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Review

Solar photovoltaic generation forecasting methods: A review

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A R T I C L E I N F O

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A B S T R A C T

Solar photovoltaic plants are widely integrated into most countries worldwide. Due to the ever-growing utilization of solar photovoltaic plants, either via grid-connection or stand-alone networks, dramatic changes can be anticipated in both power system planning and operating stages. Solar photovoltaic integration requires the capability of handling the uncertainty and fluctuations of power output. In this case, solar photovoltaic power forecasting is a crucial aspect to ensure optimum planning and modelling of the solar photovoltaic plants. Accurate forecasting provides the grid operators and power system designers with significant information to design an optimal solar photovoltaic plant as well as managing the power of demand and supply. This paper presents an extensive review on recent advancements in the field of solar photovoltaic power forecasting. This paper aims to analyze and compare various methods of solar photovoltaic power forecasting in terms of characteristics and performance. This work classifies solar photovoltaic power forecasting methods into three major categories i.e., time-series statistical methods, physical methods, and ensemble methods. To date, Artificial Intelligence approaches are widely used due to their capability in solving the non-linear and complex structure of data. The performance analysis shows that these methods outperform the traditional methods. Recently, the ensemble methods were also developed by researchers to extract the unique features of single models to enhance the forecast model performances. This combination produces accurate results compared to individual models. This paper also elaborates on the metrics assessment which was implemented to evaluate the forecast model performances. This work provides information which is beneficial for researchers and engineers who are involved in the modelling and planning of the solar photovoltaic plant.

1. Introduction

Global warming and the critical depletion of fossil fuel over the past decades have encouraged the use and development of renewable energy sources (RES). Renewable energy sources e.g., solar, wind, hydropower, and geothermal energy have not only been acknowledged as novel solutions to the issues listed above but also reflect the future of energy advancement. In substituting conventional sources, solar energy has emerged as a most popular approach and is implemented in many nations worldwide compared to others. Solar energy becomes the most promising source for generating power for residential, commercial, and industrial applications. Solar photovoltaic (PV) systems use PV cells that convert solar irradiation into electric power [1]. Solar PV is used in stand-alone and grid-connected systems to supply power for home appliances, lighting, and commercial and industrial equipment [2].

In fact, the number and the size of the solar PV plants have grown rapidly at a worldwide level, due to their essential role in generating electricity [3]. Several nations that are in collaboration with the International Energy Agency (IEA), are supposed to generate 196 GW (in most grid-connected plants) by the end of 2015. An additional 40 nations that were excluded from the IEA Photovoltaic Power System Programme (IEA PVPS) produced about 31 GW of solar power. Fig. 1 illustrates the evolution of global solar PV installation from 2000 to 2015. Solar PV installation for both IEA PVPS and other countries has increased dramatically from 2007 to 2015. About 70% of solar PV installation came from IEA PVPS countries [4]. In early 2016, 120 solar PV plants with a capacity of more than 50 MW operated in at least 23 countries i.e., Philippines, Uruguay, Pakistan, Kazakhstan, Honduras, Guatemala, Denmark, and Australia [3]. The Global Future Report 2013 Renewable Energy Policy Network for the 21st Century (REN21) has projected that the capacity of global solar PV has the potential to reach 400–800 GW by 2020 [2].

Malaysia is one of the Asian countries that receives high solar radiation. The availability of solar energy is highly influenced by climatic conditions over the year. Malaysia is located on the South China Sea and lies between 1° and 7° on the North latitude and 100° and 120° on

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Nomenclature

ACE Average Coverage Error
AGC Automatic Gain Control
AI Artificial Intelligence
AnEn Analog Ensemble
ANFIS Adaptive Neuron Fuzzy Inference System
ANN Artificial Neural Network
AR Autoregressive
ARMA Autoregressive-Moving Average
ARIMA Autoregressive Integrated Moving Average
ARIMA-BP Autoregressive Integrated Moving Average-Back-propagation
ARX Autoregressive with Exogenous Input
AWS Automated Weather Stations
BCRF Bias Compensation Random Forest
BLUE Statistical model of Blue Sky
BP Back-Propagation
BPNN Back-propagation Neural Network
Bagging-BP Bagging-Back-propagation
BSRN Baseline Surface Radiation Network
BS Brier Score
BSS Brier Skill Score
Cap cloud-advection-versus-persistence, cap
CARDS Coupled Autoregressive and Dynamical System
CC Coefficient Correlation
CDF Cumulative Distribution Function
CFB Cascaded Feed-forward Back-propagation
CDHMM Continuous Density Hidden Markov Model
CMV Cloud Motion Vector
CRPS Continuous Ranked Probability Score
CS Cuckoo Search
CSKY-Glo Clear Sky Global Horizontal Radiation
CS-OP-ELM Cuckoo Search-Optimally Pruned-Extreme Learning Machine
CSRM Clear Sky Solar Radiation Model
CVRMSE Coefficient of Variance based on Root Mean Square Error
C1 Custom Network-1
C2 Custom Network-2
DAS Data Acquisition System
DBN Deep Belief Network
DCNN Deep Convolutional Neural Network
DD Number of Day
DDM Data-Driven Model
DH Diffuse Horizontal
DHI Diffuse Horizontal Irradiance
DHR Dynamic Harmonic Regression
DN Direct Normal Radiation
DNI Direct Normal Irradiance
DNN Deep Neural Network
DP BP due point temperature
EA Evolutionary Algorithm
EBP Evidence-Based Practise
ECMWF European Centre for Medium-Range Weather Forecasts
Elman-BPNN Elman Back-propagation Neural Network
ELM Extreme Learning Machine
ESS Exponential Smoothing State
ETS Exponential Trend Smoothing
FA Fuzzy ARTMAP
FF Firefly
FFB Feed-forward back propagation
FFN Feed-forward Network
FFNN Feed-forward Neural Network
GA Genetic Algorithm
GBRT Gradient Boosted Regression Trees
GCPV Grid-connected Photovoltaic
GEM Global Environmental Multi-scale
GFM Generalized Fuzzy Model
GFS Global Forecast System
GHI Global Horizontal Irradiance
GI_{csk} Clear Sky POA irradiance
GLSSVM Group Least Square Support Vector Machine
GMDH Group Method of Data Handling
GMM Gaussian Mixture Method
GP Genetic Programming
GRNN General Regression Neural Network
GSO Genetical Swarm Optimization
GW Gigawatt
H Horizontal surface
HH Time in Hours
HMC Higher-order Markov Chain
HPANN Hybrid Physical Artificial Neural Network
HSV Hue-Saturation-Value
H_o extra-terrestrial global solar radiation on a horizontal surface
I Irradiance
ICP Internal Coverage Probability
I_{cs} Clear Sky Irradiance
IEA International Energy Agency
IS Interval sharpness
I_o Solar constant
KM Kernel Methods
kNN k-Nearest Neighbour
KSI Kolmogorov-Smirnov test Integral
k_t^* Forecast clear sky index
L Loss function
LES Linear Exponential Smoothing
LM-BP Levenberg-Marquardt Back-Propagation
LOO-CV Leave-Out-Outcross Validation
LSS Large Scale Solar
LS-SVM Least Square Support Vector Machine
LVQ Learning Vector Quantization
MA Moving Average
MAE Mean Absolute Error
MAD Mean Absolute Deviation
MAID Mean Absolute Internal Deviation
MAPE Mean Absolute Percentage Error
MARE Mean Absolute Relative Error
MARS Multivariate Adaptive Regression Splines
MASE Mean Absolute Scaled Error
MaxAE Maximum Absolute Error
MBE Mean Bias Error
MdAPE Median Absolute Percentage Error
ME Systematic Error
MeAPE Median Absolute Percentage Error
MEF Mean Error Function
MLP Multi-layer Perceptron
MM Number of months
MM-MOS MOS by the weather company Meteomedia GmBH
MOS Model Output Statistical
MPE Mean Percentage Error
MRE Mean Relative Error/Magnitude Relative Error
MRSR Multi-Response Sparse Regression
MSE Mean Square Error
MW Megawatt
NAM North American Mesoscale Forecast System
NAR Non-Linear Auto-regressive
NARX Non-Linear Auto-regressive Network with exogenous input
NCAR National Center for Atmospheric Research