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Forecasting of global horizontal irradiance by exponential smoothing, using decompositions

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Time series methods are frequently used in solar irradiance forecasting when two dimensional cloud information provided by satellite or sky camera is unavailable. ETS (exponential smoothing) has received extensive attention in the recent years since the invention of its state space formulation. In this work, we combine these models with knowledge based heuristic time series decomposition methods to improve the forecasting accuracy and computational efficiency.

In particular, three decomposition methods are proposed. The first method implements an additive seasonal-trend decomposition as a preprocessing technique prior to ETS. This can reduce the state space thus improve the computational efficiency. The second method decomposes the GHI (global horizontal irradiance) time series into a direct component and a diffuse component. These two components are used as forecasting model inputs separately; and their corresponding results are recombined via the closure equation to obtain the GHI forecasts. In the third method, the time series of the cloud cover index is considered. ETS is applied to the cloud cover time series to obtain the cloud cover forecast thus the forecast GHI through polynomial regressions. The results show that the third method performs the best among three methods and all proposed methods outperform the persistence models.

1. Introduction

Renewable energy will be heavily used in future power grids [1]. However, renewable energy facilities such as wind power plants and solar power plants need to be integrated and controlled by power system operators. Due to its non-dispatchable nature, the variable renewable generation can affect the grid voltage and frequency, reduce load predictability and cause reverse power flow [2]. Solar irradiance forecasting and hence PV (photovoltaic) power output forecasting is thus one of the key means for the safe and reliable integration of PV plants into electric power grids. Managing the intermittent solar energy generation can bring advantageous impacts to power grid operations such as load following and unit commitment.

To address irradiance forecasting properly, it is important to understand weather related irradiance transients. Unlike traditional power generation sources, solar power systems are inherently non-stationary due to changes in cloud cover. Cloud cover will cause many rapid fluctuations in the ground level irradiance during the day. A sudden and significant decrease in PV power delivery owing to the reduced irradiance can pose problems for grid operators who must compensate for the shortfall. The need for forecasting of variable renewable generation spawned a large body of literature in the field of energy over the recent years. In the case of solar energy, it requires forecasting at a variety of spatial and temporal scales. The forecast methodologies thus vary for different forecast horizons.

In a spatio-temporal context, the creation, propagation, evolution and distinction of clouds are usually considered, regardless of the choice of forecast horizons and methodologies. In a small spatial scale, pyranometer networks with designed geometries [3,4] or sky cameras [5] are used to retrieve the information on cloud movement speed and direction. Given the geographical

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List of symbols

D	diffuse horizontal irradiance
E	error component
G	global horizontal irradiance
$G^{(\mathrm{ext})}$	extraterrestrial horizontal irradiance
I	direct normal irradiance
S	seasonal component
T	trend component
a_0, a_1, a_2 and a_3	cloud cover regression parameters
b_t	growth term in trend component at time t
ℓ_t	level term in trend component at time t
$\boldsymbol{x}_t$	state vector at time t
y_t	time series $\{y_t\}$ at time t
$\hat{y}_{t+h\|t}$	h-step-ahead forecast
α, β, γ and ϕ	ETS model parameters
ε_t	white noise at time t
$\boldsymbol{\theta}$	vector notation for α, β, γ and ϕ
θ_z	zenith angle
$\mu_{t+h\|t}$	conditional expectation of y_{t+h} given $\boldsymbol{x}_t$
ϕ_h	$\phi+\phi^2+\cdots+\phi^h$
$\mathcal{CC}$	cloud cover
$\mathcal{F}$, $\mathcal{G}$, $\mathcal{R}$ and $\mathcal{W}$	functions of the state vectors
$\mathcal{L}$	likelihood function
AIC	Akaike's Information Criterion
ETS	ExponenTial Smoothing
LOESS	LOcally-wEighted Scatter plot Smoothing
STL	Seasonal-Trend decomposition procedure based on Loess

proximity, the forecast horizon of this class of methods ranges from 20 s to 15 min [6]. On the other extreme of the forecast spatio-temporal scale, satellite images can be used to detect and classify the clouds [7]. However, obtaining future cloud information is not sufficient for the forecast; ground level irradiance data must be derived from the forecast cloud images, and the mapping is not trivial [8].

One way to circumvent the cloud to irradiance conversion is to consider the stochastic nature of the irradiance. Artificial intelligence and statistical methods are the main tools for such application, as they are capable of performing input–output mapping of such nature. ANN (artificial neural networks) have been extensively investigated in the literature of irradiance forecasting e.g. [9,10,11]. However, the evident disadvantage of ANN is its black-box nature which poses limitations in terms of intuitive understanding of the irradiance temporal process. On the other hand, statistical forecasting models emphasize on evolution and dependence; they are described by parameters [12]. We therefore focus on the application of statistical forecasting models in this paper.

Among many famous time series models such as the ARMA (autoregressive moving average) model, exponential smoothing is much overlooked. Although the methods have been around since the 1950s [13], the framework of stochastic formulation, likelihood calculation and model selection was not developed until the publication of two key papers [14,15]. Since then, exponential smoothing has received attention in many developed areas including call centers, power grid, financial markets and inventory control [16–20]. However, its applications in the field of solar energy are very limited, and most of the works only considered the univariate irradiance time series with no exogenous input [21].

Although exponential smoothing has the multivariate form [22], to realize the vector exponential smoothing, a network of irradiance monitoring stations are required to sample the time series of lattice processes [23]. In addition, the selection of relevant spatial neighbors needs attention, as irrelevant information not only increases the model complexity but also introduces additional errors [24]. We therefore focus on the univariate exponential smoothing here.

This paper is organized as follows. Section 2 covers a brief introduction of univariate exponential smoothing, and knowledge based decompositions are considered in section 3. In particular, the GHI (global horizontal irradiance) time series $\{G_t\}$, $t \in \{0,1,\ldots\}$, is decomposed into the DHI (diffuse horizontal irradiance) and the DNI (direct normal irradiance) time series $\{D_t\}$ and $\{I_t\}$, $t \in \{0,1,\ldots\}$. Forecasts are produced separately using the two decomposed time series; GHI forecasts are then reconstructed through the closure equation [25]:

$$\hat{G} = \hat{I}\cos\theta_z + \hat{D} \tag{1}$$

where θ_z is the zenith angle, a deterministic quantity; the $\hat{G}$, $\hat{I}$ and $\hat{D}$ denote the forecasts of the respective quantities. We also propose a more sophisticated decomposition model, namely, GHI as a function of zenith angle and cloud cover ($\mathcal{CC}$):

$$\hat{G} = f\left(\theta_z, \widehat{\mathcal{CC}}\right) \tag{2}$$

where $\widehat{\mathcal{CC}}$ denotes the forecast cloud cover on a discrete scale of 0 (clear sky) to 10 (opaque sky). Section 4 illustrates and discusses the results. Conclusions are presented in section 5.

The TMY3 (typical meteorological year 3) data from the National Renewable Energy Laboratory is used in this work. The data is freely available online at http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/. The user manual of the datasets is found at the same website. The TMY3 dataset provides an annual dataset that holds hourly meteorological values that typify conditions at a particular site over a longer period of time, of 10 up to 30 years. There are more than one thousand sites in the TMY3 dataset; for demonstration of the proposed forecasting techniques, we choose a class one site, namely, the San Diego Lindbergh Field with USAFN number 722900.

2. Univariate exponential smoothing

2.1. Time series components

Exponential smoothing considers time series as a combination of three components, namely, the trend (T), seasonal (S) and error (E) components. The trend component consists of another combination of a level term (ℓ) and a growth term (b). When we describe the forecast trend T_h over the next h time periods, ℓ and b can be combined in the following 5 ways:

$$\begin{aligned}
&\text{None}: && T_h = \ell \\
&\text{Additive}: && T_h = \ell + bh \\
&\text{Additive damped}: && T_h = \ell + \left(\phi+\phi^2+\cdots+\phi^h\right)b \\
&\text{Multiplicative}: && T_h = \ell b^h \\
&\text{Multiplicative damped}: && T_h = \ell b^{(\phi+\phi^2+\cdots+\phi^h)}
\end{aligned}$$

where $0<\phi<1$ is a damping parameter. Beside the trend component, the seasonal components can be additive ($T+S$), multiplicative ($T\times S$) or none. This gives rise to the 15 combinations of time

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