



Assessment of forecasting methods on performance of photovoltaic-battery systems



G.B.M.A. Litjens*, E. Worrell, W.G.J.H.M. van Sark

Copernicus Institute of Sustainable Development, Utrecht University, PO Box 80.115, 3508TC Utrecht, The Netherlands

HIGHLIGHTS

- Development and assessment of forecast methods and predictive control strategy.
- Strategies tested on 48 residential and 42 commercial PV-battery systems.
- Predictive control greatly decreases feed-in losses with minor loss of self-consumption.
- Recommended to customize forecast methods based on PV system boundary conditions.

ARTICLE INFO

Keywords:

PV-battery systems
Battery control strategies
Forecasting methods
Self-consumption
Feed-in limit
Storage revenues

ABSTRACT

Photovoltaic (PV) systems are increasingly deployed on buildings in urban areas, causing additional power flows and frequency fluctuation on the low voltage electricity grid. Control strategies for PV-battery energy storage systems (BESS) assist in reducing power flows to the grid and improve the self-consumption of PV generated electricity. Therefore, these control strategies require accurate forecasts of PV electricity production and electricity consumption. We developed and assessed relatively simple forecasting methods using 5 min resolution data, to predict the PV yield and to forecast electricity consumption for one year. We used these forecasts with a predictive control strategy to increase PV self-consumption, decrease curtailment losses and improve BESS revenues. Electricity demand patterns of 48 residential and 42 commercial Dutch buildings were used. PV yield forecast methods that uses predicted weather data shows the lowest forecast error. The best performing forecast method for predicting energy consumption of residential buildings requires historical energy consumption data of the previous seven days. Commercial systems require historical energy consumption of the previous weekday. Significant reduction in curtailment losses is achieved using predictive control strategies, especially in combination when clear-sky radiation data is used to forecast PV yield. Similar self-consumption rates were found for predictive control as for real-time control. This indicates that reduction of curtailment loss can be combined while maintaining the level of PV self-consumption. Revenues from battery storage are increased by forecast methods and are highly dependable on boundary condition of a PV-battery system, such as the feed-in limit (FIL) and the feed-in tariff. Therefore, we recommend customizing battery control strategies based on these system boundaries conditions to improve energy storage potential.

1. Introduction

Optimal integration of photovoltaics (PV) produced energy in the low voltage electricity grid supports cost effective transition towards a fully sustainable energy system. One way to enhance PV system integration is using battery energy storage systems (BESS). PV systems with batteries enable the use of PV produced energy at later moments. Subsequently, more locally produced energy is used and thus PV self-consumption increased. PV-battery systems can reduce the impact on low voltage electricity grids when using algorithms that properly

reduce PV peak power. Consequently, investments in new cables and transformers can be deferred to later years, thus saving on necessary update investments. Higher PV self-consumption lower grid losses and potentially reduces CO₂ emissions from fossil-based backup power generation, especially when curtailment of PV energy is avoided [1]. Another important economic incentive for self-consumption is the absolute difference in consumption tariff and feed-in tariff. This difference indicates the economic value of the self-consumed electricity. Due to all these benefits, PV self-consumption is becoming a major incentive for continued PV market growth in urban areas [2]. Subsequently, policies

* Corresponding author.

E-mail addresses: g.b.m.a.litjens@uu.nl (G.B.M.A. Litjens), e.worrell@uu.nl (E. Worrell), w.g.j.h.m.vansark@uu.nl (W.G.J.H.M. van Sark).

Nomenclature*Abbreviations*

AC	alternating current
BESS	battery energy storage systems
CEC	California Energy Commission
DC	direct current
FIL	feed-in limit
PC	predictive control
PV	photovoltaics
RC	real-time control
RER	relative electricity revenue
SOC	state of charge
SPR	sales to purchase ratio
TSO	transmission system operator

Forecast methods

D-PD	demand pattern using previous day
D-PW	demand pattern using average of previous week
D-PWD	demand pattern using previous weekday
PV-CS	PV pattern using clear-sky radiation
PV-PD	PV pattern using previous day
PV-PW	PV pattern using average of previous week
PV-WX	PV pattern using weather prediction data

Performance indicators

Δ_{se}	performance indicator difference between a forecast scenario and the exact forecast [%p]
CLR	curtailment loss ratio [%]
MAPE	mean absolute percentage error [%]
nMBE	normalized mean bias error [%]
nRMSE	normalized root mean square error [%]
SCR	self-consumption ratio [%]
SRR	storage revenue ratio [%]

Time-independent parameters

Δt	5 min
RER_{PV-B}	relative electricity revenue of a PV system with BESS installed

RER_{PV}	relative electricity revenue of a PV system
π_{cons}	consumption tariff [€/W h]
$\pi_{feed-in}$	feed-in tariff [€/W h]
E_{Bmax}	maximum battery state of charge [W h]
E_{Bmin}	minimum battery state of charge [W h]
E_{PV}	PV produced energy [W h]
E_{RIE}	reduced imported energy [W h]
E_{SC}	self-consumed energy [W h]
E_{SE}	sold energy [W h]
n	number of timesteps
$P_{Binvmax}$	battery inverter rating [W]
P_{FIL}	power feed-in limit [W]
t	time

Time-dependent parameters

ΔE_{Bpot}	battery charge or discharge energy potential [W h]
ΔE_B	battery charge or discharge energy [W h]
η_{charge}	battery charge efficiency [%]
$\eta_{discharge}$	battery discharge efficiency [%]
$E_{B,t}$	battery state of charge [W h]
$E_{Brespot}$	potential battery storage capacity reserved [W h]
E_{Bres}	storage state of charge reserved [W h]
$E_{FILloss}$	lost PV energy due to feed-in limitation [W h]
P_{actual}	actual power of PV yield or demand [W]
P_{FC}	forecasted power of PV yield or demand [W]
P_{Binv}	battery inverter load [W]
P_{Bpot}	battery load potential [W]
P_{Bres}	battery charge capacity reserved [W]
P_B	battery load [W]
P_{charge}	power charged to the battery [W]
P_{DFC}	forecasted electricity demand [W]
$P_{directSC}$	direct self-consumed power [W]
P_D	electricity demand [W]
P_{FILFC}	forecasted feed-in power exceeding the feed-in limited [W]
$P_{FILloss}$	power loss due to the feed-in limit [W]
P_G	load from or to the grid [W]
P_{pot}	load potential [W]
P_{PVFC}	forecasted PV production [W]
P_{PV}	PV produced power [W]
P_R	residual power flow [W]

supporting PV self-consumption are developed and implemented in multiple countries [3].

Feed-in limits (FIL) restrict the maximum power flow which is exported back to the electricity grid. These are usually given as a percentage of the installed PV system capacity. Therefore, high PV peak power is avoided on the local electricity grid which increases power quality in low voltage grid. Electricity from PV systems that is not exported nor used is lost, also known as curtailment losses. Consequently, financial support schemes are developed that support the storage of PV peak power. For instance, PV-battery systems in Germany can apply for financial support when the power flow back to the grid is limited to 0.5 kW for each kWp of installed PV capacity [4]. Furthermore, a lower feed-in power results in a lower grid connection and potentially a reduced grid connection fee. In choosing the best charging and discharging times, forecasts of PV electricity production and electricity consumption are essential. Therefore the curtailment losses will be reduced and the level of PV self-consumption can be maintained.

1.1. Literature review

Several studies examined forecasting methods for PV yield and electricity consumptions. A comprehensive overview of PV forecasting methods has been given in a recent review [5]. This study divided forecasting methods into probabilistic forecasting and deterministic forecasting. Most of these studies used historical measured data and/or weather data. For example, PV forecast methods have been developed that used power output of neighbouring PV systems [6]. Also, various methods have been proposed to demand forecasting in a recent literature review, which made a division between statistical based and artificial intelligence based models [7]. Time-of-use models have been proposed to predict energy consumption based on the user and appliances within a building [8].

A limited amount of studies assess the influence of these forecasts on the performance of control strategies for PV-battery systems. A recent review found that control strategies using forecasting data with feed-in power limits showed manageable curtailment losses. These strategies are promising, especially when feed-in limitations are further reduced [9]. A study including a German residential demand profile has shown

Download English Version:

<https://daneshyari.com/en/article/6680139>

Download Persian Version:

<https://daneshyari.com/article/6680139>

[Daneshyari.com](https://daneshyari.com)