Energy Conversion and Management 75 (2013) 701–709

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Impact of onsite solar generation on system load demand forecast

Amanpreet Kaur, Hugo T.C. Pedro, Carlos F.M. Coimbra *

Department of Mechanical and Aerospace Engineering, Jacobs School of Engineering, Center for Energy Research and Center of Excellence in Renewable Resource Integration, University of California, San Diego, La Jolla, CA 92093, USA

ARTICLE INFO

Article history:
Received 19 June 2013
Accepted 18 August 2013

Keywords:
Load forecasting
Solar forecasting
High solar penetration
Error distribution
Photovoltaic farms

ABSTRACT

Net energy metering tariffs have encouraged the growth of solar PV in the distribution grid. The additional variability associated with weather-dependent renewable energy creates new challenges for power system operators that must maintain and operate ancillary services to balance the grid. To deal with these issues power operators mostly rely on demand load forecasts. Electric load forecast has been used in power industry for a long time and there are several well established load forecasting models. But the performance of these models for future scenario of high renewable energy penetration is unclear. In this work, the impact of onsite solar power generation on the demand load forecast is analyzed for a community that meets between 10% and 15% of its annual power demand and 3–54% of its daily power demand from a solar power plant. Short-Term Load Forecasts (STLF) using persistence, machine learning and regression-based forecasting models are presented for two cases: (1) high solar penetration and (2) no penetration. Results show that for 1-h and 15-min forecasts the accuracy of the models drops by 9% and 3% with high solar penetration. Statistical analysis of the forecast errors demonstrate that the error distribution is best characterized as a *t*-distribution for the high penetration scenario. Analysis of the error distribution as a function of daily solar penetration for different levels of variability revealed that the solar power variability drives the forecast error magnitude whereas increasing penetration level has a much smaller contribution. This work concludes that the demand forecast error distribution for a community with an onsite solar generation can be directly characterized based on the local solar irradiance variability.

1. Introduction

California generated approximately 20% of its in-state power using renewable energy resources in 2011 [1]. This percentage must increase substantially by 2020 if the state is to meet the guidelines mandated by its Renewable Portfolio Standard (RPS), which stipulates that a minimum of 33% of in-state electricity must originate from renewable resources like solar, wind, tidal and small hydroelectric power plants. To achieve this aggressive goal of RPS, California's AB 920 assembly bill allows customer-generators to receive a financial credit for the power fed back into the grid by their renewable generation system. Due to the inherent variability of renewable resources, most notably solar and wind, the increase in renewable energy penetration results in additional variability and uncertainty in the power put into the electric grid [2,3]. This situation can also result in additional variability and uncertainty in customer demand if the onsite power generation is not enough to meet the customer's demand. Given that the concept of onsite renewable energy generation is relatively new, its impact on customer demand and load forecast is unclear. This impact needs to be well understood to ensure a reliable grid operation as the planning of resource allocation depends greatly on demand load forecast. Accurate load forecasts are important given that, according to Western Electricity Coordinating Council (WECC) [4], the power systems must maintain an operating reserve to balance against the forecasting error and other unexpected power source failures in the electric grid. To fill this gap, we present a comprehensive case study of UC Merced campus with 1 MW of onsite solar generation plant.

Through a Power Purchase Agreement UC Merced campus contracted a single-axis tracking solar farm that annually produces 3–54% of the daily daytime campus power demand, making the campus a good proxy to study the impact of onsite solar generation. The centralized HVAC (Heating, Ventilation and Air Conditioning) system for the campus includes a Thermal Energy Storage (TES) water tank that operates at night when electricity prices and ambient temperature are lowest. For these reasons the load profile of UC Merced has a lower power demand during the day and higher power demand during the night which, generally speaking, is inverted with respect to the usual load profile for similar facilities

* Corresponding author.
E-mail address: ccoimbra@ucsd.edu (C.F.M. Coimbra).

0196-8904/$ - see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.enconman.2013.08.026

Nomenclature

$\hat{\cdot}$	forecast of $\cdot$
$A(q)$	polynomial of order n_a
$C(q)$	polynomial of order n_c
d	given day
e	disturbance
$Eavg$	mean forecast error
L_g	load with onsite generation
L_{ng}	load with no onsite generation
L_{PV}	solar power generation
N	number of 15-min time steps
P	polynomial fit
q	shift operator
R^2	coefficient of determination
s	forecast skill
$S_{PV}(d)$	daily solar penetration (%)
V_{Lg}	step changes in load with onsite generation
V_{Lng}	step changes in load without onsite generation
$V_{PV,N}$	solar power variability between N steps
AR	Autoregressive Model
ARMA	Autoregressive Moving Average Model
GHI	Global Horizontal Irradiance
HVAC	Heating, Ventilation and Air Conditioning
kNN	k Nearest Neighbors Model
MAE	Mean Absolute Error
MBE	Mean Bias Error
P	Persistence Model
RMSE	Root Mean Square Error
SP	Smart Persistence Model
TES	Thermal Energy Storage

[5] – see Fig. 1. With current efforts to integrate more solar energy into the power grid, such as the net energy metering, we expect that such load profiles will become more common in the future. The additional variability in the demand load together with diurnal and annual solar cycles results in bigger challenges in load forecasting, balancing the power grid and managing ancillary systems [2,6,7]. Accurate forecasts of both demand and supply profiles are being pursed to mitigate these issues and guarantee adequate supply of electricity and reliable grid operation.

The earliest efforts to forecast electrical demand go back to the 1960s [8]. Several reviews on load forecasting methods have been published [9–18] and there is continuous research to develop better methods [19–31]. Because load profiles are expected to change with onsite renewable energy generation especially with intermittent solar generation [6]. It is very important to analyze the forecast model performance for such scenarios. Therefore, two cases were studied for 15-min and 1-h forecasting horizon: onsite generation and no onsite generation. Onsite generation case represents the campus power demand from the grid after consuming all the solar power produced on campus. No generation refers to the power demand that campus would have extracted from the electric grid if there was no solar generation on the campus. As seen in Fig. 1 the former is greatly affected by the variability of the solar resource. Several well established Short-Term Load Forecast (STLF) methods were applied to predict these two time-series: persistence models, regression based models and machine learning models. To make it simple and rely less on inputs, methods with non-exogenous inputs were applied in line with some of our previous work [32]. Like previous works that have studied the error distribution for wind forecasts [33–36], we characterized the error distribution of our predictions in order to understand the impact of additional variability in forecast accuracy.

The data used for this study is presented in Section 2. The models are described in Section 3. Results and discussion are presented in Section 4, where the accuracy of the forecasting models is evaluated and compared using standard statistical error metrics. The forecast error distribution is presented and characterized for the two scenarios, and the impact of onsite solar generation on forecast error is analyzed for different solar power variability levels. The main conclusions of this study are presented in Section 5.

2. Data

In this work we used two datasets: UC Merced demand load from the grid (campus demand after consuming all the solar power produced on campus) which represents the onsite generation case (L_g) and total UC Merced power demand (demand that the campus would extract from the grid if there was no solar power plant), which represents the no onsite generation case (L_{ng}). L_{ng} was obtained by adding the power consumed from the grid and the solar farm power output, that is $L_{ng}(t) = L_g(t) + L_{PV}(t)$ where L_{PV} represents the solar power generation on the campus. For all cases the data points consisted of 15 min backward averages.

2.1. Preprocessing data

The time-series was decomposed by removing the daily trend calculated over the whole year. A 6th order polynomial (P) was fit to both cases as shown in Fig. 2. The detrended demand loads can be represented as no onsite generation $L_{ng}^{dt}(t) = L_{ng}(t) - P_{ng}(t)$ and onsite generation $L_g^{dt}(t) = L_g(t) - P_g(t)$.

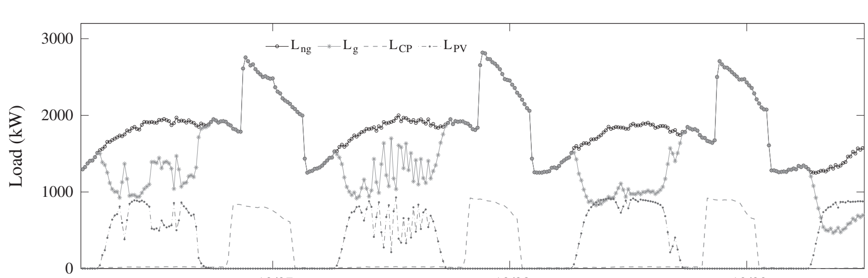

Fig. 1. UC Merced load profile for 06-Oct-2010 through 09-Oct-2010. The UC Merced campus has a unique load shape because the majority of the HVAC load (L_{CP}) has been shifted to the night time using Thermal Energy Storage (TES). The total energy consumed by the campus (L_{ng}), comprise of the energy from the solar farm and energy from electric grid, is comparatively smoother than the demand load (L_g) that is affected by onsite solar generation.