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A hybrid solar radiation modeling approach using wavelet multiresolution analysis and artificial neural networks

Sajid Hussain, Ali AlAlili*

Department of Mechanical Engineering, Khalifa University of Science and Technology, Petroleum Institute, P.O.Box 2533, Abu Dhabi, United Arab Emirates

HIGHLIGHTS

- Hybridization is usually performed to improve the modeling performance of the solar radiation models.
- This research investigates a new hybrid approach based on wavelet decomposition and neural network.
- The proposed approach successfully captures the temporal and spectral non-linearities present in the signals.
- A comparison of different neural network models is presented, and models are validated in time, frequency, and phase domains.

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ABSTRACT

Assessment of solar potential over a location of interest is an important step towards the successful planning of renewable energy projects. However, solar data are not available for every point of interest due to the absence of meteorological stations and sophisticated solar sensors, so solar radiation has to be estimated using models. This paper presents a hybrid technique to improve the performance of a widely used modeling technique i.e. artificial neural network (ANN). Four different architectures of ANN, namely: multilayer perceptron (MLP), Adaptive neuro-fuzzy inference system (ANFIS), Nonlinear autoregressive recurrent exogenous neural network (NARX), and generalized regression neural networks (GRNN), are used in this study. A wavelet multiresolution analysis is applied to decompose the complex meteorological signals into relatively simple parts, wavelet sub-series, using discrete wavelet transformation (DWT) algorithm. The wavelet sub-series are modeled by the ANN models and reconstructed to estimate the original signal. Hence, enhancing the learning process of these models. Four meteorological parameters, namely: temperature (T), relative humidity (RH), wind speed (WS), and sunshine duration (SSD), are used to mode the global horizontal irradiation (GHI) over Abu Dhabi, the United Arab Emirates. The proposed approach is compared to standalone ANN models and validated using well-known statistical validation metrics including coefficient of determination (R^2), root mean square error (RMSE), mean bias error (MBE), mean absolute percentage error (MAPE), and *t*-statistics. In addition, wavelet cross spectrum (WCS) is used as a visual indicator of the model performance in time, frequency, and phase domains. The results show that using the proposed strategy considerably improves the modeling performance of the ANN with a maximum improvement of 6.84% in R^2 for MLP. In addition, minimum RMSE of 2.78% is observed for GRNN.

1. Introduction

Over the past couple of decades, renewable energy resources such as the wind, solar, biomass, and geothermal, have been investigated as alternatives to fossil fuels. Solar energy is one of the promising alternatives that reduce the carbon emissions and decreases the risks associated with traditional energy. The development of solar projects requires an accurate estimation of solar potential at the location of interest. In addition, the information is useful for utilities to forecast the electricity generation potential, and to better manage the gap between supply and demand in case of grid-connected solar generations. It is shown that an abundance of solar energy is available between 40°N and 40°S latitudes, also referred as solar belt [1]. The United Arab Emirates (UAE) is one of the solar-rich countries in the world located at 23.4241°N and 53.8478°E. This gives the UAE an opportunity to harness this energy source, and to promote a healthy, sustainable, and clean environment in the region. The solar energy is not only useful for electrification, but it is also equally useful for desalinating seawater, drying crops, and heating water in the form of solar-thermal energy. All the applications mentioned above increase the importance of an

* Corresponding author.
E-mail address: alialalili@pi.ac.ae (A. AlAlili).

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Nomenclature

$W_x(d,s)$	continuous wavelet transform
$S_{y\hat{y}}^{w}(d,s)$	wavelet cross spectrum (WCS)
$\Psi(t)$	mother wavelet
$\Psi_{d,s}(t)$	daughter wavelets
d	translation in time
s	dilation or scale operator
σ_t^2	time variance
σ_ω^2	frequency variance
ω_0	reference frequency
t_0	reference time
$x(t)$	time signal
$x(n)$	discrete version of the signal $x(t)$
h[n]	impulse response of high-pass decomposition filter
g[n]	impulse response of high-pass decomposition filter
H[n]	impulse response of high-pass reconstruction filter
G[n]	impulse response of high-pass reconstruction filter
$A_1, \ldots, A_n$	approximation wavelet coefficients
$D_1, \ldots, D_n$	detailed wavelet coefficients
R^2	coefficient of determination
ANN	artificial neural network
GHI	global horizontal irradiance
DoF	degree of freedom
CI	confidence interval
MOY	month of year
RF	rainfall
T	temperature
RH	relative humidity
WS	wind speed
SSD	sunshine duration
MLP	multi-layer perceptron
ANFIS	adaptive neuro-fuzzy information system
NARX-NN	nonlinear autoregressive with exogenous inputs neural network
RBFNN	radial basis functional neural network
WNN	wavelet neural network
GRNN	generalized regression neural network
RMSE	root mean square error
nRMSE	normalized root mean square error
rRMSE	relative root mean square error
MSE	mean square error
MBE	mean bias error
MABE	mean absolute bias error
MAPE	mean absolute percentage error
PSO	particle swarm optimization
RBF	radial basis function
ARMA	auto regressive moving average
MJ m^{-2} day^{-1}	megga joule per meter square per day
W m^{-2}	watts per meter square
Wh m^{-2} day^{-1}	watts hour per meter square per day
EKF	extended Kalman filter
OBS	optimal brain surgeon
FFT	fast Fourier transform
JTFA	joint time–frequency analysis
STFT	short-time Fourier transform
WT	wavelet transform
CWT	continuous wavelet transform
DWT	discrete wavelet transform
IDWT	inverse discrete wavelet transform
db4	Daubechies 4 wavelets
WCS	wavelet cross spectrum
COI	cone of influence

accurate assessment of solar potential in the region.

The solar potential is normally measured and quantified through different ground-based sensors including radiometers, pyranometers, and pyrheliometers. Therefore, alternative ways of solar assessment are needed for this purpose, and solar modeling and prediction algorithms play an important role in this regard. To this approach, various prediction techniques are developed including statistical [2,3], biologically inspired [4,5] and hybrid [6,7]. Historical solar and weather data are used to train and validate a model at certain geographical location. The trained model is used to estimate the solar potential at nearby sites. Different geographical and climatological parameters namely: latitude (Lat), longitude (Long), height (H), month of year (MOY), rainfall (RF), temperature (T), relative humidity (RH), wind speed (WS), and sunshine duration (SSD) are used to estimate global horizontal irradiance (GHI). Many authors used satellite-based solar radiation prediction models [8,9].

Among biologically inspired models, ANN is commonly used in the solar research community. Yadev et al. [10] and Zhang et al. [11] presented a very comprehensive review on ANN for solar radiation modeling where the authors reviewed different versions of ANN including MLP, ANFIS, NARX-NN, radial basis function neural networks (RBFNN), wavelet neural networks (WNN), and GRNN. Yadev et al. [12,13] used MLP to model 14-year of solar data from 26 states in India and reported the best MLP with MAPE of 6.89%. Bosch et al. [14] used an ANN to model 3-year of solar radiations in Spain, and reported RMSE of 6% and mean bias error (MBE) of 0.2%. Fadare [15] used 10-year data from 195 stations in Nigeria and modeled solar radiations with ANNs. The author reported the R^2 values for training, testing, and the whole dataset as 97.8%, 97%, and 95.6%, respectively. Amrouche and Pivert [16] used an ANN to model high-resolution solar radiation in France from June 2008 to May 2009 and reported the best model with RMSE of 33.10 W m^{-2} and MSE of 16.45 W m^{-2}. Senkal and Kuleli [17] used solar data from 12 (training: 9 stations, testing: 3 stations) stations in Turkey from August to December 1997. The RMSE values for training and testing are reported as 54 W m^{-2} and 125 W m^{-2}, respectively. Vector at al. [18] used ANN for modeling solar radiations for six locations in Mexico. The authors used daily averages data for solar radiation and other meteorological variables and reported RMSE, MAE, and R^2 values of the best ANN for each location.

Tymvios et al. [19] presented a comparative analysis of ANN and Ångström models in modeling solar radiations over Athalassa, Cyprus. The data spanned a range of 7-year from 1986 to 1992 and included GHI (W m^{-2} h^{-1}), SSD (hours), extraterrestrial irradiance, daily theoretical SSD, and daily minimum and maximum temperatures. The authors reported three Ångström models and seven ANN models with different combinations of input variables. The best model reported was the ANN with two hidden layers having 46 and 23 hidden neurons. The MBE and RMSE values were 0.12% and 5.67%, respectively.

Jacovides et al. [20] reported another interesting research on ANN modeling of daily solar fluxes over Athalassa, Cyprus. Three-year data, from 2004 to 2006, of daily global solar radiant flux (G_h), photosynthetic photon flux density (Q_P), and global ultraviolet solar radiant flux (G_{UV}) were used. Six different ANN models with different combinations of input variables were obtained to estimate G_h, Q_p, and G_{UV}. The input variables included air mass, ozone, sunshine fraction, T, and RH. The authors reported a MAPE of 5.9% for the ANN with a sunshine fraction as an input.

Often, the modeling performance of the ANN is improved by using a combination of hybrid techniques or different ANNs are used to model different seasons in the data or more specifically, to cater for temporal nonlinearity in the data. Alam et al. [21] used data from different stations in India and developed 16 different ANNs for solar radiation