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Effects of Temperature and Pressure Information in a Hybrid (Fourier Series / Neural Networks) Solar Radiation Model

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Abstract

Solar radiation modeling is a critical step in efficient management of solar energy. In this study, a novel solar radiation modeling procedure is developed with the a-priori information of temperature and pressure values, which are naturally dependent on solar radiation via indirect atmospheric phenomena. Firstly, daily behavior of hourly solar radiations is considered in frequency domain. Initial nine Fourier series coefficients are calculated for each day. Secondly, various neural networks models are built for prediction of these nine Fourier coefficients using the input data gathered from early morning hours and previous day. Apart from the solar radiation readings, temperature and pressure data are also used for developing a more accurate model. It is concluded that, the support of temperature and pressure data of the region improves the solar radiation model. Finally, differences between the performances of the proposed models reveal correlative relationships between atmospheric parameters and solar radiation.

1. Introduction

An accurate hourly solar radiation forecasting and modeling is a difficult issue because of its dependence on stochastic atmospheric events. Markov [1] and Auto-Regressive Moving-Average [2] models are some of the proposed attempts for the solution of this problem. In addition, neural network (NN) based models are considered alternatively [3]. 2-dimensional image and optimal coefficient linear filters with NNs are recently adopted for solar radiation forecasting by Hocaoglu et al [4-5]. Finally, climatic effects such as cloudiness index on solar radiation are also handled by some recent studies [6-7].

In this study, Fourier series coefficients of the hourly solar radiation data with one day period are predicted by NNs. The reason of selecting Fourier coefficients instead of the radiation values, themselves, is their efficient approximation property with less number of coefficients than the original time series. The NN prediction was also supported by data of related atmospheric entities such as pressure and temperature. Constructed models are applied and tested on the hourly solar radiation data measured in Izmir region of Turkey in 2004 and 2005. First nine Fourier series coefficients of hourly data are calculated for each day in a year and these coefficients are used as desired outputs of the neural networks. Naturally, the actual time-domain solar radiation predictions are then achieved by applying Fourier series inversion. The first four early morning radiation values after sun rising are used as first four inputs of all models. Consequently, the problem boils down to the prediction of the whole day's solar radiation from only the first few recordings. The hour of sun rising is used as fifth input. Proposed models vary according to their additional inputs which carry information about past temperature and pressure values. The purpose of these additional inputs is to exploit further relation to achieve better approximation in nonlinear cases. The Fourier series representation of the solar radiation data is explained in Section 2. In Section 3, the selected type of NN and the input / output parameters of the constructed NNs are explained. Finally, accurate results are obtained and presented in Section 4.

2. Fourier series representation of hourly solar radiation data

According to the previous works, it is observed that hourly solar radiation data with one day period can be modeled with variants of sinusoidal functions. For instance, the, so called, *classical model* for hourly solar radiation presented in the work of S. N. Kaplanis [8] has one DC and one cosine component for expressing the one-day behavior of solar radiation.

In this work, another classical model is developed using Fourier series. This is not the first work to apply Fourier series analysis for solar radiation modeling. For example, in works in [9-11], Fourier series were already used. However, those utilizations were for modeling *daily* solar radiation. On the other hand, our model is designed for approximating and predicting *hourly* solar radiation.

The original classical model can be thought as a Fourier series with one cosine harmonic. Therefore, that model can be expanded using *other* cosine and sinus harmonics as expressed in Eq. (1).

$$I(h,n_j)=a_{n_j,0}+\sum_{i=1}^{N}\left(a_{n_j,i}\cdot\cos\left(\frac{2\pi ih}{24}\right)+b_{n_j,i}\cdot\sin\left(\frac{2\pi ih}{24}\right)\right) \quad (1)$$

The purpose of this expansion is to improve the accuracy of the model. The accuracies of Fourier series expansions are shown for the hourly solar radiation data of İzmir in 2004 and 2005 in Table I, which presents the differences (RMSEs) of the Fourier series model outputs from the actual values for different number of applied harmonics. The root mean energies of the data of 2004 and 2005 are 349.7303 and 354.4961 respectively. According to these results, it can be claimed that the Fourier harmonics after 4th order only weakly enhance the accuracy of Fourier series model. Consequently, the number of complex harmonics (N) is taken as 4 in this work (corresponding to 9 real Fourier series coefficients). Selection of higher number of harmonics was observed to only increase the complexity of the model without a significant accuracy improvement.

Table I. Errors of Fourier series models with various numbers of harmonics for İzmir solar radiation data

	RMSE for 2004	RMSE for 2005
***N*=1**	104.1308	106.9926
***N*=2**	41.5939	41.9409
***N*=3**	32.4458	31.6160
***N*=4**	25.3592	24.4032
***N*=5**	21.0878	20.0298
***N*=6**	18.1533	16.9909
***N*=7**	15.5025	14.7525

If the solar radiation is measured for all hours of a day, the coefficients $a_{n_j,0}$ and $a_{n_j,i}$ can be computed from these values via Eq. (2). Similarly, $b_{n_j,i}$ can be calculated as shown in Eq. (3).

$$a_{n_j,0}=\frac{\sum_{h=-11}^{12} I\left(h,n_j\right)}{24},\quad a_{n_j,i}=\frac{\sum_{h=-11}^{12}\left[I\left(h,n_j\right)\cos\left(\frac{2\pi ih}{24}\right)\right]}{\sum_{h=-11}^{12}\left(\cos\left(\frac{2\pi ih}{24}\right)\right)^2} \quad (2)$$

$$b_{n_j,i}=\frac{\sum_{h=-11}^{12}\left[I\left(h,n_j\right)\sin\left(\frac{2\pi ih}{24}\right)\right]}{\sum_{h=-11}^{12}\left(\sin\left(\frac{2\pi ih}{24}\right)\right)^2} \quad (3)$$

3. Forecast of Fourier series coefficients using NNs

The goal of the work is forecasting the (first nine) Fourier series coefficients of the hourly solar radiation data of the current day. Therefore the unknown future solar radiation values can be reconstructed from these Fourier series estimates using Fourier inversion. For all proposed NN model variants, these nine coefficients, which were calculated for each day, were selected as desired outputs. Training inputs and outputs were constructed from solar radiation, temperature and pressure data of İzmir in year 2004. Test inputs and outputs were selected as the data of the same region in year 2005. Desired outputs for training and test sets can be seen in Fig. 1 and Fig. 2, respectively.

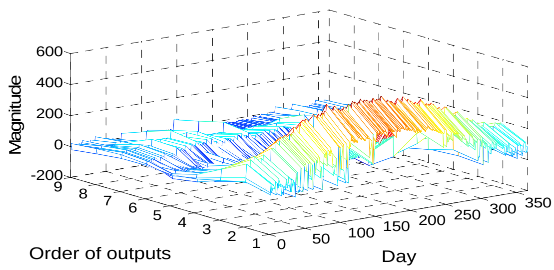

Figure 1. Desired outputs for training sets

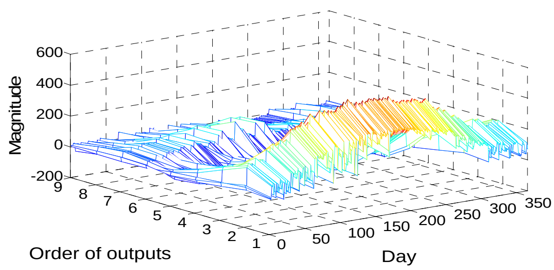

Figure 2. Desired outputs for test sets

The main information about these coefficients can be obtained from history of solar radiation data. Therefore solar radiation values of first four hours after sun rising for the current day were used in inputs of all purposed NN models. In addition, the hour of sun rising is used as the fifth input of all NN models. This model will be named the pure model. In this work, effects of different additional inputs which carry temperature or pressure information were tested. These additional inputs were explained in Table II and Table III for temperature and pressure respectively.

Table II. NN models with temperature data

NN Models	*Order of Inputs*	*Inputs*
Model-T1	6	T_{pm}
Model-T2	6	T_{pd}
	7	T_{pn}
Model-T3	6	T_{pd}
	7	T_{pn}
	8-11	T_{cffh}
Model-T4	6	T_{pd}
	7	T_{pn}
	8	T_{cn}
	9-12	T_{cffh}
Model-T5	6	T_{pm}
	7	T_{cn}
	8-11	T_{cffh}

Table III. NN models with pressure data

NN Models	*Order of Inputs*	*Inputs*
Model-P1	6	P_{pm}
Model-P2	6	P_{pd}
	7	P_{pn}
Model-P3	6	P_{pd}
	7	P_{pn}
	8-11	P_{cffh}
Model-P4	6	P_{pd}
	7	P_{pn}
	8	P_{cn}
	9-12	P_{cffh}
Model-P5	6	P_{pm}
	7	P_{cn}
	8-11	P_{cffh}

In the Table II and III, T_{pm} and P_{pm} refer to means of the previous day's temperature and pressure. Similarly, T_{pd} and P_{pd} refer to means of the previous day's temperature and pressure during day-time, T_{pn} and P_{pn} refer to mean of the previous day's temperature and pressure after sunset, T_{cn} and P_{cn} refer to means of the current day's temperature and pressure until sun rises, and finally, T_{cffh} and P_{cffh} refer to temperature and pressure values of the current day's first four hours after sun rises.

All of the input parameters were normalized to the interval [0,1] by dividing all input values to their maximum observations within the training year.

In all proposed input patterns, a multilayer perceptron model with one hidden layer is selected. At hidden layer, five nerons are used. For the training of models, Levenberg-Marquardt algorithm is used due to its fast convergence characteristics. The maximum number of epochs for training is limited to 500.

4. Results and discussion

After obtaining predictions of Fourier series coefficients of a day, the Fourier inversion is applied and the time-domain solar radiation estimate is reconstructed. The difference between the forecasted sequences and real recordings are measured in terms of RMSEs for both the training and the test years (as presented in Table IV). These results show that additional information of temperature and pressure data provides better fitting results particularly on training data. This improvement does not appear to stay valid for the test data. On the other hand, Model-P3 (with inputs P_{pd}, P_{pn} and P_{cffh}) give better results than pure model in all cases.

Table IV. RMSEs of all proposed NNs

Model	*RMSE for training data*	*RMSE for test data*
Pure Model	56.771	91.074
Model-T1	54.2382	92.954
Model-T2	52.131	97.521
Model-T3	49.209	94.472
Model-T4	46.626	107.67
Model-T5	46.726	101.6
Model-P1	54.731	101.67
Model-P2	52.601	91.057
Model-P3	47.879	90.065
Model-P4	49.018	96.493
Model-P5	46.076	103.57

As a final step, the measured solar radiation data are compared with best forecast results as shown in Fig.'s 3-6.

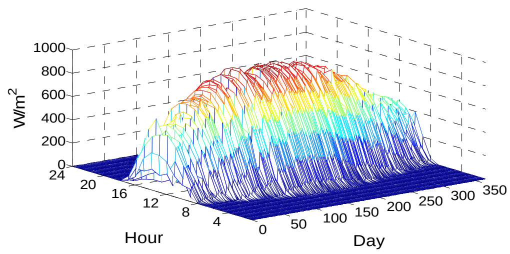

Figure 3. Original solar radiation data for training

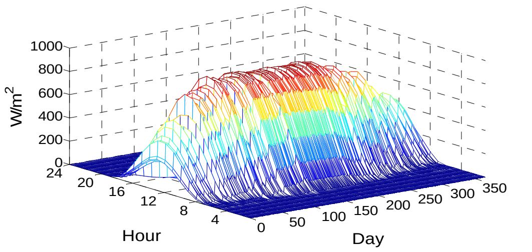

Figure 4. Best forecast result for training data with Model-P5

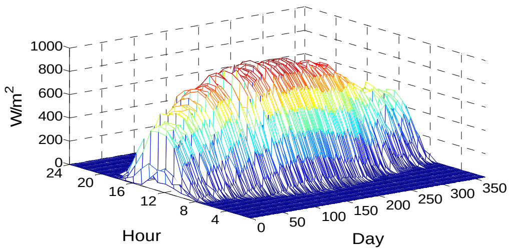

Figure 5. Original solar radiation data for testing

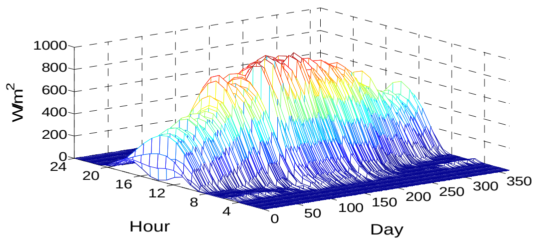

Figure 6. Best forecast result for test data with Model-P3

5. Conclusions

The experiments show that temperature and pressure data have a fair correlation with solar radiation data, making them candidates for better models through forecasting of hourly solar radiation. It is also observed that first few Fourier series coefficients are robust parameters for the estimation of the daily solar radiation function. Consequently, these coefficients are selected as the prediction outputs of the proposed NNs while the inputs are selected as the first few solar radiation values after the sun-rise together with the aforementioned atmospheric parameters. Despite the improvements in the prediction accuracy for the training year, the next year (which is constitutes the test data) performance was not observed to improve. This indicates that effects of the climatic parameters are apparently varying yearly. The exploitation of this variation via other atmospheric or solar parameters remains to be issues for future studies. Following the plausible results presented here, further studies may be performed to construct an analytical model, or longer data can be considered for more geographical locations for achieving a general idea about the characteristics of the solar radiation.

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6. References

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