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Predicting Global Solar Radiation Using Recurrent Neural Networks and Climatological Parameters

Rami El-Hajj Mohamad, Mahmoud Skafi, Ali Massoud Haidar

***Abstract*—**Several meteorological parameters were used for the prediction of monthly average daily global solar radiation on horizontal using recurrent neural networks (RNNs). Climatological data and measures, mainly air temperature, humidity, sunshine duration, and wind speed between 1995 and 2007 were used to design and validate a feed forward and recurrent neural network based prediction systems. In this paper we present our reference system based on a feed-forward multilayer perceptron (MLP) as well as the proposed approach based on an RNN model. The obtained results were promising and comparable to those obtained by other existing empirical and neural models. The experimental results showed the advantage of RNNs over simple MLPs when we deal with time series solar radiation predictions based on daily climatological data.

***Keywords*—**Recurrent Neural Networks, Global Solar Radiation, Multi-layer perceptron, gradient, Root Mean Square Error.

I. Introduction

NOWADAYS, we are witnessing a serious intention for transition from almost complete dependency of petrol oil to growing usage of further alternative resources of energy. This is due to several economic reasons and more importantly other environmental protection goals. Global solar radiation (GSR) is considered as one of the most important sources of energy that reach our planet. For example, the potential of solar radiation in the Gulf area is significant, and may reach an average annual solar radiation of 2285 k Wh/m2 (about 6.3 K Wh/m2 per day) [1], [2]. In spite of the importance of solar radiation measurements in several applications like solar energy systems, agriculture, and architecture, they are not easily available in all places. This is due to cost, regular maintenance, and tuning requirements. These issues and others make the availability of solar radiation measures not an easy matter [1]. Thus, suggesting adequate alternatives to estimate such measures based on easily available climatologic data.

The intensity of solar radiation on a particular location is influenced by several climatological measures and factors such as air temperature, sunshine duration, humidity, vapor pressure, and wind speed. Those factors and measures are important and essential to design and implement an automatic system for the prediction of global solar radiation on horizontals and surfaces. Many studies were made and others are still conducted in order to design and build such automatic prediction systems.

Falayi et al. [4] have developed multi-linear regression equations, namely the Angestrom models, to predict global solar radiations in Nigeria. The input parameters to the models included mean daily temperature, relative humidity, and relative sunshine duration. Alawi and Henai [3] used meteorological data and Artificial Neural Networks ANN to build a system for solar radiation prediction. The input data to the adopted models included: location, month of the year, mean pressure, mean vapor, mean temperature, mean wind speed, and mean duration of sunshine. Ahmed and Adam [5] applied a feed forward back- propagation neural network on weather data measured at Qena-Egypt during 2007. The proposed approach used location coordinates and sunshine hours to estimate monthly average daily global solar radiation. The authors presented a comparative study between the described MLP-based approach and other empirical models. Based on their experimental results, they showed the advantages of the MLP-based estimation technique for solar radiation estimation over the existing empirical regression models. Khatib et al. [6] developed a Feed Forward multi-layer perceptron with four inputs: longitude, latitude, day of the month, and sunshine radiation to predict the clearance index. The clearance index is useful to calculate the solar irradiation. The experiments were based on long term data for solar radiation (from 1984 till 2004) taken from 28 sites in Malaysia. Jiang et al. [7] elaborated a Feed-Forward Neural Network model to estimate monthly mean daily global solar radiation of 8 cities in China. The input data of the ANN model included latitude, altitude, and mean sunshine duration. The authors indicated that the obtained solar radiation estimation by ANN were superior to those of empirical methods. Assi et al. [2] used four meteorological data between 1995 and 2007 to train and validate a Feed Forward ANN-based prediction system of solar radiation in Al-Ain city in UAE. The authors examined several MLP architectures and tested more than twelve alternatives of the back-propagation training algorithms.

In this paper we presented our experimental works on designing, implementing, and validating a new approach to predict GSR using climatologic factors along with RNNs, namely the Jordan Recurrent Neural Networks [11], [12]. This type of Neural Networks is appropriate to time series prediction. Furthermore, we indicated the advantages of using such type of recurrent networks over the Feed Forward MLPs

R El-hajj Mohamad, Ph.D., is with the Industrial Engineering Dept., American University of Middle East, Kuwait. P.O.Box.220 Dasman-Kuwait (phone: +965-22251400–ext: 1284; Fax: +965-22251427; e-mail: rami.alhajj@aum.edu.kw).

M. Skafi is with the Dept. of Mathematics and Computer Sciences, in Beirut Arab university, Lebanon (phone: +961-1300110, e-mail: mskafi@bau.edu.lb).

A. M. Haidar, Ph.D., is with the Electrical and computer Engineering Dept., Beirut Arab University, Lebanon (phone: +961-1300110, e-mail: ari@bau.edu.lb).

when we deal with such type of time series data. The remaining of this paper is organized as following: in Section II, we introduced the special type of Recurrent Neural Networks that we adopted in our modeling. In Section III, we described our experimental methodology. We described the reference system of prediction of solar radiation based on simple multi-layers perceptron MLPs, then we introduced our enhanced system based on RNNs. In plus, we described the data that we used for the design and the validation of our proposed approaches approach. In Section IV, we discussed the obtained results by the two systems. Section V includes a conclusion and some future perspectives.

II. Recurrent Neural Networks

Artificial Neural Networks became an interesting tool of modeling of linear and non-linear systems without the need to make implicit assumptions as in most of classical statistical modeling approaches. Nowadays, ANNs are widely used in many applications in various aspects of science and engineering [8], [10].

Recurrent Neural Networks RNNs are special types of general neural networks. They are useful in situations when there is a temporal relationship in data. In other word, when data are presented in time sequential order. An RNN is obtained by adding to a Feed Forward ANN one or many feedback connections to previous layers [9]-[11]. The structure of a recurrent neural network is characterized by the presence of one or many extra nodes, also named context units, beside the input layer. Such context units are connected to the hidden layer and hold the output of the neural network to feed it back to the hidden layer. So, the network can perceive previous experience it had about preceding inputs. Therefore, the context nodes are referred as networks' short-term memory that is able to represent information about preceding inputs [9], [10]. That information is significant when the goal is a long-term prediction.

In general, the RNNs show a good performance if there is temporal structure in data. Otherwise, the short-term memory nodes will represent a random noise to the recurrent neural model.

Jordan neural networks are ones of the primary types of recurrent neural networks [11], [12]. In this type, the output layer feds back the units of the input layer, so the context units remember outputs related to previous inputs. Fig. 1 represents the general structure of Jordan recurrent neural networks where the network outputs are fed back into the context units.

III. MLP and RNN-Based Solar Radiation Prediction

In our works we designed, implemented, and validated an RNN-based prediction system of solar radiation. In the first phase, we proposed a reference MLP-based system that showed good performance. In the second phase, we suggested an enhanced system based on a RNN model. All the components of our two proposed approaches were designed, implemented, and tested on our neural network frame work written in Java™ language.

In the design and validation phases we used a meteorological database provided by the National Center of meteorology and Seismology in Abu-Dhabi – UAE [2]. The database consists of daily data records for the period between 1995 and 2007. Each daily record includes the following meteorological information: relative humidity, air temperature, wind speed, and sunshine duration. In our experiments, we divided the data into two subsets; a design subset having records for the years from 1995 to 2006 (12 years) and a test subset having records for the year 2007.The training subset was used to train the neural models, while the test subset was used to validate these models.

In the first stage of our experiments, we preprocessed the data by normalizing the weather factors as well as the target values of measured solar radiations to be in the range [0, 1] by using the following re-scaling formula:

$$X* = \frac{X - MinX}{\mathrm{MaxX} - MinX} \qquad (1)$$

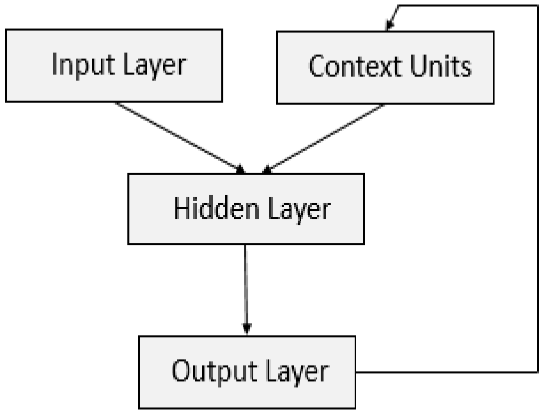

Fig. 1 Jordan Recurrent Neural Network general structure. The network has as many context units as output nodes

In the reference system, we created a simple MLP-based solar radiation prediction approach. The core component of this system consists of a feed forward fully connected MLP composed of three layers: an input layer of four inputs to percept the four weather input data, one hidden layer, and an output layer of one output node. In order to study the optimal structure of our neural network, we examined several structures in term of number of hidden neurons, and we have tested several learning parameters. The basic version of the back-propagation learning algorithm was used to train the feed-forward MLP of the reference estimation system. Fig. 2 illustrates the fully connected MLP adopted in our reference system.

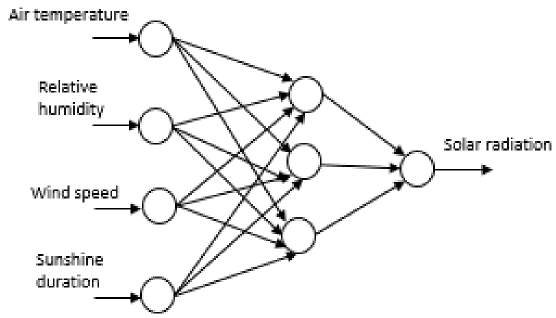

Fig. 2 The fully connected MLP used in the reference estimation system

In the enhanced system, we created and trained a recurrent neural network that included: an input layer of four inputs, a hidden layer, an output layer of one node that outputs the estimated solar radiation for each input vector of weather, and a feedback connection that represents a short term memory. The feedback connection was made to feed the hidden layer by the output of the network for a previous input.

We used the basic descendant gradient back-propagation training algorithm to train the neural network by passing the instances of the training subset several times.

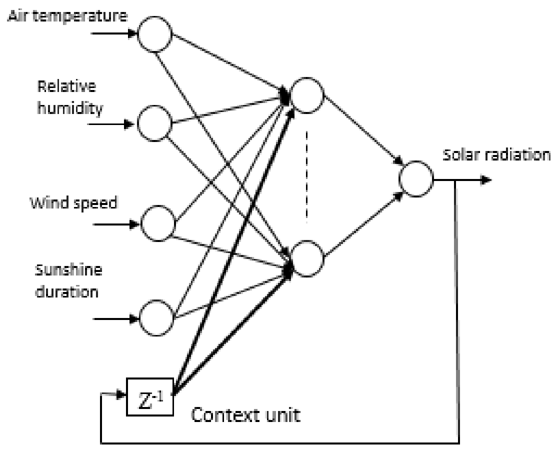

Fig. 3 The recurrent neural network used in the enhanced estimation system

The outcome values of the neural systems were generated and de-normalized, and then compared to the desired values in order to evaluate the estimation performance.

IV. Experiments and Results

The performance of our two proposed approaches was studied by comparing the estimated values against measured values through correlation and error statistical analysis. The later one was conducted by computing the mean bias error (MBE) and root mean square error (RMSE). The MBE indicates the average of deviation of the estimated values from the corresponding target data. The lower MBE is desirable. A positive MBE value designates the amount of overestimation in predicted values and vice versa. The RMSE measures the variation of predicted values around the measured data. The lower RMSE is desired and indicates an accurate estimation. MBE provides information on the long term performance, whereas the RMSE provides information about short term performance [4]. The MBE and RMSE are computed by the following equations:

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(\mathrm{H}_{\mathrm{p,i}} - H_i) \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(\mathrm{H}_{\mathrm{p,i}} - H_i)^2}{N}} \quad (3)$$

where $H_{p,I}$ represents the estimated value of global solar radiation (kWh/m^2), H_i is the measured value (exact) of global solar radiation, and N is the total number of observations.

Table I shows some of the architectures of the developed reference and enhanced models along with the obtained values of MBE and RMSE.

TABLE I
ARCHITECTURE, MBE, AND RMSE FOR SOME DEVELOPED MODELS

System	Architecture	RMSE	MBE
1	MLP 4 –6 –1	0.065969	0.008580
2	MLP 4 – 12 –1	0.068025	-0.008051
3	RNN 5 – 4 – 1	0.073104	-0.000342
4	RNN 5 – 9 – 1	0.052008	-0.000687

In Table I, it can be clearly shown that the recurrent neural models provide the lowest value of RMSE (0.052008) by the model RNN 5-9-1, and the best value of MBE (-0.000687) by the model RNN 5-9-1. The acquired values of MBE with negative values designate an underestimation of our models of the exact values. The low RMSE values for the models which vary from 0.052008 to 0.073104 indicate that they have a good short term performance.

The obtained results are better than those obtained by other empirical regression models applied on the same data [1]. In plus, the results obtained by our RNN models are comparable to those obtained by several ANN-models also applied on the same data [2].

Figs. 4 and 5 illustrate comparisons between measured and predicted values of monthly average daily global solar radiation for the models MLP 4-12-1 and RNN 5-4-1 respectively. The two figures indicate that the two models show an underestimation between January and August, and an overestimation between September and December.

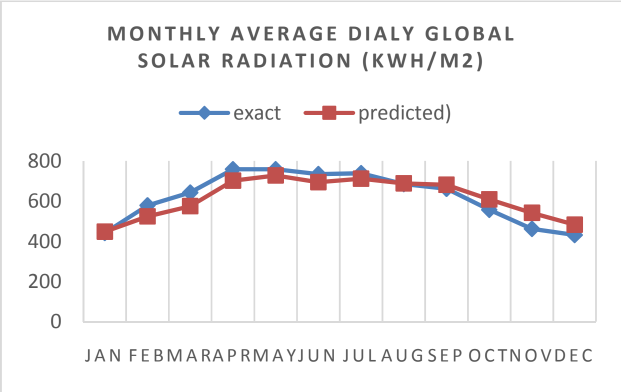

Fig. 4 Monthly average daily global solar radiation estimation of model MLP 4-12-1

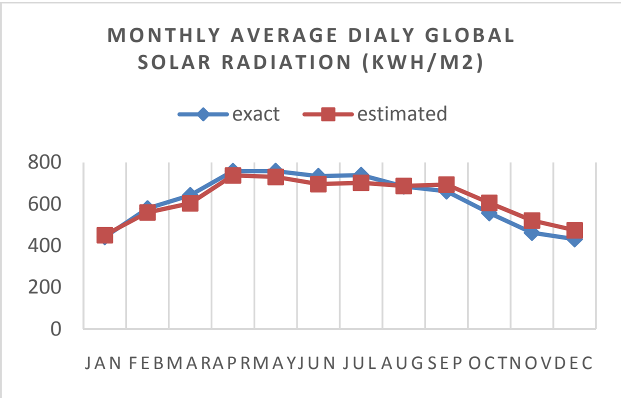

Fig. 5 Monthly average daily global solar radiation estimation of model RNN 5-4-1

V. Conclusion and Future Perspectives

In this paper we described our neural-based systems for global solar radiation estimation. The first one is based on a simple feed forward MLP, whereas the second one is based on recurrent neural models that are appropriate to time series predictions. The comparison of our systems shows the advantages of using of recurrent models in term of prediction correctness and in term of performance and time of convergence toward good estimation. The obtained results by the RNN-based system are comparable to those obtained by other empirical and neural based systems examined on the same database that we used in our experiments.

Two main perspectives can be drawn for our works. The first one consists of increasing the time delay of the recurrent neural network in order to take in consideration, and for each new input vector, the two previous outputs of the network. This may improve the long term performance of the recurrent models. The second perspective consists of applying our technique on new meteorological data.

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