

Solar Radiation Forecasting Model

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INTRODUCTION

The prediction of hourly solar radiation data has important consequences in many solar applications (Markvart, Fragaki & Ross, 2006). Such data can be regarded as a time series and its prediction depends on accurate modeling of the stochastic process. The computation of the conditional expectation, which is in general non-linear, requires the knowledge of the high order distribution of the samples. Using a finite data, such distributions can only be estimated or fit into a pre-set stochastic model. Methods like Auto-Regressive (AR) prediction, Fourier Analysis (Dorvlo, 2000) Markov chains (Jain & Lungu, 2002) (Muselli, Poggi, Notton & Louche, 2001) and ARMA model (Mellit, Benghanem, Hadj Arab, & Guessoum, 2005) for designing the non-linear signal predictors are examples to this approach. The neural network (NN) approach also provides a good to the problem by utilizing the inherent adaptive nature (Elminir, Azzam, Younes, 2007). Since NNs can be trained to predict results from examples, they are able to deal with non-linear problems. Once the training is complete, the predictor can be set to a fixed value for further prediction at high speed. A number of researchers have worked on prediction of global solar radiation data (Kaplanis, 2006) (Bulut & Buyukalaca, 2007). In these works, the data is treated in its raw form as a 1-D time series, therefore the inter-day dependencies are not exploited. This article introduces a new and simple approach for hourly solar radiation forecasting. First, the data are rendered in a matrix to form a 2-D image-like model. As a first attempt to test the 2-D model efficiency, optimal linear image prediction filters (Gonzalez, 2002) are constructed. In order to take into account the adaptive nature for complex and non-stationary time series, NNs are also applied to the forecasting problem and results are discussed.

BACKGROUND

This article presents a two-dimensional model approach for the prediction of hourly solar radiation. Before proceeding with the prediction results, the following technical background is provided. Using the described tools, the approach is tested with optimal coefficient linear filters and artificial NNs (Hocaoglu, Gerek & Kurban, 2007).

The 2-D Representation of Solar Radiation Data

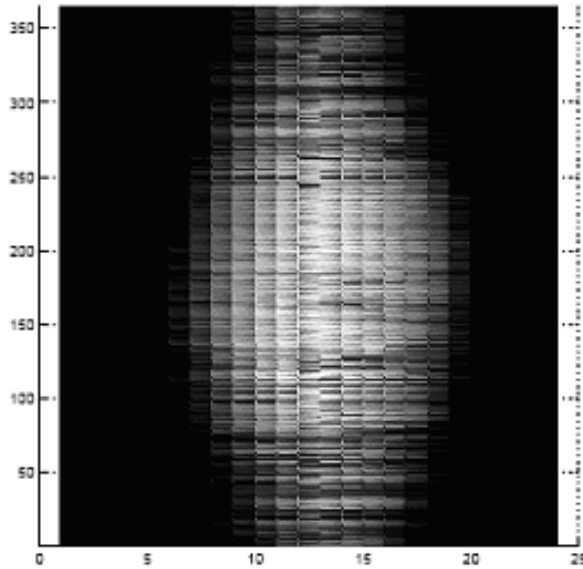
The collected hourly solar radiation data is a 1-D discrete-time signal. In this work, we render this data in a 2-D matrix form as given in equation 1.

$$Rad = \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \quad (1)$$

where the rows and columns of the hourly solar radiation matrix indicate days and hours, respectively. Such 2-D representation provides significant insight about the radiation pattern with time. First surface plot of the data is obtained then image view of the data is obtained and given in Fig 1.

By inspecting the image version of the data in Fig. 1, it is easy to interpret daily and seasonal behavior of solar radiation. Dark regions of the image indicate that there is no sun shine on horizontal surface. The transition from black to white indicates that solar radiation fall on horizontal surface is increasing or decreasing. During winter time, the dawn to dusk period is shorter, producing a narrower protruding blob. Conversely, the

Figure 1. Image view of solar radiation data



white blob is wider during summer times, indicating that the day-time is longer. The width behavior of the white blob clearly indicates the seasonal changes of sun-light periods. The horizontal *and* vertical correlations within the 2-D data are quite pronounced. This implies that, given the vertical correlation among the same hours of consecutive days, it is beneficial to use 2-D prediction for hourly forecasting. The prediction efficiency of the proposed model is illustrated with 2-D optimum linear prediction filters and NNs.

Optimal 2-D Linear Prediction Filter Design

Due to predictive image coding literature, it is known that a 2-D matrix can be efficiently modeled by linear predictive filters (Gonzales, 2002) (Sayood, 2000). The prediction domain is a free parameter determined according to the application. Consider a three coefficient prediction filter structure as given in expression 2:

C	$x_{i,j+1}$
$x_{i+1,j}$	$\hat{x}_{i+1,j+1} = ?$

(2)

The linear filter coefficients a_1 , a_2 and a_3 are optimized, and the prediction result $\hat{x}_{i+1,j+1}$ is estimated as

$$\hat{x}_{i+1,j+1} = x_{ij} \cdot a_1 + x_{i(j+1)} \cdot a_2 + x_{(i+1)j} \cdot a_3 \tag{3}$$

The prediction error for this term is:

$$\epsilon_{i+1,j+1} = \hat{x}_{i+1,j+1} - x_{i+1,j+1} \tag{4}$$

The total error energy corresponding to the whole image prediction can be calculated as:

$$\epsilon = \sum_{i=2}^m \sum_{j=2}^n \epsilon_{ij}^2 \tag{5}$$

where m and n correspond to the width and height of the image, which are, for the solar data, 365 and 24, respectively. The filter coefficients that minimize this function can be found from the solution of the minimization derivative equation:

$$\frac{\partial \epsilon}{\partial a_1} = \frac{\partial \epsilon}{\partial a_2} = \frac{\partial \epsilon}{\partial a_3} = 0 \tag{6}$$

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