Solar radiation time-series prediction based on Empirical Mode Decomposition and Artificial Neural Networks

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Abstract This paper presents a new model for daily solar radiation prediction. In order to capture the hidden knowledge of existing data, a time-frequency analysis on past measurements of the solar energy density is carried out. The Hilbert-Huang transform (HHT) is employed for the representation of the daily solar irradiance time series. A set of physical measurements and simulated signals are selected for the time series analysis. The empirical mode decomposition is applied and the adaptive basis of each raw signal is extracted. The decomposed narrow-band amplitude and frequency modulated signals are modelled by using dynamic artificial neural networks (ANNs). Nonlinear autoregressive networks are trained with the average daily solar irradiance as exogenous (independent) input. The instantaneous value of solar radiation density is estimated based on previous values of the time series and previous values of the independent input. The results are promising and they reveal that the proposed system can be incorporated in intelligent systems for better load management in photovoltaic systems.

1 Introduction

Today there is an obvious need for eco-friendly and sustainable energy sources. It is well known that in developed world the daily life depends on the continuous supply of energy. Unfortunately, the exponential increase in energy demand compromises the ability of future generations to meet their needs. The provision of fossil fuel cannot be taken for granted. In recent years many European govern-

ments introduced subsidy programs in order to encourage the utilization of alternative energy resources with high efficiency and environmentally sound.

Nowadays, there are many options for renewable energy sources. One of the most attractive and promising resource is the solar irradiance. Solar energy usage is small globally, but it is commonly accepted that it will increase substantially in the near future.

Solar energy is one of the most considerable design parameters in many research fields such as bioclimatic design of buildings, analysis of the performance of photovoltaic systems, agriculture science and meteorology. Moreover, in the case of autonomous energy systems with solar power source an automatic and efficient management of solar energy is required in order to minimize the strain of storage components and increase their lifetime.

Due to the widely use of solar energy there is an obvious need for a more precise modeling and close prediction of the solar irradiance future trend. Several studies for solar prediction exist in the literature. These studies involve empirical models [1, 2], statistical approaches [3, 4] and intelligent system approaches [5, 6].

This paper presents a new approach for solar radiation prediction by taking into account the past measurements of the series. The HHT operates on the original signal in order to extract the different spectral components. Afterwards, nonlinear autoregressive neural networks are trained with the average daily solar irradiance as exogenous input. The instantaneous values of solar radiation density are predicted for each of the partial component and are summarized in order to estimate the original signal's prediction.

The paper is organized as follows: Section 2 introduces the HHT. Section 3 refers to the nonlinear autoregressive networks, while section 4 deals with the proposed model implementation. Section 5 presents the experimental results.

2 The Hilbert Huang Transform

The HHT is an appropriate tool for analyzing non-stationary and nonlinear data. The HHT, a NASA's designated name, is proposed by Huang et al [7]. The essential difference between HHT and most currently data decomposition methods is that HHT provides an adaptive analysis of data. The term adaptivity refers to the requirement for an adaptive basis. There is no a priori reason to believe that an arbitrarily selected basis is able to describe the underlying processes of any given phenomenon. This algorithm comprises Empirical Mode Decomposition (EMD) and Hilbert Spectral Analysis (HSA). The combination of EMD and HSA provides a consistent and physically meaningful definition for instantaneous frequency and amplitude. First, the EMD process decomposes any complicated set of data into a finite and often small number of intrinsic mode function components. This decomposition is adaptive since it is based on local characteristics of the original signal and it can be applied to nonlinear and nonstationary signals. Second, the

HSA is applied to the generated components in order to provide a meaningful time-frequency-energy distribution of time series.

2.1 Empirical Mode Decomposition (EMD)

The EMD step is based on the assumption that any time series consists of different, intrinsic modes of oscillation. Each mode of oscillation is derived from the data and fulfills the following conditions:

1 In the whole data set, the number of extrema and the number of zero-crossings must be equal or differ at most by one.
2 At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

An intrinsic mode function (IMF) represents a simple oscillatory mode similar to a component in the Fourier-based simple harmonic function. IMFs constitute an a posteriori adaptive basis. The decomposition of any time series is described below.

First, all the local extrema of the series x*(t)* are extracted. The local maxima are connected by a cubic spline to produce the upper envelope *u(t)*. Similarly the lower envelope *v(t)* is created with the connection of the local minima. The mean of these two envelopes is designated as m_1, and the difference between *x(t)* and m_1 is the first component h_1.

$$m_1 = [u(t) + v(t)]/2 \quad (1)$$

$$h_1 = x(t) - m_1 \quad (2)$$

Usually, h_1 does not satisfy all the requirements of an IMF. Therefore, the previous process, entitled "sifting process", is repeated more times. In the subsequent sifting process, h_1 is treated as the data, then

$$h_{11} = h_1(t) - m_{11} \quad (3)$$

where m_{11} is the mean of the upper and lower envelopes of h_1. After repeated sifting, up to *k* times which is usually less than 10, h_{1k}, given by

$$h_{1k} = h_{1k-1}(t) - m_{1k} \quad (4)$$

is designated as the first IMF component c_1 from the data, or

$$c_1(t) = h_{1k}(t) \quad (5)$$

Typically, c_1 will contain the shortest-period component of the signal. The c_1 component is removed from the original signal in order to obtain the residue

$$r_1(t) = x(t) - c_1(t) \quad (6)$$

The residue r_1, which contains longer-period components, is treated as the new data and subjected to the same sifting process as it has been described above. This procedure can be repeated to obtain all the subsequent r_j functions as follows:

$$r_{j-1}(t) - c_j(t) = r_j \quad (7)$$

The sifting processs is terminated by either of the following predetermined criteria: either the component c_n or the residue r_n becomes so small that it is less than a predetermined value of consequence, or the residue, r_n, becomes a monotonic function, from which no more IMF can be extracted. Using the above equations the original data is the sum of the IMF components plus the final residue

$$x(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \quad (8)$$

2.2 Hilbert Spectrum Analysis (HSA)

In HSA the Hilbert transform (HT) is applied in each extracted IMF to obtain the representation of the original signal in time-frequency-energy domain. The application of HT in each IMF yields sharp frequency and time localization. For an arbitrary function, *x(t)* its Hilbert transform, *y(t)*, is defined as

$$y(t) = \frac{1}{\pi} P \int_{-\infty}^{\infty} \frac{x(t')}{t-t'} dt' \quad (9)$$

and the analytic signal z(t) is described by

$$z(t) = x(t) + iy(t) = a(t)e^{i\theta(t)} \quad (10)$$

where $a(t) = [x(t)^2 + y(t)^2]^{\frac{1}{2}}$, $\theta(t) = \arctan\left(\frac{y(t)}{x(t)}\right)$ (11)

the instantaneous frequency is given by

$$f(t) = \frac{1}{2\pi} \frac{d\theta}{dt} \quad (12)$$

and the original signal can be expressed by

$$x(t) = \sum_{j=1}^{n} a_j(t) \exp\left(i \int 2\pi f(t)\, dt\right) + r(t) \quad (13)$$

where (13) represents the general form of Fourier equation

$$x(t) = \sum_{j=1}^{\infty} a_j \exp\left(i2\pi f t\right) \quad (14)$$

3 Nonlinear Autoregressive Network with Exogenous Inputs

3.1 NARX Networks

Several processes in real world are described by time series. The ANNs have been widely used in the scientific field of time series prediction due to their inherent nonlinearity and high robustness in noise. It is well-known that ANN represents a nonparametric approach since there is no need to have any knowledge of the underlying processes that generate the original signal.

Typically, the challenge task of time series prediction can be expressed as finding the appropriate function *I* so as to acquire an estimate $\hat{y}(t+D)$ of the time series *y* at time *t+D* (*D*=1,2 …) given the past values of *y* up to time t, plus the values of exogenous input *x:*

$$\hat{y}(t+D) = I(y(t), \dots y(t-d_y), x(t), \dots, x(t-d_x)) \quad (15)$$

where *y(t) and x(t)* represent the values of *y* and *x* in time *t* respectively. *The variables* d_y and d_x are the *lags* parameters of model and in case of D>1 we have the multi step ahead prediction of time series *y.*

NARX networks are recurrent neural architectures and it has been demonstrated that they are powerful in theory and at least equivalent to Turing machines. One can utilize those models rather than conventional recurrent networks without any computational loss [8]. The main advantages of NARX networks are: more effective learning of models and faster convergence than in other ANNs [9].

4 Proposed Method

4.1 Solar radiation dataset

In this paper, a study of forecasting half daily solar radiation is presented by taking into consideration past values of the solar radiation time series. The dataset contains solar radiation measurements provided by the Joint Research Centre (JRC) Renewable Energies unit of the European Commission [10]. Cubic spline interpolation is utilized in order to increase the size of data. Thus, from a 15-minute sample frequency is created a 1-minute sample frequency time series. Each daily artificial solar irradiance signal is a vector of length 840 which represents the daily 1-minute time interval solar irradiance samples. The geographic parameters latitude and longitude were set to 35°27'29" and 24°9'5", respectively. These parameters refer to Koiliaris river region in Crete, where the solar radiation prediction is studied to manage the energy demands of the CyberSensors monitoring system [11]. The daily solar power density samples, which are utilized in our analysis, are records that refer to the most adverse solar radiation conditions. This data is taken in December, which is the month that provides the lowest amount of solar energy.

4.2 Solar radiation analysis

In the present study the “clear-sky” values and the data for “real” conditions were taken into account. The former refers to values of irradiance where the sky is completely free of clouds. This signal is valuable since it provides the maximum values of solar irradiance that may appear at a given time in the examined month. The latter refers to values of solar irradiance with average cloud cover for the given month. In Fig.1 the “clear-sky” and the time series with average values of solar irradiance in December are presented for the examined region.

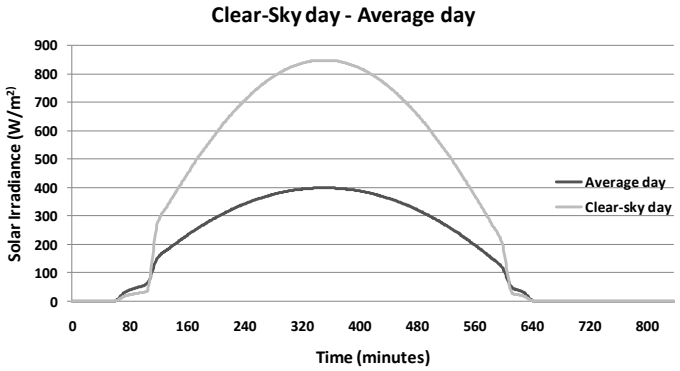


Fig. 1. Solar irradiance plot in December for the examined region with 25° angle.

A typical solar radiation power density for a cloudy day is shown in Fig.2.

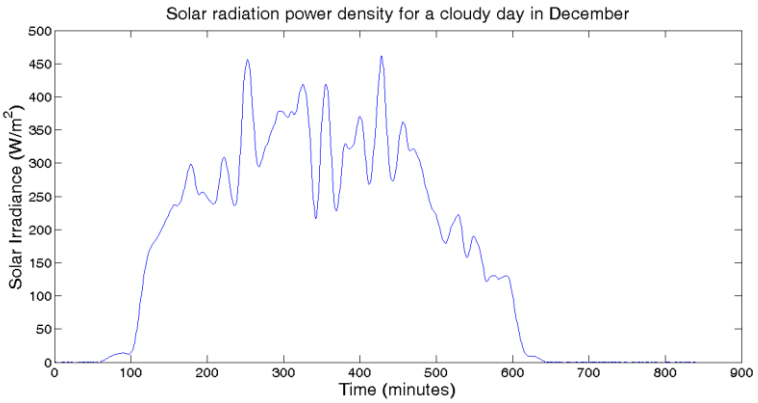


Fig. 2. Solar radiation power density for a cloudy day in December.

The decomposition of each examined signal is implemented by means of EMD. An example of the EMD is presented in the following figure, where the solar power density signal from the previous figure is analyzed into a set of IMFs. It should be mentioned that the generated basis is an a posteriori basis created based on the local characteristics (local maxima and minima) of the time series. From Fig. 3 it can be noticed that the initial signal consist of five IMFs and a residue.

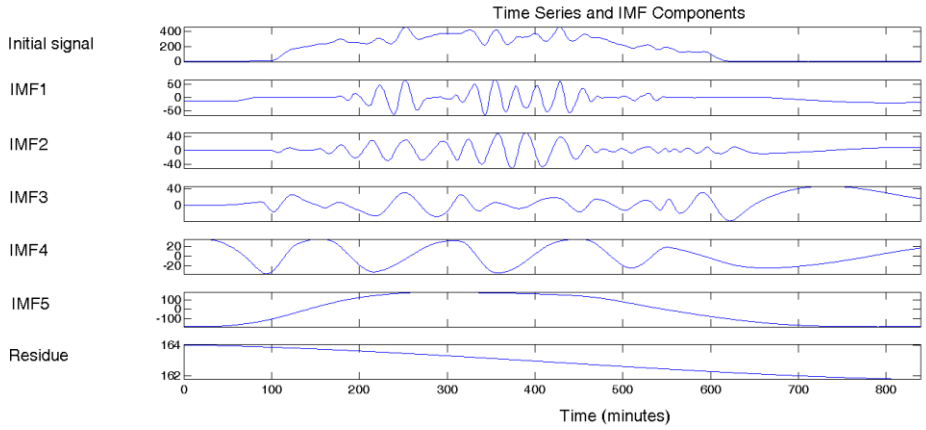


Fig. 3. Decomposition of a solar radiation signal into IMF components.

4.3 The NARX models

Nonlinear autoregressive with exogenous inputs networks were used for the solar radiation prediction. For each extracted intrinsic mode function a NARX network is trained and used for the prediction of the specific mode of oscillation. The NARX network is a two-layer feed forward artificial neural network. In the hidden layer a sigmoid transfer function is utilized and a linear transfer function is set to the output layer. In order to predict the future values of the time series *y(t)*, which in our case represents the solar radiation intrinsic mode function, the past values of time series *x(t)* are also required. In the present study the clear-sky solar irradiance power density is treated as the exogenous input *x(t)*. Fig. 4 shows the topology of the NARX network, where the values d_y and d_x are the delays of *y(t)* and *x(t)* respectively.

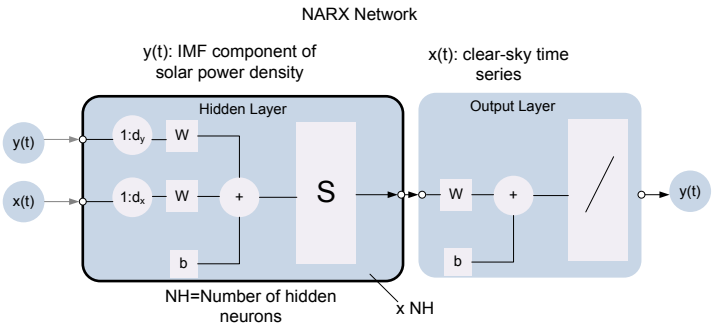


Fig. 4. Topology of the NARX network.

5 Results

NARXs models are trained taking into account the solar radiation time series, which is derived from measurements of twenty five days. Five days records are utilized to assess the performance of the algorithm. The training function is set to Levenberg-Marquardt algorithm and the performance metric is the Mean Squared Error (MSE). The maximum horizon, which is taken, is 420 time steps ahead. The performance is estimated by taking into consideration the root-mean squared error (RMSE) and the maximum error. Table 1 shows the simulation results. The number of hidden neurons is set to 10 and the number of delays is 30. The validation and test data points are set to 15% of the original data, while the rest 70% is used for training.

Fig. 5 shows the simulation results of solar radiation for a half day horizon. As it can be seen from the below figures, solar radiation prediction is a complex task due to the extremely uncorrelated high frequency components. These high frequency components represent clouds and atmosphere attenuation, which are extremely difficult to predict using only past information. Thus, additional inputs are required in order to optimize the simulation results. Fig 6 shows an alternative view of the difference between the desired and predicted solar radiation values for the first day.

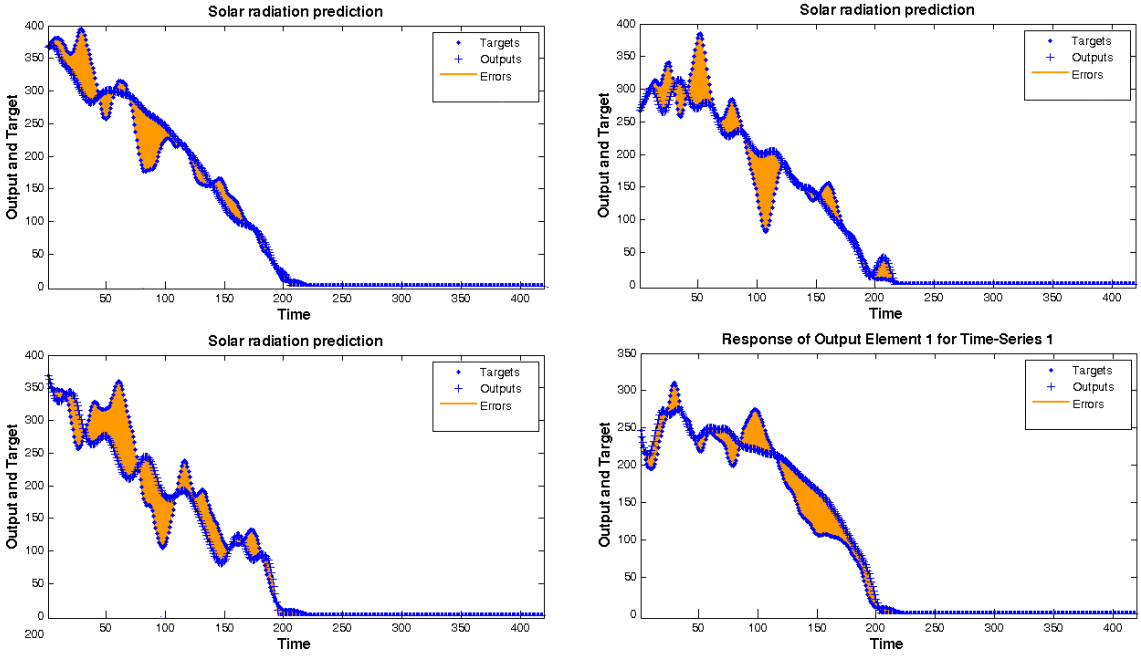


Fig. 5. Simulation of solar radiation for a half day maximum horizon.

Table 1. RMSE from simulation results.

	1st day	*2nd day*	*3rd day*	*4th day*	*5th day*
RMSE (W/m^2)	26.891	21.732	31,009	39,658	35,729
MAX Error	97.847	60.130	120.510	129.815	128.858

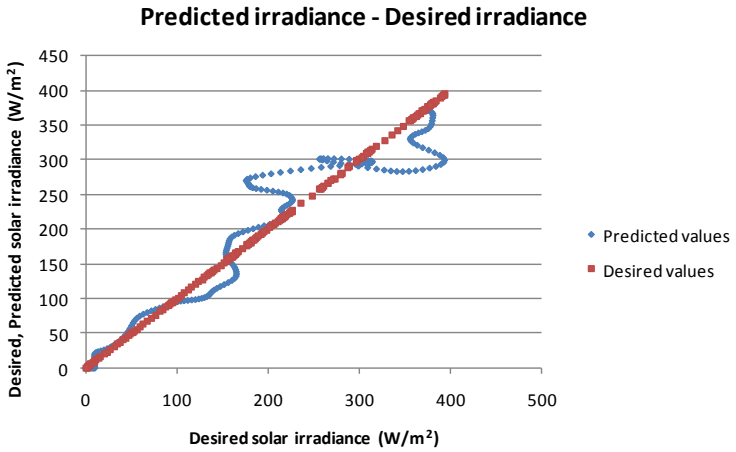


Fig. 6. Desired and predicted solar radiation values for the first day.

6 Conclusions

In this paper the HHT is used for the decomposition of solar irradiance time series in order to predict solar radiation within a time horizon of half day ahead. From the results it can be seen that a more accurate prediction is required for the higher frequency components of the solar radiation time series. Taking into account extra data such as images from satellites, additional information regarding the impact of cloudiness on ground irradiance will be obtained. Moreover, deferencing of solar irradiance time series may generate stationary signals which are relatively easy to predict. In the nearby future, research will continue in this line by following the aforementioned approaches with ultimate goal to integrate this technique in an intelligent Energy Consumption Controller.

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References

1. F.J. Batlles, M.A Rubio, J. Tovar, F.J. Olmo and L. Alados-Arboledas. Empirical modelling of hourly direct irradiance by means of hourly global irradiance, Energy, 25, 2000, 675–688.
2. P.G. Loutzenhier, H. Manz, C. Felsmann, P.A. Strachan, T. Frank and G.M. Maxwell. Empirical validation of models to compute solar irradiance on inclined surfaces for building energy simulation. Sol Energy 81, 2007, 254–267.
3. S. Safi, A. Zeroual and M. Hassani. Prediction of global daily solar radiation using higher order statistics. Renew Energy, 27, 2002, 647–666.
4. S. Kaplanis, E. Kaplani. A model to predict expected mean and stochastic hourly global solar radiation *I(h;nj)* values. Renew Energy, 32, 2007, 1414–1425.
5. K. Moustrisa, A.G. Paliatsos, A. Bloutsos, K. Nikolaidis, I. Koronaki and K. Kavadias. Use of neural networks for the creation of hourly global and diffuse solar irradiance data at representative locations in Greece. Renew Energy, 33, 2008, 928–932.
6. S. Rehman and M. Mohandes. Artificial neural network estimation of global solar radiation using air temperature and relative humidity. Energy Policy, 36, 2008, 571–576.
7. N. E. Huang, Z. Shen, and S. R. Long et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society, London, Series A, 1998, 903–995.
8. H. T. Siegelmann, B. G. Horne, and C. L. Giles, Computational capabilities of recurrent narx neural networks, IEEE Trans. Syst., Man Cybern., pt. B, 27, 1997, 208.
9. Yang Gao, Meng Joo Er, NARMAX time series model prediction: feedforward and recurrent fuzzy neural network approaches, Fuzzy Sets and Systems, 150, 2005, 331-350.
10. http://re.jrc.ec.europa.eu/pvgis/apps4/pvest.php
11. K. Moirogiorgou, D. Efstathiou, M. Zervakis, N.P. Nikolaidis, G. Stamatellos, I. Andreadis, N. Georgoulas and A.E. Savakis,, "High Frequency Monitoring System for Integrated Water Resources Management of Rivers", 1st EWaS-MED International Conference: Improving Efficiency of Water Systems in a Changing Natural and Financial Environment, Thessaloniki, Greece, April 2013, pp. 1-6.