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ORIGINAL ARTICLE

Application of clear sky and neural network models for prediction of weekly solar radiation and sunshine hours

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ABSTRACT
This research study presents an investigation about the application of Artificial Neural Networks (ANN) model for prediction of Global Horizontal solar Radiation (GHR) and Sunshine Hours(SSH) for the city of Yazd, Iran.ANN is used for modelling of weather conditions effects on the GHR and SSH.The GHR and SSH for clear sky are calculated using referenced clear sky models. Afterwards, the amount of solar radiation attenuation which is occurred through the atmosphere is modeled using an ANN. The ANN includes two layers perceptron with feed-forward architecture. Standard error back propagation method was applied for training of the ANN using 21 years weekly data. ANN inputs are the weather variables including dry bulb temperature, wet bulb temperature and relative humidity, whereas the attenuation of the GHR and SSH are considered as the ANN outputs.The trained ANN was validated using measured data of one year. Low RMSD, less than 9% for predicted data via the developed model, confirms the adequacy of the obtained model for weekly prediction of the GHR and SSH. For each season, correlation between the GHR and inputs was obtained using the ANN. For all seasons, the GHR increases with increasing the DBT and WBT, however; it decreases with increasing the RH. Developed ANN-Clear Sky model could be applied for any specific geographical location and climate, however; it should be retrained using the weather data of the location.
Keywords: Clear Sky Model, Global Horizontal Solar Radiation, Sunshine Hours, Artificial Neural Network

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Nomenclature

AM	air mass
ANN	artificial neural network
DOY	day of year
DBT	Dry bulb temperature (°C)
E_{Co}	cumulative error
GHR	global horizontal radiation (Wh/m^2)
G_0	solar constant (W/m^2)
I_0	extraterrestrial solar radiation (W/m^2)
N_{Out}	number of outputs of ANN
N_{Tr}	number of training data
Q^{ANN}	data predicted by ANN
$Q^{Measured}$	measured data
TL	Linke Turbidity
RH	Relative Humidity (%)
SSH	sunshine hours (h)
WBT	wet bulb temperature (°C)
c_{g1}, c_{g2}	coefficients
f_{h1}, f_{h2}	coefficients
h	high (m)
t	epoch number in training process of ANN
z	zenith angle (degree)
Greek Letters	
ε	coefficient

λ	adaptive learning rate
φ	geographical latitude (degree)
ω	hour angle (degree)
δ	declination angle (degree)

INTRODUCTION

Due to the exhaustibility of the fossil fuels resources and increasing of the environmental pollutants, the renewable energies are most interested energy resources in the recent decades. Solar energy is one of the favorable renewable energy resources, which is clear and free. Beside its potential and availability is sufficient over most of the regions in the world.

However solar energy is free, using solar energy is not free and needs high investment. Developed countries as well as developing countries devoted great investments in order to enhance efficiency of solar energy conversion systems alongside decrease the capital costs of these systems. In order to design solar energy conversion systems, it is essential to have available weekly and monthly average values of solar radiation with sufficient reliability. Therefore, solar radiation availability affects the capital costs of the solar systems because the optimum application and utilization of solar energy depends on the amount of available solar radiation [1-2].

The adequate potential of solar energy harvesting in the Iran, the use of the solar systems are cost effective. Average annual sunshine hours in Iran is2966 h (i.e., 8.1 h/day), which corresponds to an average annual solar radiation of approximately 2285kWh/m2, that is, 6.0 kWh/m2 per day.

For a specific location, the geographical location and weather conditions specify the availability and the intensity of solar radiation on the ground level. The solar radiation data should be measured continuously and accurately over the long term. Unfortunately, in most areas of the world, solar radiation measurements are not easily available due to financial, technical or institutional limitations.

Therefore, many studies have been carried out in order to develop models to predict the solar radiation for specific locations [3-4]. Furthermore, some models have been developed as general models which can be applied for different geographical conditions and climates [5-6]. In general, the accuracy of general models is less than models which are applied for a specific location.

It is remarkable that the climate changes are occurring in long-term periods. Since the lifetime of the solar systems is less than the climates changes periods, the climate changes are not important to be considered as the cause of solar radiation changes and thus, seasonally, monthly, weekly, daily and hourly variations are more favorable.

Hassan et al. considered a time-series regression with ARIMA modeling to establish a weather model for Al-Ain, UAE [3]. The model has been built based on 10 year data (1995-2004) and validated with 3 year data (2005-2007). The R^2 values for predicted monthly and daily solar radiation were 99.88 and 92.60 respectively which illustrated suitable performance of the model for prediction of solar radiation in the Al-Ain.

Moradi et al. evaluated Heliostat II model using global daily solar radiation measured in 4 radiometric stations in Iran and images recorded by an spacecraft over 63°E [4]. Mean RMSD% and MBD% has been obtained as 11.7% and 1.9% respectively. Maximum RMSD was 22.1% for autumn while the minimum was in spring, 8.4%. It could be found that the resulted accuracy in predicted data is a good achievement for Iran in which there are sparse radiometric network and unreliable solar radiation data.

Paoli et al. used a new methodology for solar radiation prediction in which weather time series data have been pre-processed [5]. Afterwards, a multilayer ANN has been trained with the pre-processed data. Prediction results have been validated using 6 month data from a 1.175 kW photovoltaic site in Corsica, France. The results indicated pre-process could improve the prediction error around 6% in comparing with other models such as ARIMA, Bayesian inference and Markova Chains.

Most of the mentioned research studies indicate the ANN is one of the formidable and favorable mathematic models for prediction of solar radiation using Meteorological parameters. Thus, the objective of this work is to predict the global horizontal radiation and sunshine hours as the function of dry bulb temperature, wet bulb temperature and relative humidity by an ANN.

MATERIALS AND METHODES

Data

Meteorological data and the solar radiation data recorded in 22 meteorological stations for period 1975-2010 were received from Meteorological Organization of Iran [7]. For validation of the model, as a case study for the Yazd city, the data for period 1989-2009 and the 2010 data considered as the training and test data, respectively. The pyranometer has been used to record the global solar radiation on horizontal surface. In order to estimate lost data in the data set, the lost values of the parameters in a specific year was calculated using the average of the parameters in the last and next years. Frequency of data (DBT, WBT and RH) recording in the data set is one time per three hours.

Methodology

From the sun to the ground level, for various effects such as sun to earth distance, geographical location and weather conditions, the solar radiation attenuates and scatters in several stages. On cloudy days, prediction of the solar radiation by analytical models is difficult, because many parameters affect the solar radiation and its availability, however; modeling of solar radiation in the clear sky could be carried out by analytical models with adequate accuracy.

In this work, a referenced analytical clear sky model was used to predict the GHR and SSH in the clear sky. Afterwards, ANN model was used to model the attenuation of the GHR and SSH.

Modeling of the solar radiation attenuation rather than the solar radiation was preferred because the analytical models can calculate the GHR and SSH in the clear sky properly.

Considering this methodology, the knowledge among data which is needed for prediction decreases, and consequently, the ANN capability for prediction of GHR and SSH attenuation increases. Figure 1 shows the modeling flowchart for GHR.

Clear sky model

Many models have been developed for prediction of extraterrestrial solar radiation [8], clear sky solar radiation [9], air mass [10] and Linke Turbidity [11-12]. Matthew et al. have published a report entitled "Global Horizontal Irradiance Clear Sky Models: Implementation and Analysis" in the Sandia National Laboratories in which most of developed models from very simple to complex have been reviewed [13].

The results of the referenced report were used as the base of clear sky model. According to the mathematical relationships in the mentioned report for simple clear sky models, the horizontal global solar radiation is obtained using equation (1):

$$GHR = c_{g1} I_0 \cos(z) \exp\left[-c_{g2} AM \left(f_{h1} + f_{h2}(TL-1)\right)\right] \exp(0.01 AM^{1.8}) \qquad (1)$$

c_{g1}, c_{g2}, f_{h1} and f_{h2} are estimated according to equations (2) to (5):

$$c_{g1} = 5.09 \times 10^{-5} h + 0.868 \qquad (2)$$

$$c_{g2} = 3.92 \times 10^{-5} h + 0.0387 \qquad (3)$$

$$f_{h1} = \exp\left(-\frac{h}{8000}\right) \qquad (4)$$

$$f_{h2} = \exp\left(-\frac{h}{1250}\right) \qquad (5)$$

Extraterrestrial solar radiation, I_0, is calculated using equation (6)[8]:

$$I_0 = G_0 \left[1 + 0.033 \cos\left(\frac{2\pi}{365} DOY\right)\right] \qquad (6)$$

Equation (7) presents a formula for AM [20]

$$AM = \frac{1}{\cos(z) + 0.50572(96.07995 - z)^{-1.6354}} \qquad (7)$$

Zenith angle, z, is calculated using declination angle (δ) and hour angle (ω) according to equations (8) to (10) [14]:

$$\cos(z) = \cos(\varphi)\cos(\delta)\cos(\omega) + \sin(\varphi)\sin(\delta) \qquad (8)$$

$$\delta = 23.45 \sin(x) \qquad (9)$$

$$x = \frac{360^\circ}{365}(DOY - 81) \qquad (10)$$

Hour angle varies 15 degree per hour. Therefore, as is shown in equation (11), in the clear sky, sunshine hours is obtained by setting equation 8 to zero and solving the equation respect to ω [14]:

$$SSH = \frac{2}{15} Arc\cos\left[-\tan(\varphi)\tan(\delta)\right] \tag{11}$$

Artificial Neural network model

Because of non-linearity of relation between the GHR/SSH and weather variables as well as high correlation between the inputs, the prediction accuracy of analytical and numerical models is not adequate for these applications. Moreover, using numerical models is time consuming. For this reason, an input-output mathematical model, the ANN model was used [15]. The ANN is a two layer feed forward perceptron with 9 inputs, 2 outputs and 1 hidden layer. Since the attenuation of GHR and SSH vary with time, the week number is included as an input. The outputs of ANN are the attenuation of weekly GHR and SSH.

Feedback loop between the layers of the ANN were not considered, because the forecast horizon (weekly) was in the mid-term range. The use of feedback loops increases the performance of the ANN in the case the aim of ANN is short-term predictions such as daily or hourly [15]. In the short-term predictions, the outputs of previous time points include useful information for the next time points while for mid-term or long-term predictions such as weekly or yearly predictions, the outputs of the next time points would not be affected by the previous time points, obligatorily.

ANN model: Inputs and outputs-Data scaling.

Week number, the mean WBT and the mean, maximum and minimum values of the DBT as well as RH in the week were considered as the ANN inputs while the attenuation of weekly GHR and weekly SSH were considered as the ANN outputs.

Table 1. Characteristics of the ANN

Inputs	DBT_{mean}
	DBT_{min}
	DBT_{max}
	WBT_{mean}
	RH_{mean}
	RH_{min}
	RH_{max}
	Week Number
Outputs	Attenuation of weekly GHR
	Attenuation of weekly SSH
Number of layers	2
Input data scale	[0.5 1.5]
Neuron's activation function	Linear, Unipolar sigmoid, Bipolar sigmoid

Table 2.ANN outputs data scale for different types of activation functions of neurons

Type of activation function of neurons	Output data scale
Linear	[-1 1]
Unipolar sigmoid	[0 1]
Bipolar sigmoid	[-1 1]

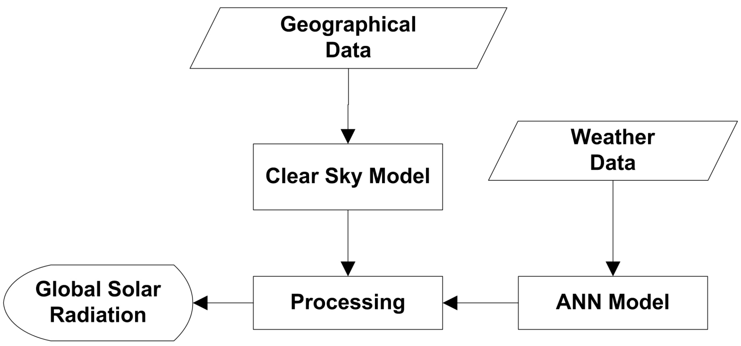

Figure 1. Flowchart of solar radiation modelling by clear sky and ANN models

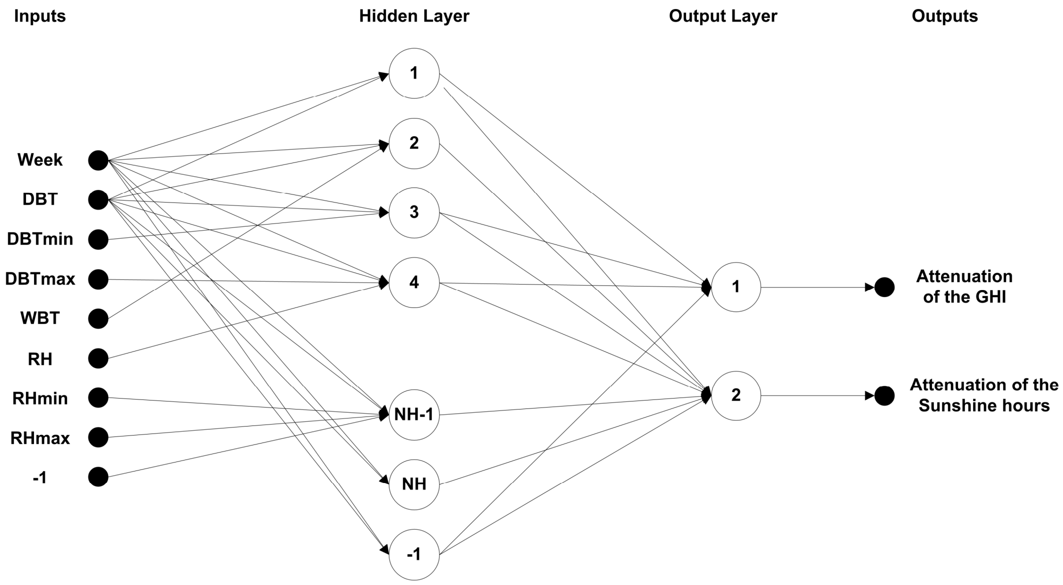

Figure 2. Inputs, outputs and architecture of the ANN

ANN model: Neural network training.

Standard error back propagation method was used as the training procedure, in which the network weights were iteratively corrected to reduce the network error, and the process continued until an acceptable error was achieved [15]. Number of training data and test data were 1092 (21 years) and 52 (1 year), respectively. During the training, the network parameters including the initial learning rate from 0.04 to 0.11, number of neurons in hidden layer from 20 to 120, and type of activation function of the neurons were modified in order to converge to a high performance network. In order to prevent the neural network from local minimum traps in the training process, as are shown in the equations (12) and (13), the adaptive learning rate was altered according to Simulated Annealing (SA) algorithm [15].

$$\Delta E_{Co}(t) = E_{Co}(t) - E_{Co}(t-1) \tag{12}$$

$$\begin{cases} \Delta E_{Co}(t) < 0 & \Rightarrow \quad \lambda(t+1) = 1.01 \times \lambda(t) \\ \Delta E_{Co}(t) > 0 & \Rightarrow \quad \begin{cases} \lambda(t+1) = 1.01 \times \lambda(t) & \text{if} \quad \exp(-\dfrac{\Delta E_{Co}(t)}{\tau}) \geq \varepsilon \\ \lambda(t+1) = \lambda(t) & \text{if} \quad \exp(-\dfrac{\Delta E_{Co}(t)}{\tau}) < \varepsilon \end{cases} \end{cases} \tag{13}$$

The data were trained using an integrated algorithm, and during each training epoch, the cumulative error was obtained from equation (14) [15].

$$E_{Co}(t) = \frac{1}{2}\sum_{i=1}^{N_{Tr}}\sum_{j=1}^{N_{Out}}\left(Q_{i,j}^{Measured} - Q_{i,j}^{ANN}(t)\right)^2 \tag{14}$$

As mentioned, the number of neurons in the hidden layer was changed from 20 to 120 for fixed maximum number of training epochs. As is shown in figure 3, the optimum number of neurons in the hidden layer is 80 in which the cumulative error of the ANN is equal to its minimum value.

For each specific maximum number of training epochs, best results were obtained by bipolar sigmoid activation function, and learning rate of 0.05. For the best architecture of the ANN, as is shown in the figure 4, cumulative error of the network was decreased by around 50 at the end of training epochs.

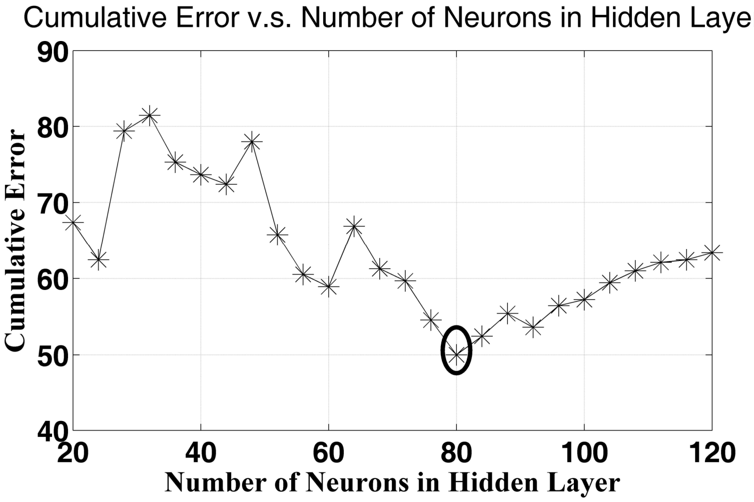

Figure 3. Cumulative error of the ANN at the end of training process v.s. number of neurons in the hidden layer

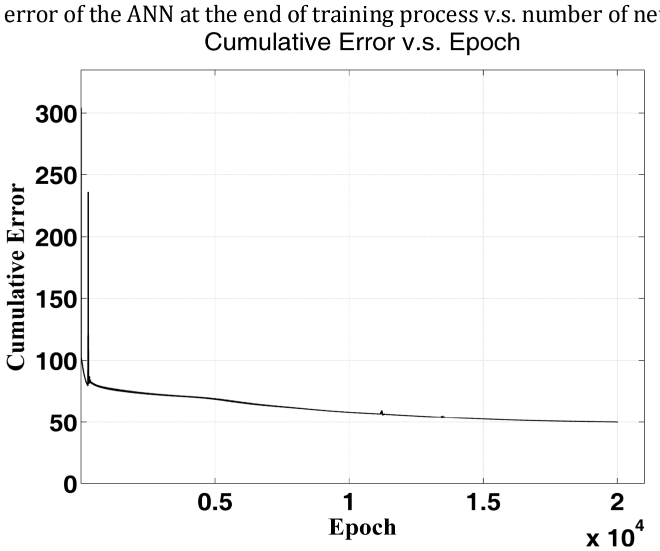

Figure 4. Cumulative error of the best architecture of the ANN v.s. training epochs

RESULTES AND DISCUSSION

The profiles of the weekly GHR and SSH in the clear sky are presented in figures 5 and 6, respectively. As are shown in these figures, the GHR and SSH varies as the function of week number, and there is no unexpected variations in the clear sky profiles. The solar radiation intensity changes from 420 W/m2 in winter to 690 W/m2 in summer.

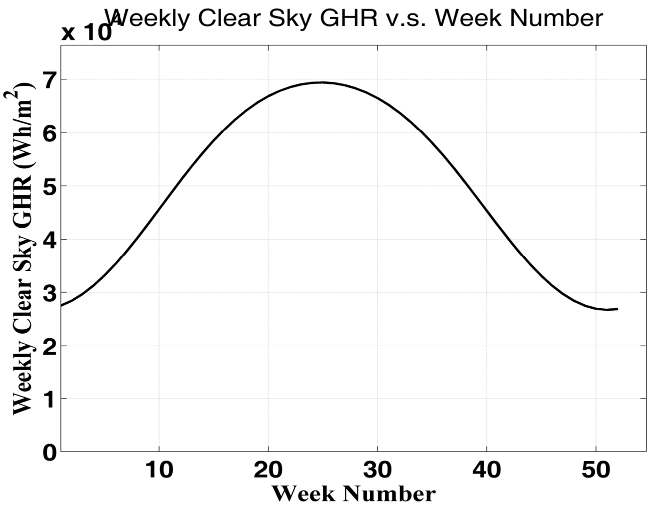

Figure 5. Weekly clear sky GHR v.s. week number

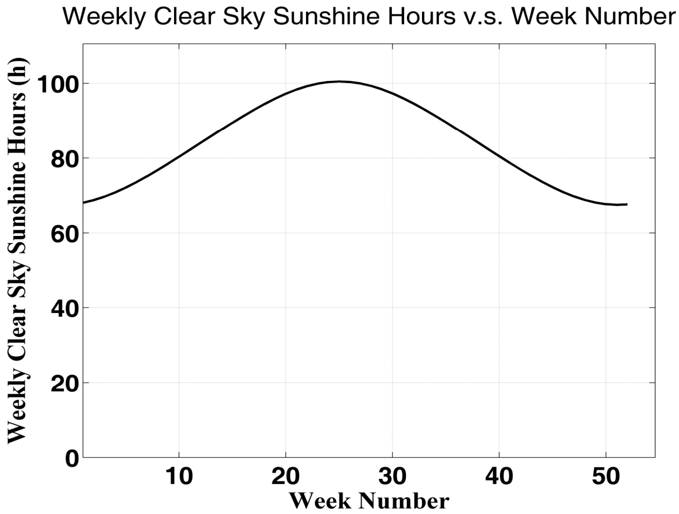

Figure 6. Weekly clear sky SSH v.s. week number

For 156 of 1092 training data, the clear sky GHR, the measured GHR, and the calculated GHR data using ANN outputs are shown in figure 7. As is shown, measured data and the predicted data are in good agreement. Similarity, figure 8 illustrates the clear sky SSH, the measured SSH, and the calculated SSH data using ANN outputs.

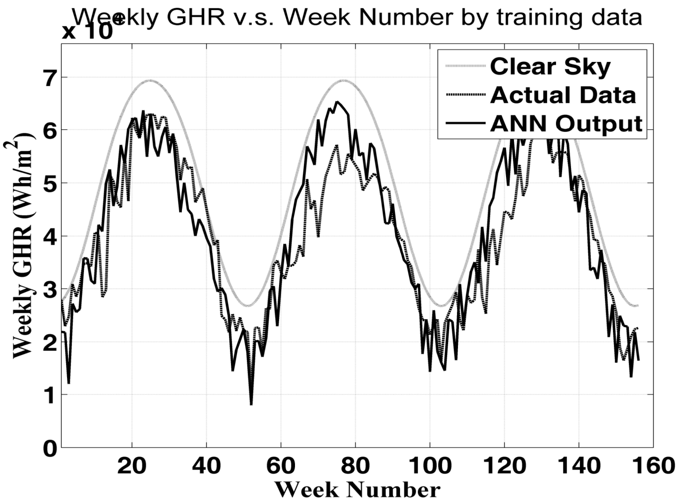

Figure 7.Measured GHR and predicted GHR v.s. week number for three years of training data

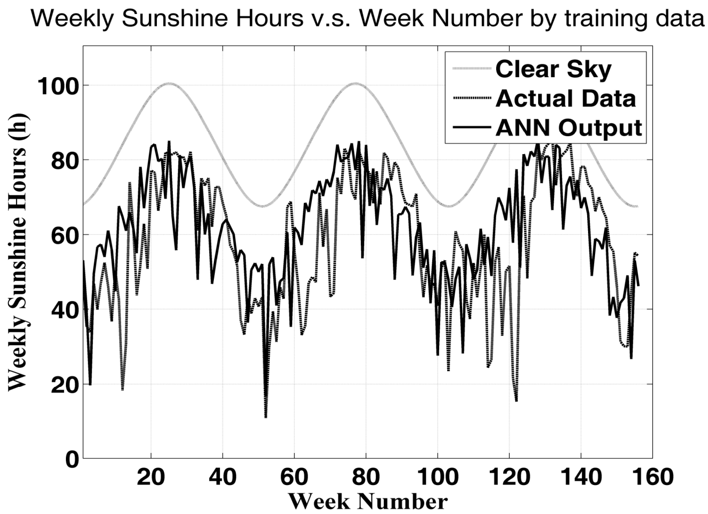

Figure 8. Measured SSH and predicted SSH v.s. week number for three year of training data

For performance evaluation of the ANN, the test data were entered to the network and the network outputs were used to calculate the GHR and SSH. Afterwards, the predicted GHR and SSH were compared with the measured data. As are indicated in the figures 9 and 10, the ANN predicts the attenuation of the GHR and SSH and consequently the GHR and SSH with good accuracy.Since the unexpected variations in the GHR and SSH in summer is lower than winter, the ANN predicts the GHR and SSH with higher accuracy in the summer in comparing with the winter.

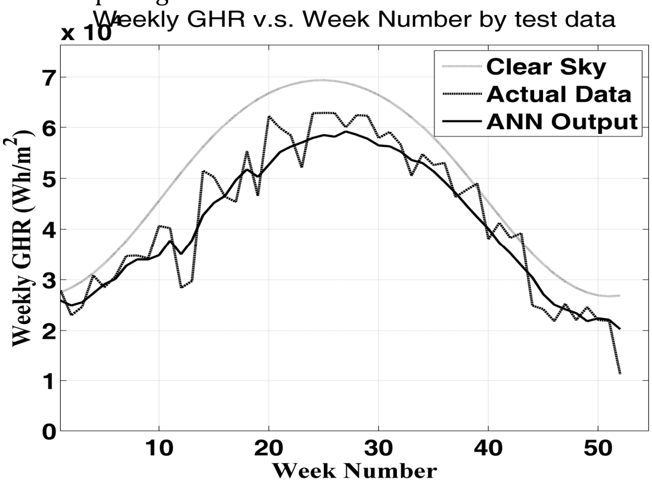

Figure 9. Measured GHR and predicted GHR v.s. week number for the test data

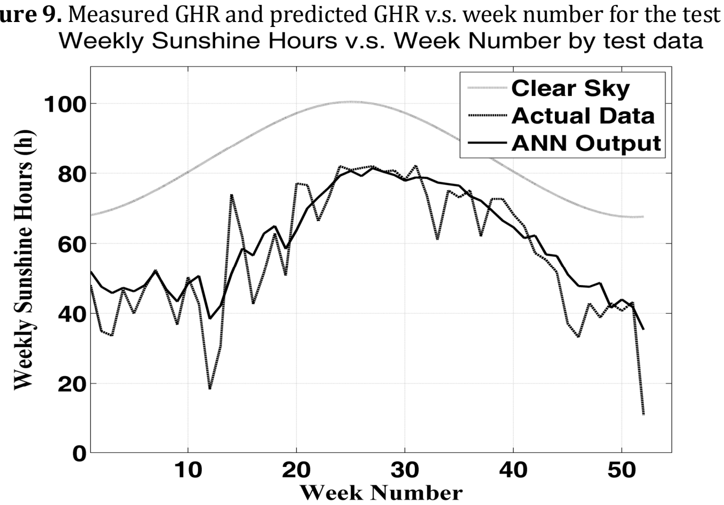

Figure 10. Measured SSH and predicted SSH v.s. week number for the test data

For test data, the predicted data are plotted versus measured data in the figures 11 and 12. As are illustrated in the figures, the prediction error of GHR is less than 15% for around 93% of test data while for around 73% of test data the prediction error of SSH is less than 15%.

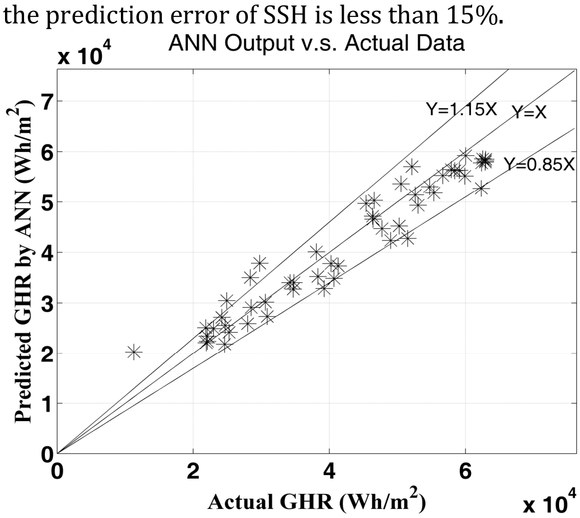

Figure 11. Comparing the predicted GHR data with the measured GHR data

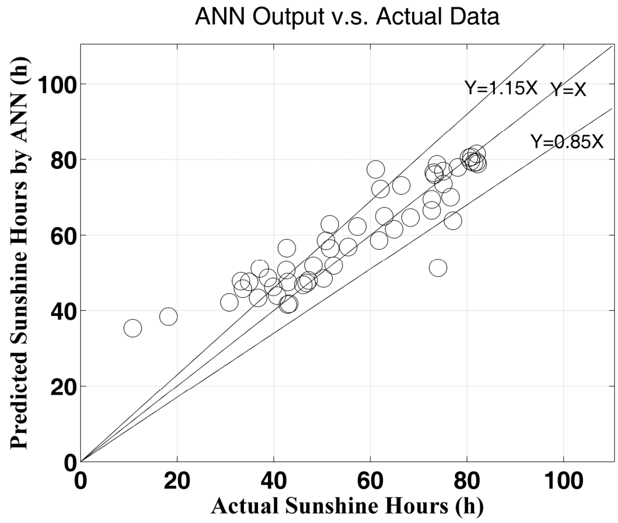

Figure 12. Comparing the predicted SSH data with the measured SSH data

The effects of DBT, WBT and RH on the solar radiation were individually evaluated for all seasons as a comprehensive sensitivity analysis. In a specific season, the input under consideration was linearly changed from its minimum value to its maximum value, while all of the other inputs were set to their mean values in the season.

The GHR decreases with increasing of the WBT in winter and spring seasons, however the GHR increases with increasing of the WBT in summer and autumn seasons. There is similar behaviour for variations of the GHR versus the DBT and RH. The results are shown in figures 13 to 15.

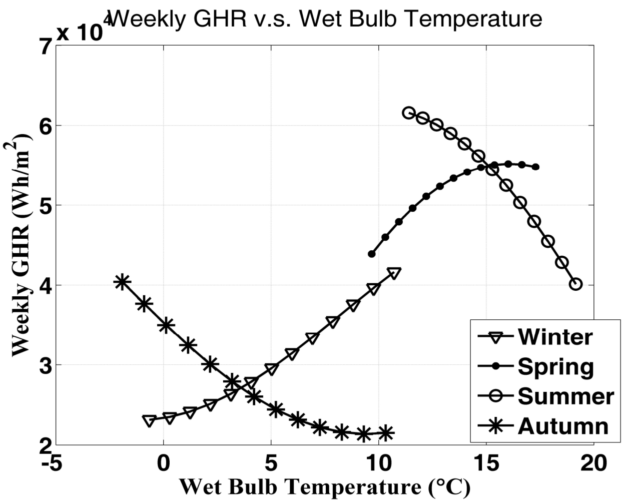

Figure 13. Variation of the GHR v.s. the WBT

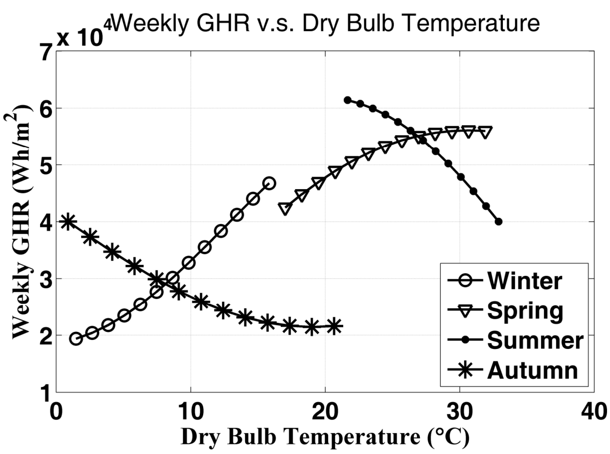

Figure 14. Variation of the GHR v.s. the DBT

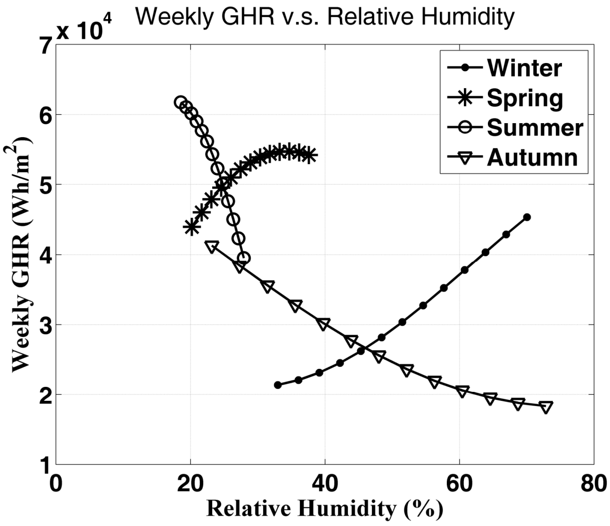

Figure 15. Variation of the GHR v.s. the RH

CONCLUSION

In this research study, an integrated clear sky-neural network model was developed and used for prediction of the solar radiation and sunshine hours in the Yazd city. Since complication of relations between inputs and outputs reduces the performance of the ANN, using clear sky model decreases the needed knowledge for prediction, resulting to optimal use of the ANN. Comparing the predicted GHR and SSH with the measured data indicates the neural network error for prediction is around 7% and consequently the network has an acceptable accuracy in comparison with the referenced studies. Results of this work presented the ability of the ANN in prediction of the GHR and SSH. The integrated model could be applied for any specific geographical location and climate; just it should be retrained using the meteorological data of the location. The developed model could be improved by considering wind velocity and air pressure as the ANN inputs. Creating the single variable correlations between the GHR and inputs in the sensitivity analysis are the important results of this work. Variations of the GHR are sensitive function of the WBT and RH, however; the DBT is more effective in summer and winter.

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