business models (Lehr, 2013; Richter, 2013; Satchwell et al., 2014). Recently at the federal level, the U.S. Congress (U.S. Congress, 2015) approved a five-year phase-down extension of the investment tax credit (ITC) for solar energy. In California, a February 2016 decision by the California Public Utilities Commission (CPUC) on the successor to net energy metering (NEM) maintained retail electricity rates for DGPV owners at previous levels, while introducing new tariff features—a system interconnection fee, a non-bypassable charge, and a minimal monthly bill—that anticipate higher levels of DGPV deployment.

To analyze the impact of enacted or future policy actions, it is necessary to have a valid forecast for the future technology diffusion; however, forecasting DGPV deployment is fundamentally challenging for several reasons. First, the DGPV market has historically relied on policy support (DSIRE, 2016), so future policy changes create forecasting uncertainty. Second, DGPV is a new and durable technology; so, many non-economic factors may influence adoption, such as customers' environmental attitudes, peer effects, and risk preferences (Rai et al., 2016). Finally, even forecasting future DGPV prices alone is challenging because of the global nature of the technological change and supply chain (Choi and Anadón, 2014).

The objectives of this research are to model future residential PV deployment in California leveraging a suite of techniques and then use our

* Corresponding author at: Renmin University of China, Beijing, China.
E-mail address: rosenbloog@gmail.com (C. Dong).

[1] DGPV is in comparison with utility-scale PV. In this research, we define DGPV as PV systems that are generally small (<5 MW), connect to the distribution network (rather than the transmission network), and are either behind the meter or in front of it and connected to the low-voltage distribution network.

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Nomenclature

ACS	American Community Survey
ARIMA	autoregressive integrated moving average
BNEF	Bloomberg New Energy Finance
CEC	California Energy Commission
CPUC	California Public Utilities Commission
CSI	California Solar Initiative
CSS	California Solar Statistics
DGPV	distributed-generation photovoltaics
DSIRE	Database of State Incentives for Renewables & Efficiency
dSolar	Distributed Solar Market Demand model
E3	Energy and Environmental Economics
EIA	Energy Information Administration
GTM	Greentech Media
GW_{DC}	gigawatts in direct current
IOUs	investor-owned utilities
ITC	investment tax credit
kWh	kilowatt-hour
LHS	Latin hypercube sampling
MW	megawatts
NEM	net energy metering
NEMS	National Energy Modeling System
NPV	net present value
NREL	National Renewable Energy Laboratory
OOH	owner-occupied houses
SEIA	Solar Energy Industries Association
STD	standard deviation
TPO	third-party owned
TTS	Tracking the Sun
VOS	value-of-solar

baseline results to study the impact of potential policy changes on PV deployment. Without a solid baseline forecast of PV adoption, the assessment of policy impacts could be biased from the very beginning. As California and other states in the U.S. are progressing in making policy changes related to DGPV, establishing common ground for forecasting future PV adoption should be critical during the policy-making process. That is why in this research we include multiple forecasting methods, covering both top-down and bottom-up models.

Existing forecasting of future PV adoption usually comes from three sources: research institutes, industry experts, and utility companies. However, the methods they have used vary dramatically. Research institutes and industry experts often rely on bottom-up customer adoption models, whereas utility companies sometimes simply assume an endpoint DGPV deployment level or extrapolate from historical data (Mills et al., 2016). Even for the bottom-up models, they differ in specific model configuration, parameter setting, and geographic resolution. For instance, the geographic resolution could range from nationwide, to state-level, to utility area; however, few studies go to county levels. Another issue with these forecasts is that they tend to have a limited time frame, usually not exceeding 2030.

Our work extends the PV forecasting literature in several ways. First, we use and compare multiple forecasting techniques. We leverage not only bottom-up models, but also top-down models. Although all bottom-up models are based on the classical Bass diffusion model, we also introduce a different type of diffusion model, i.e., the threshold-heterogeneity model. These two types of models represent two fundamentally different views on how to generate an S-type diffusion curve. Second, in our bottom-up model, we cover the two major business models of DGPV, i.e., the customer-owned and the third-party-owned (TPO) systems, whereas most other literature does not include the most recent DGPV business model—TPO. Third, we make our forecasts for California at the county level and cover periods from now until 2050. Lastly, before making forecasts for 2050, we carefully calibrate our methods based on the extensive DGPV historical data in California.

The top-down models and bottom-up model used in this research are as follows. First, following the forecasting literature (Forte, 2015; Hyndman and Athanasopoulos, 2013) and diffusion[2] of innovation literature (Bass, 1969; Bass et al., 1994; Bemmaor, 1994), we build three top-down models that are based on theory and calibrated with real market data: a time-series forecasting model, a threshold-heterogeneity diffusion model, and a Bass diffusion model. Then, we compare these models to a more complex bottom-up techno-economic model, the dSolar model maintained by the National Renewable Energy Laboratory (NREL).[3] Furthermore, as a demonstration of uncertainties in forecasting DGPV technology diffusion, we conduct sensitivity analysis based on the dSolar model around certain key economic parameters. For simplicity, we only focus on the largest residential market segment in this research, i.e., the owner-occupied housing (OOH) market, rather than the non-OOH market or PV adoption in the commercial sector.

After first reviewing the relevant literature (Section 2), we discuss our data inputs and four methods (Section 3). We then present our baseline results for California's residential PV sector in Section 4. We use the dSolar model and the threshold-heterogeneity diffusion model to conduct three policy scenario analyses of the recent federal ITC extension, the newly approved California NEM policy, and a hypothetical value-of-solar compensation scheme (more detail in Section 4.4). Section 5 provides a conclusion.

2. Literature review

This research builds on several strands of literature: general forecasting, diffusion of innovation, PV financial attractiveness, and existing DGPV forecasting models. General forecasting is essential for planning purposes, and the methods can be very simple, such as using most recent observation as a forecast or developing a complex model such as neural networks (Forte, 2015; Hyndman and Athanasopoulos, 2013). When time-series data are available, two of the most popular univariate time-series models are the autoregressive integrated moving average (ARIMA) model and the exponential smoothing model. ARIMA focuses on the autocorrelations in the data, whereas the exponential smoothing model detects trends and seasonality in the time series (Hyndman and Athanasopoulos, 2013; Hyndman et al., 2008). Time-series forecasting uses only historical information for the variable being forecasted and assumes that the observed trend and seasonality will continue. As such, time-series models are easy to implement and rely on only one assumption (i.e., continuing trend) to work. Nevertheless, time series method can miss other external factors that affect the variable of interest, such as policy changes or changes in the sub-populations considering adoption.[4]

The literature on diffusion of innovation is vast and good review work can be seen in Sultan et al. (1990), Meade and Islam (2006), and Rogers (2003). Diffusion of innovation models started in late 1960s, with the Bass diffusion model (Bass, 1969) probably being the most commonly used model to predict technology adoption. Generalized Bass models have been proposed to incorporate other variables such

[2] Technology diffusion refers to the process of how new technologies spread throughout society over time. This paper uses the terms "diffusion," "adoption," and "deployment" interchangeably.

[3] We consider these two types of models complementary to each other (Section 3), and together they establish a more reliable baseline for future PV deployment in the sense that they represent two extremes of modeling efforts: the top-down models are generally easy to implement and require much fewer assumptions, whereas the bottom-up models are more modular and have more assumptions embedded, but are more flexible in modeling PV economics.

[4] Only future values of those external factors are relevant here, because their historical values should already be incorporated into the historical values of the variable of interest.