Daily Global Solar Radiation Modeling Using Multi-Layer Perceptron (MLP) Neural Networks

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***Abstract*—**Predict daily global solar radiation (GSR) based on meteorological variables, using Multi-layer perceptron (MLP) neural networks is the main objective of this study. Daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, and soil temperature values between 2002 and 2006 for Dezful city in Iran (32° 16' N, 48° 25' E), are used in this study. The measured data between 2002 and 2005 are used to train the neural networks while the data for 214 days from 2006 are used as testing data.

***Keywords*—**Multi-layer Perceptron (MLP) Neural Networks; Global Solar Radiation (GSR); Meteorological Parameters; Prediction;

I. Introduction

IRAN possesses rich and diversified sources and potential for developing renewable energy, namely solar, wind, geothermal and biomass. The values of the global solar radiation (GSR) are the most important parameter for the solar energy applications [1- 3]. For low-priced and effective development and utilization of solar energy, a complete knowledge about the accessibility and variability of solar radiation intensity in time and special domain is of great importance [1]. Several models have been presented by researchers to predict global solar radiation (GSR) using different meteorological variables (see [2-28]). In the present study, day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, and soil temperature values are to predict the daily GSR on a horizontal surface using ANN technique. Safiabad station located in Dezful city, Iran, is the case of this study.

II.Artificial Neural networks (ANNs)

Neural networks are computational models of the biological brain. Like the brain, a neural network comprises a large

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performing only simple computation [29].Anyhow; the architecture of an artificial neuron is simpler than a biological number of interconnected neurons. Each neuron is capable of neuron. ANNs are constructed in layer connects to one or more hidden layers where the factual processing is performance through weighted connections. Each neuron in the hidden layer joins to all neurons in the output layer. The results of the processing are acquired from the output layer. Learning in ANNs is achieved through particular training algorithms which are expanded in accordance with the learning laws, assumed to simulate the learning mechanisms of biological system [30]. However, as an assembly of neurons, a neural network can learn to perform complex tasks including pattern recognition, system identification, trend prediction, function approximation, and process control [29]. MLPs are perhaps the most common type of feedforward networks. For more details about neural networks the readers are referred to [29-32].

III. . Problem definition

Day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, soil temperature values, measured by Safiabad station (located in Dezful city, a city in southwestern of Iran (32° 16' N, 48° 25' E)), between 2002-2006, were applied for forecasting daily GSR using MLP. The data for 1398 days from 2002 (February) to 2005 (December) were applied for the purpose of training and the data for 214 days from 2006 were used for testing. The data for testing were not applied to train the neural networks. Multi-layer perceptron (MLP) neural networks were applied for daily GSR prediction.

IV. Results and discussion

Multi-layer perceptron (MLP) neural networks were used by using neural network toolbox of MATLAB 2007 software. Day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, soil temperature, and daily GSR were normalized in rage (0, 1).In order to determine the optimal network architecture various network architectures were designed; different training algorithms were used; the number of neuron and hidden layer and transfer functions in the hidden layer/output layer were changed. eventually, a network with 2 hidden layer (three neurons in first hidden layer and two neurons in second hidden layer), logistic sigmoid transfer function (logsig) for all hidden layers, linear transfer function (purelin) for output layer and LM (Levenberg–Marquardt) training algorithm were found to perform reasonably good prediction. Fig.1 shows the comparison between predicted and measured GSR for presented model in this study and by [20].

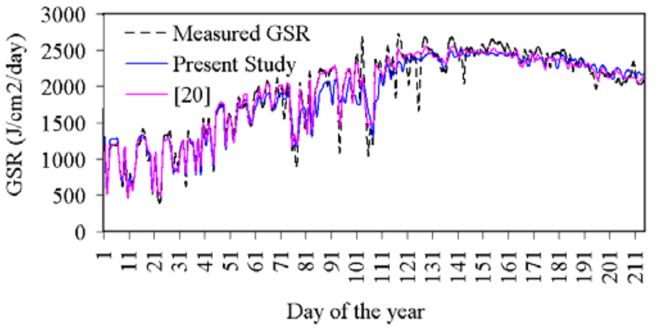

Fig. 1 Comparison between measured and estimated daily GSR (on testing data)

The obtained results indicate that using soil temperature along with day of the year, daily mean air temperature, relative humidity, sunshine hours, evaporation, and wind speed base on MLP network has comparable performance with the presented model by [20] which has mean absolute percentage error (MAPE) of 6.08% and absolute fraction of variance (R^2) of 99.03% (on testing data) and mean square error (MSE) of 0.0042 and sum of square error (SSE) of 5.9278 (on training data).

TABLE I
COMPARISON BETWEEN RESULTS OF PRESENT AND OTHER STUDIES ON GSR MODELING USING ANNS

Source	Network Type	Location of station (s)	MAPE (%)
Rehman and Mohandes [1]	MLP	Saudi Arabia,	4.49
A. Azadeh et al. [14]	MLP	Iran	6.70
Sozan et al. [17]	MLP	Turkey	6.70
Sozan et al. [18]	MLP	Turkey	6.78
M. Mohandes et al. [21]	MLP	Saudi Arabia,	12.61
M. Mohandes et al. [22]	RBF	Saudi Arabia,	10.09
Behrang et al. [20]	MLP	Iran	5.21
Behrang et al. [20]	RBF	Iran	5.56
Present study	MLP	Iran	6.08

V. CONCLUSION

This study developed a model to forecast the daily GSR according to measured values of daily mean air temperature, relative humidity, sunshine hours, evaporation, wind speed, and soil temperature. This is of great importance because above parameters are commonly accessible. Data for Safiabad station, located in Dezful city, a city in southwest of Iran, from 2002 to 2005 were used to train different ANN techniques. Data for 214 days of the year 2006 were used for testing. These results indicated that using soil temperature along with day of year, daily mean air temperature, relative humidity, sunshine hours, evaporation, and wind speed base on MLP network had acceptable accuracy to GSR modeling. Future work is focused on comparing the methods presented here with other available tools. Predicting of global solar radiation can also be investigated with neural networks trained with intelligent optimization techniques like Particle Swarm Optimization, Bees Algorithm and etc. The results of the different methods can be compared with available methods.

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REFERENCES

[1] S. Rehman, M. Mohandes, Artificial neural network estimation of global solar radiation using air temperature and relative humidity, Energy Policy .63 (2008) 571–576.

[2] M.A. Behrang, E. Assareh, A.R. Noghrehabadi, and A. Ghanbarzadeh. New sunshine-based models for predicting global solar radiation using PSO (particle swarm optimization) technique. Energy 2011; 36: 3036-3049. doi:10.1016/j.energy.2011.02.048.

[3] K. Bakirci, Correlations for estimation of daily global solar radiation with hours of bright sunshine in Turkey, Energy (2009), doi: 10.1016/j.energy.2009.02.005.

[4] A. Angstrom, Solar and terrestrial radiation, Journal of the Royal Meteorological Society.50 (1924) 121–126.

[5] V. Bahlel, H. Bakhsh, R. Srinivasan, A correlation for estimation of global solar radiation, Energy. 12(2) (1987) 131-5.

[6] J. Almorox, C. Hontoria, Global solar estimation using sunshine duration in Spain, Energy Conversion and Management. 11 (1967) 170-2.

[7] B.G. Akinoglu, A. Ecevit, Construction of a quadratic model using modified Angstrom coefficients to estimate global solar radiation, Solar Energy. 45 (2) (1990) 85–92.

[8] S. Rehman, Solar radiation over Saudi Arabia and comparison with empirical models, Energy .23 (12) (1998) 1077–1082.

[9] R. Aguiar, M. Collares-Pereira, A time dependent autoregressive, Gaussian model for generating synthetic hourly radiation., Solar Energy. 49 (1992) 167–174.

[10] G. lewis, Estimates of irradiance over Zimbabwe, Solar Energy. 31 (1983) 609-612.

[11] R.K. Swartman, O. Ogunlade, Solar radiation estimates from common parameters. Solar Energy 11 (1967) 170-172.

[12] Y.A.G Abdallah, New correlation of globar solar radiation with meteorological parameters for Bahrain. Solar Energy 16 (1994) 111-120.

[13] J.I. Prieto, J.C.Martines-Garcia, D. Garcia, Correlation between global solar irradiation and air temperature in Asturias, Spain, Sol. Energy (2009), doi: 10.1016/j.solener.2009.01.012.

[14] A. Azadeh, A. Maghsoudi and S.Sohrabkhani, An integrated artificial neural networks approach for predicting global radiation. Energy Conversion and Management doi: 10.1016/j.enconman.2009.02.019.

[15] D. Elizondo, G. Hoogenboom and R. McClendon, Development of a neural network to predict daily solar radiation, Agricultural and Forest Meteorology.71 (1996) 115–132.

[16] S.M. Al-Alawi, H.A. Al-Hinai, An ANN-based approach for predicting global solar radiation in locations with no measurements, Renewable Energy. 14 (1–4) (1998) 199–20.

[17] I.T. Togrul, E. Onat, A study for estimating the solar radiation in Elazıgˇ using geographical and meteorological data, Energy Conversion and Management. 40 (1999) 1577–1584.

[18] A. Sozena, E. Arcaklioglub, M. Ozalpa, E.G. Kanitc, Use of artificial neural networks for mapping of solar potential in Turkey, Applied Energy. 77 (2004) 273–286.

[19] S.M. Robaa, Validation of existing models for estimating global solar radiation over Egypt, Energy Conversion and Management. 50 (2009) 184–193.

[20] M.A. Behrang, E. Assareh, A. Ghanbarzadeh, A.R. Noghrehabadi. The potential of different artificial neural network (ANN) techniques in daily global solar radiation modeling based on meteorological data. Solar Energy 2010; 84: 1468–1480.

[21] M.Mohandes, S.Rehman and T.O.Halawani, Estimation of global solar radiation using artificial neural networks, Renewable Energy. 14 (1–4) (1998) 179–184.

[22] M.Mohandes, A.Balghonaim, M.Kassas, S.Rehman, T.O.Halawani, Use of radial basis functions for estimating monthly mean daily solar radiation, Solar Energy. 68 (2) (2000) 161–168.
[23] L.Hontoria, J.Aguilera, J.Riesco, P.J. Zufiria, Recurrent neural supervised models for generating solar radiation, Journal of Intelligent& Robotic Systems. 31 (2001) 201–221.
[24] L.Hontoria, J. Aguilera, P.J. Zufiria, Generation of hourly irradiation synthetic series using the neural network multilayer perceptron, Solar Energy. 75 (2) (2002) 3441–446.
[25] I.Tasadduq, S.Rehman, K. Bubshait, Application of neural networks for the prediction of hourly mean surface temperature in Saudi Arabia, Renewable Energy. 25 (2002) 545–554.
[26] F.S.Tymvios, C.P. Jacovides ,S.C.Michaelides, C. Scouteli, Comparative study of Angstrom's and artificial neural networks' methodologies in estimating global solar radiation, Solar Energy. 78 (2005) 752–762.
[27] J.L. Boscha, G. Lopez, F.J. Batllesa, Daily solar irradiation estimation over a mountainous area using artificial neural networks, Renewable Energy. 33 (2008) 1622–1628.
[28] J. Mubiru, E.J.K.B. Banda, Estimation of monthly average daily global solar irradiation using artificial neural networks, Solar Energy. 82 (2008) 181–187.
[29] D.T. Pham, E. Koç, A. Ghanbarzadeh, S. Otri, Optimisation of the Weights of Multi-Layered Perceptrons Using the Bees Algorithm. in: Proceedings of 5th International Symposium on Intelligent Manufacturing Systems, Sakarya University, Department of Industrial Engineering, May 29-31, 2006, pp. 38-46
[30] A.S. Yilmaz, Z. Ozer, Pitch angle control in wind turbines above the rated wind speed by multi-layer percepteron and Radial basis function neural networks, Expert Systems with Applications. 36 (2009) 9767–9775.
[31] D.T. Pham, X. Liu, Neural Networks for identification, prediction and control, Springer verlag, london,1995.
[32] C.M. Bishop, Neural Networks for Pattern Recognition, Clarendon Press, Oxford, 1995.