Energy Conversion and Management 153 (2017) 409–422

Contents lists available at ScienceDirect

Energy Conversion and Management

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

Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network

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ARTICLE INFO

Keywords:
Deep convolutional neural network (DCNN)
Photovoltaic power forecasting
Quantile regression
Wavelet decomposition
Deep learning

ABSTRACT

The penetration of photovoltaic (PV) energy into modern electric power and energy systems has been gradually increased in recent years due to its benefits of being abundant, inexhaustible and clean. In order to reduce the negative impacts of PV energy on electric power and energy systems, advanced forecasting approach with high-accuracy is a pressing need. Aimed at this, a novel hybrid method for deterministic PV power forecasting based on wavelet transform (WT) and deep convolutional neural network (DCNN) is firstly proposed in this paper. WT is used to decompose the original signal into several frequency series. Each frequency has better outlines and behaviors. DCNN is employed to extract the nonlinear features and invariant structures exhibited in each frequency. Then, a probabilistic PV power forecasting model that combines the proposed deterministic method and spine quantile regression (QR) is originally developed to statistically evaluate the probabilistic information in PV power data. The proposed deterministic and probabilistic forecasting methods are applied to real PV data series collected from PV farms in Belgium. Numerical results presented in the case studies demonstrate that the proposed methods exhibit the ability of improving forecasting accuracies in terms of seasons and various prediction horizons, when compared to conventional forecasting models.

1. Introduction

Due to the global warming and climate change concerns, many energy legislations and incentives, that can promote the use of renewable energy, have been established worldwide [1,2]. Among renewable energy resources, PV energy, as one of the promising supplements for fossil fuel-generated electricity, has received much attentions recently because of the advantages of being abundant, inexhaustible and clean [3]. The average annual growth of PV system is already up to 30% in recent years [4]. Together with the ever-decreasing prices of PV modules and continuous depletion of fossil fuel, it is expected that the penetration level of PV energy into modern electric power and energy systems would be further increased. However, due to the chaotic and erratic nature of the weather systems, the power output of PV energy system always exhibits strong uncertainties in terms of intermittency, volatility and randomness [5]. These uncertainties may potentially degrade the real-time control performance, reduce system economics, and thus pose a great challenge for the management and operation of electric power and energy systems [6]. One of the promising solutions for alleviating these negative impacts of these uncertainties on electric energy system is the use of advanced forecasting methods of PV power. Recognizing this task, indirect and direct forecasting models were generally proposed in the literature.

In indirect methods, the environmental parameters associated with PV system, like solar radiance, are firstly predicted [7], and then converted to PV power via predetermined mathematical model relevant to ambient temperature, panel areas and efficiency. In [8], a series of smart baseline models for solar irradiation forecasting based on machine learning and genetic algorithm were originally proposed and competitive performance was obtained accordingly. In [9], a hybrid forecasting model combining Éclat data-mining algorithm, SVM and glowworm swarm optimization was developed, and high forecasting preciseness and reliability were statistically demonstrated. To improve the forecasting accuracy, a transformation K-means based advanced forecasting framework was mooted and applied to real PV data collected from isolated PV farm in Iowa State [10]. While, direct methods are designed to directly predict the output of PV system accordingly to the historical PV data and relevant weather conditions. In [11], a multi-step PV forecasting strategy in combination with least square SVM and group data handling technique was proposed and a comprehensive

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http://dx.doi.org/10.1016/j.enconman.2017.10.008
Received 18 April 2017; Received in revised form 21 September 2017; Accepted 3 October 2017
0196-8904/

Nomenclature

ACE	average coverage error
BPNN	back-propagation neural network
db	Daubechies
DCNN	deep convolutional neural network
MAE	mean absolute error
PI	prediction interval
PV	photovoltaic
RMSE	root mean square error
SVM	support vector machine
A_n	wavelet approximation signal
DS_u	input dataset
$H(\bullet)$	indicative function
I_i^α	PI at time step i given PINC
L	number of layers
L_i^α	lower bound of PI given a target i and PINC
N	number of samples
N_S	number of training samples
PV_i^f	the forecasting PV power
T	length of a given signal
$\boldsymbol{W}$	weight matrix of DCNN
$\boldsymbol{W}_{log}^L$	weight matrix at Lth logistic regression layer
$\boldsymbol{W}_{j,con}^{l+1}$	weight matrix of jth map at lth convolution layer
ε	parameters used in cubic B-splines
b_{con}^l	bias at lth convolution layer
$\boldsymbol{b}_{log}^L$	bias matrix at Lth logistic regression layer
c_i	weight parameter in back propagation process
c_j^l	additive bias of the jth output map at lth layer
$c_{sub,j}^l$	additive bias matrix of jth map at lth layer
$down(\bullet)$	down-sampling function
$g(t)$	signal required to be decomposed by wavelet
m	mini-batch size of a training sample
q	translation variable
t_j^i	the jth target of the ith sample in mini-batch
$\boldsymbol{u}^L$	output vector of the neurons at $(L-1)$th layer
$\boldsymbol{u}_j^l$	the jth input at ith layer
$w_{i,j}^l$	weight between the ith input map and jth output map
$x_{i,j,k}$	the element in a volume with $i \times j \times k$
x_i^{l-1}	the ith input map at $(l-1)$th layer
y_j^l	the jth output map at lth layer
α_i	weight parameter in back propagation process
$\boldsymbol{\beta}$	multiplicative bias matrix of DCNN
β_j^l	multiplicative bias of the jth output map at lth layer
$\widehat{\beta}(\cdot)$	loss function of QR
δ_j^l	the jth sensitivity map at lth layer
τ	quantile parameter
$\phi(\bullet)$	mother wavelet function
ANN	artificial neural network
CRPS	continuous ranking probability score
DBN	deep belief network
IS	interval sharpness
MAPE	mean absolute percentage error
PINC	prediction interval nominal confidence
QR	quantile regression
SAE	stacked auto-encoder
WT	wavelet transform
D_n	wavelet detail signal
E_m	squared-error loss function with m batches
Hei	height of a given map
K	parameters in cubic B-splines
Len	length of a given map
M_j	number of selected input maps
N_L	number of elements in a given volume
PV_{av}	average power of PV output
PV_i^t	the real PV power
U_i^α	upper bound of PI given a target i and PINC
Wid	width of a given map
W_{con}^l	weight matrix at lth convolution layer
$\boldsymbol{b}$	bias matrix of DCNN
b_j^l	jth bias at lth layer
$\boldsymbol{b}_{j,con}^{l+1}$	bias matrix of the jth map at lth convolution layer
$\boldsymbol{c}$	additive bias matrix of DCNN
c_{ij}	underlying weight
$\boldsymbol{c}_{sub}^l$	additive bias matrix at lth sub-sampling layer
d	output vector size of a training samples
$f(\bullet)$	sigmoid activation function
l_i	indicator of PI coverage probability
p	scaling variable
t	discrete time step
t_i	the real power at ith time step
$up(\bullet)$	up-sampling function
w_i	weight parameter in feed forward process
x	explanatory variable
$\boldsymbol{x}^{L-1}$	the output vector at $(L-1)$th layer
y_j^i	the real value with respect to t_j^i
α	confidence level parameter
α_{ij}	weight of the ith input map when forming jth output map
$\boldsymbol{\beta}_{sub}^l$	multiplicative bias matrix at lth sub-sampling layer
β_s	coefficient vector
δ_i^α	width of the PI at time step i given PINC
ρ_τ	piecewise check function
η	learning rate

analysis was performed and discussed. In [12], a novel PV power forecasting approach based on dynamic ANN was proposed. It was numerically demonstrated that the proposed approach has a better learning capability and higher prediction accuracy compared to other benchmarks. In [13], a family of multivariate adaptive regression model was presented to predict the daily output of grid-connected PV system.

The methodologies used in indirect and direct methods can be divided into three categories: physical methods, statistical approaches and soft-computing techniques [14]. Physical methods try to establish an analytical model by using meteorological and geological parameters, but they may not be suitable for fulfilling the real-time short-term forecasting task due to the involved high-computational cost [15]. Statistical approaches manage to optimize a mapping relationship from historical samples to real PV power via error minimization [16]. While, soft-computing techniques are generally implemented to extract the nonlinear features in parameters relevant to PV system [17]. It is these features that can be utilized to improve PV forecasting accuracy. Therefore, soft-computing based forecasting methods always exhibit a more competitive performance than physical methods and statistical approaches [18]. In [19], a feed-forward ANN based PV power forecasting framework was developed, and the model parameters were further optimized by particle swarm optimization. In [20], a 24-hours-ahead forecasting model based on fuzzy logic and ANN was developed.

However, the above-mentioned methods for PV power forecasting and most of the published researches concentrate only on deterministic forecast, i.e., point forecast. As presented in [21], deterministic forecasting methods fail to evaluate the uncertainties exhibited in PV power data. Therefore, probabilistic PV power forecasting models that can statistically describe these uncertainties have received much attention recently. One of the mainstreams for generating probabilistic uncertainty is to use an ensemble of deterministic forecaster. In [22], an