Contents lists available at ScienceDirect

Applied Energy

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

Economic assessment of photovoltaic battery systems based on household load profiles



AppliedEnergy

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HIGHLIGHTS

- Techno-economic model analyzing profitability of PV-battery systems.
- · Heterogeneity analysis based on 4190 real-world load profiles.
- Predictor for optimal PV-battery system configuration for individual households.
- Large variance in profitability, even for households with comparable annual demand.
- Good prediction accuracy with only one month of smart-meter data.

ARTICLE INFO

Keywords: Solar energy Storage Smart-meter data Techno-economic simulation Load profile Machine learning

ABSTRACT

Technical advances and decreasing costs of photovoltaic (PV) and battery (B) systems are key drivers for the consumer-prosumer transition in many countries. However, the installation of a photovoltaic-battery (PVB) system is not equally profitable for all consumers. This study systematically assesses how heterogeneity in realworld electricity load profiles affects the optimal system configuration and profitability of PVB systems. To that end, we develop a techno-economic simulation model that optimizes the PVB configuration for given electricity load profiles. The analysis uses real-world energy consumption data from 4190 households and is conducted for current electricity rates and weather conditions in Zurich, Switzerland. To account for future price reductions of PV and PVB systems, we conduct a sensitivity analysis that assesses how different cost scenarios influence optimal system configuration and profitability. Finally, we develop and validate a machine learning algorithm that can predict system profitability based only on a limited set of features and on shorter measurement timeframes of smart-meter data. We find that under the current cost scenario (PV: 2000 €/kWp, B: 1000 €/kWh) and without subsidies, about 40% of the analyzed households reach a positive net present value (NPV) for a PVsystem, but only for 0.1% of households is the integration of a battery profitable. Under the most optimistic cost scenario for both technologies (PV: 1000€/kWp, B: 250€/kWh), 99.9% of the households benefit from the integration of battery storage into their optimal system configuration, with a mean installed PV power of 4.4 kWp and a mean battery size of 9.6 kWh. In all cost scenarios, system profitability varies considerably between households, even for households with comparable total annual demand, primarily due to the heterogeneity in the load profiles. Thus, being able to identify households for whom the installation is profitable is important. The proposed machine learning algorithm predicts optimal configuration, profitability, self-sufficiency, and self-sufficiency ratios with good accuracy, even when only relatively short timeframes of smartmeter data are available. The results of this study are relevant for households making individual investment decisions as well as for utility companies to more effectively identify and approach relevant customers for the installation of PVB systems. Furthermore, the findings enable policymakers to determine the critical levers for increasing private investments into PVB systems in their region and to predict how future developments like component costs will affect the future diffusion of these systems.

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https://doi.org/10.1016/j.apenergy.2018.03.185

Received 25 November 2017; Received in revised form 29 March 2018; Accepted 30 March 2018

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Nomenclature

Abbreviations

В	battery
DoD	depth of discharge (-)
DoF	degrees of freedom
EoL	end of life
FiT	feed-in tariff
MAE	mean absolute error
ML	Machine Learning
MPP	maximum power point
NPV	net present value (€)
PDR	production to demand ratio (-)
PV	photovoltaic
PVB	photovoltaic-battery
SCR	self-consumption ratio (–)
SDR	storage to demand ratio (-)
SSR	self-sufficiency ratio (–)
STC	standard testing conditions ($T_{STC} = 25$ °C, $G_{STC} = 1.0$ kW/m ²)
TMY	typical meteorological year

Greek symbols

α_I	temperature coefficient of current at STC (%/K)
α_V	temperature coefficient of voltage at STC (%/K)
Δt	time step (s)
δ	PV technology coefficient (-)
η_c	battery charging efficiency (-)
η_d	battery discharging efficiency (-)
η_{inv}	inverter efficiency (–)
σ_{CL}	effective fraction of battery capacity usable due to cycle
	life degradation (–)
Ω_x	sampling distribution for x_{DOF}
Symbols	
A_m	module surface area (m ²)
C_0	investment costs (€)
C_i	costs in year $i \in $
c_{bat}	specific battery system costs (€/kWh)
c_{bat}^{a}	replacement cost of battery (€/kWh)
c_{pv}	specific PV system costs (€/kWp)
c _{rem}	feed-in remuneration (€/kWh)
	high tariff electricity cost (€/kWh)
c_{lt}	low tariff electricity cost (€/kWh)

1. Introduction

Many countries have put forward ambitious targets to increase the share of energy they generate from renewable sources. For instance, the Energy Roadmap 2050 of the European Commission foresees an almost emission-free electricity production in Europe by 2050 [1]. Photovoltaic (PV) systems, which are seen as a cornerstone of these plans, have recently experienced a considerable increase in market diffusion in many countries. Spurred by a rapid price decline with prices for residential PV system falling by over 80% from 2008 to 2016 in most competitive markets [2], solar PV represented almost half of newly installed renewable power capacity in 2016 [3]. As a result, global PV deployment increased from 3.7 GW in 2004 to more than 300 GW at the end of 2016 [4].

Small-scale PV systems on residential or commercial buildings account for about a third of the globally installed PV capacity and generation [5,6]. Owners of small-scale PV systems can either inject the

E_{bat}	battery charging state (kWh)
E_{bat}^{max}	upper bound charging state (kWh)
E_{bat}^{min}	lower bound charging state (kWh)
E_{hat}^R	rated battery capacity (kWh)
G	total in plane radiation (kW/m ²)
G_{STC}	in plane radiation under testing conditions (1 kW/m ²)
<i>I</i> _{MPP}	module current at MPP (A)
I _{MPP,STC}	module current at MPP and STC (A)
I _{SC}	short circuit current of PV module (A)
I _{SC,STC}	short circuit current of PV module at STC (A)
L	snippet length (days)
Ν	number of load profiles/households
N _c	number of cycles before EoL is reached
N_T	time horizon (years)
P_{DC}	DC power of all PV modules (kW)
$P_{DC,Nm}$	DC power of a PV module (kW)
P_L	load (kW)
r	discount rate (-)
R_i	revenues in year $i \in \mathbf{I}$
r _{esc}	escalation rate on electricity prices (-)
r _{rem}	annual reduction rate for feed-in remuneration rate (-)
r _{om}	share of C_0 that accounts for operation and maintenance
	cost (–)
T _{amb}	ambient temperature (°C)
t _{ht}	daily high tariff hours
t _{lt}	daily low tariff hours
T_m	module temperature (°C)
$V_{\rm MPP}$	module voltage at MPP (V)
V _{MPP,STC}	module voltage at MPP and STC
V _{OC}	open circuit voltage of PV module (V)
V _{OC,STC}	open circuit voltage of PV module at STC (V)
$W_{B \rightarrow L}$	energy supplied to load from the battery bank (kWh)
$W_{G \rightarrow L}$	energy supplied to load from the grid (kWh)
W_{PV}	energy (DC) produced by the solar panels (kWh)
$W_{PV \rightarrow B}$	energy supplied to battery from the PV modules (kWh)
$W_{PV \rightarrow G}$	energy supplied to grid from the PV modules (kWh)
$W_{PV \rightarrow L}$	energy supplied to load from the PV modules (kWh)
W_L	annual energy demand (kWh)
\overline{w}_L	daily average electricity demand (kWh)
\widehat{w}_L	normalized daily average electricity demand (-)
$\overline{w}_L(t_i)$	daily average electricity demand during hour <i>i</i> (kWh)
$\widehat{w}_L(t_i)$	normalized daily average electricity demand during hour <i>i</i>
	(-)
$x_{ m DoF}$	degree of freedom vector (P_0, E_{bat}^R)

electricity produced into the distribution grid at a feed-in tariff, or selfconsume it to cover the building's electricity demand. Adding on-site battery (B) storage to PV systems makes it possible to store PV-produced electricity for later use. Similar to the declining costs of PV modules, the price of lithium-ion batteries has also started to decrease substantially and is expected to follow a similar price decline as that seen for PV panels [7–9]. In particular, for consumers whose production and demand times do not correspond, the addition of battery storage increases the self-consumption ratio (SCR) - the ratio of electricity generated by the PV system that is directly used at the installation site to the total amount of electricity generated [10]. When the generation cost of PV and battery-supplied electricity is below the retail price, selfconsumption is favorable from an owner's perspective. In most regions, the remuneration for feeding electricity into the grid was gradually reduced and many policymakers push to remove feed-in tariffs [11]. Consequently, self-consumption has become increasingly attractive in many countries over the past few years due to increasing electricity Download English Version:

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