

# Evaluating Potential of Artificial Neural Network and Neuro-Fuzzy Techniques for Global Solar Radiation Prediction in Isfahan, Iran

S. Taghadomi-Saberi<sup>1\*</sup>, and S. J. Razavi<sup>1</sup>

## ABSTRACT

In this study, two widely used artificial intelligence techniques, i.e. Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS), were applied for global solar radiation (GSR) prediction in Isfahan Province, Iran. Different sets of meteorological data were used as inputs to specify the best set of inputs. Relative humidity and precipitation had an unfavorable effect on radiation prediction, while the number of days, sunshine duration, minimum temperature, maximum temperature, daylight hours and clear-sky radiation were effective parameters to determine GSR. Using the mentioned parameters as inputs, 6-5-1 architecture had the best performance without overtraining. In ANFIS models, 'triangular-shaped' had the highest performance amongst different types of membership functions. Resulted correlation coefficients and errors showed that ANN was generally better than ANFIS for this purpose.

**Keywords:** ANFIS, ANN, GSR, Meteorological data, Modeling.

## INTRODUCTION

A rapid trend in dwindling the nonrenewable energy resources has brought the global attention towards the consequences and effects of their application on the environment and living organisms. Hence, in the past decade, renewable energy investments have been prevailing worldwide to look for other resources to meet the growing global demand for energy (Akhyani *et al.*, 2015). In fact, the new paradigm shift in the energy sector and the impositions for a gradual reduction of greenhouse gas emissions made the producers deliver electricity using clean energy sources, in competitive deregulated electricity markets (Osorio *et al.*, 2015). The total investment for renewable power and fuels in 2012 (\$244 billion) was six times that of 2004. Renewable energy development is beneficial for reducing environmental pollution, enhancing energy security, creating new jobs,

and accessibility in areas far from power lines. However financing renewable energy projects and managing the attributed risks are still highly challenging (Lee and Zhong, 2015).

The budget from the government is limited. So, public, private and institutional investors have an important role in future green energy developments. Consequently, it is necessary to apply different incentive to encourage investors to support renewable energy efforts. One of the most common methods used by governments is to set renewable energy targets and obligations. However, simply establishing targets and obligations, while still employing the same financing paradigm, does not proactively encourage investors and developers to develop renewable energy resources (Klessmann *et al.*, 2013; Lee and Zhong, 2015). Therefore, effective finance and risk management tools are essential elements in the successful development of renewable energy projects.

<sup>1</sup> Department of Biosystem Engineering, College of Agriculture, Isfahan University of Technology, Islamic Republic of Iran.

\*Corresponding author: e-mail: s.taghadomi-saberi@ag.iut.ac.ir



Reliable solar resource information, such as Global Solar Radiation (GSR) data, is required for desirable planning of solar projects. Meteorological stations in Iran do not provide complete coverage all over the country. Besides, there may be many days with missing or outlier GSR data. Due to the difficulties and challenges of GSR measurement at meteorological stations, analysis of GSR can be done with experimental techniques. The major disadvantage of regression analysis is its requirement of some assumptions about the functional form (Pahlavan *et al.*, 2012). Thus, Artificial Intelligent (AI) techniques can be used as powerful tools to analyze and predict GSR. Artificial Neural Networks (ANNs) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) are two main AI modeling techniques which are widely applied recently because of their fast and efficient performance in modeling complicated data compared to other mathematical models such as regression (Pahlavan *et al.*, 2012; Khoshnevisan *et al.*, 2015).

The ANN approach has been applied to the solar radiation prediction using various geographical and meteorological parameters. In a research by Jiang (2009), ANN was applied for estimating monthly mean daily GSR of 8 typical cities in China. He found that the solar radiation estimations by ANN were in good agreement with the measured values and were superior to those of other available empirical regression models. A direct and inverse ANN approach were also developed by Hernandez *et al.* (2012) to predict the required coefficient of performance of a solar intermittent refrigeration system for ice production under various experimental conditions. The architecture 6-6-1 showed an excellent agreement ( $R > 0.986$ ) between experimental and simulated values. Mubiru and Banda (2008) and Mellit and Pavan (2010) used ANN for estimation of average daily global solar irradiation. Kumar *et al.* (2013b) developed a regression model to estimate GSR using ANN in hilly areas of North India by considering latitude and altitude of the

place. Overall, ANNs are now accepted as an alternative technology offering a way to tackle complex and ill-defined problems. They are not programmed in the traditional way, but they are trained using past history data representing the behavior of a system (Kumar *et al.*, 2013a).

The tremendous attention towards solar energy makes it necessary to search for higher performance and higher certainty in the predictions. Therefore, this study aimed to propose an appraisal of two widely used techniques, namely, ANN and ANFIS, to gain a better knowledge of the distribution of solar radiation on a specific territory and to understand the very important potential of the solar energy in Iran.

## MATERIALS AND METHODS

### Study Area and Data Set

Considerable effort has been undertaken for developing procedures and software for GSR prediction due to the difficulties in its measurement and the reliability of the measured data. Certainly, it is crucial to ensure the highest possible quality of the data chosen for various applications. Meteorological data other than GSR are parameters which are easily recorded by most meteorological stations with inexpensive recording instrumentation (Ramedani *et al.*, 2014). The area of the study for this research was Isfahan Province, with an area of about 107,045 square kilometers, equivalent to 6.3% of the total area of Iran, located in  $32^{\circ} 39' 08''$  N latitude and  $51^{\circ} 40' 28''$  E longitude. The province altitude is 1,550 meters above the mean sea level. The province experiences a moderate and dry climate on the whole, with a temperature ranging between 41 and  $-12.6^{\circ}\text{C}$  on a cold day in the winter season. The average annual temperature has been recorded as  $17.2^{\circ}\text{C}$  and the annual rainfall has been reported as 169.6 mm in 2014 (IRIMO, 2015). The high level of air pollution and its role in emergence of cardiovascular

diseases are causing concern now in Isfahan and the main counties of the province. As a result, avoiding the use of air pollutant fuels or using them as little as possible, could be very useful to decrease air pollution and its consequences, (Rashidi *et al.*, 2012). Moreover, Isfahan has a very strong potential for the utilization of solar technologies due to its high insolation, which is by far its largest renewable energy resource. The average bright sun shine hours was reported to be higher than  $8.9 \text{ h d}^{-1}$  (IRIMO, 2015). It is estimated that average solar irradiance over this territory is higher than  $20.9 \text{ MJ m}^{-2} \text{ d}^{-1}$  (IRIMO, 2015) (Figure 1). However, to date, there is a lack of precise knowledge about this resource. Measured daily data for an eleven-year period (1995 to 2005) was obtained from the Islamic Republic of Iran Meteorological Office (IRIMO, 2015) data center.

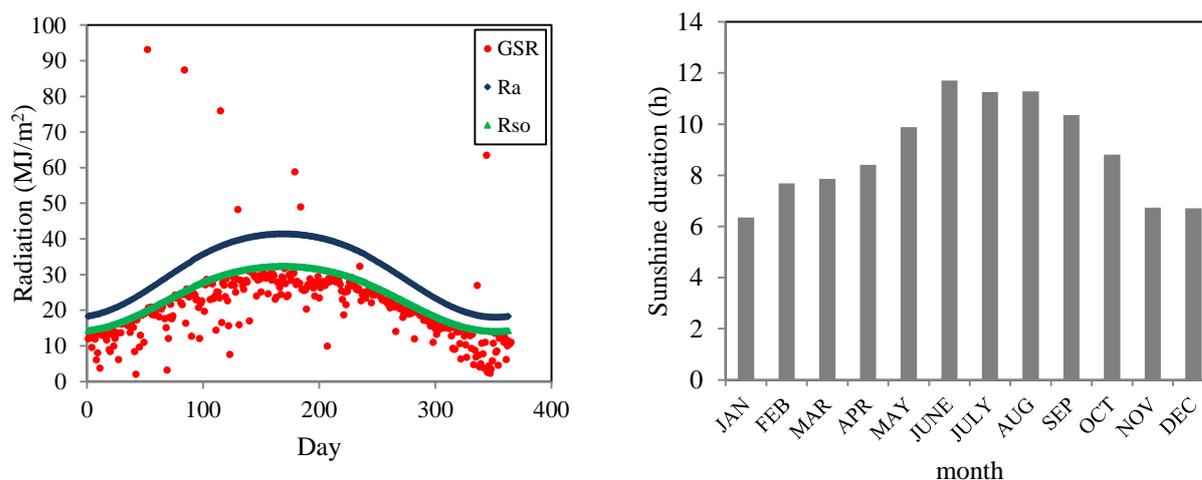
Certain meteorological data (nine parameters) to estimate solar radiation were chosen as inputs for AI techniques, including: daily values of maximum and minimum temperatures ( $^{\circ}\text{C}$ ), relative humidity (%), sunshine duration (h), precipitation (mm), daylight hours (h), number of days between 1 (January 1st) and 365 or 366 (December 31st), clear-sky solar Radiation ( $R_{\text{so}}$ ,  $\text{MJ m}^{-2} \text{ d}^{-1}$ ) and extraterrestrial Radiation ( $R_{\text{a}}$ ,  $\text{MJ m}^{-2} \text{ d}^{-1}$ ). Corresponding global solar radiation (GSR,  $\text{MJ m}^{-2} \text{ d}^{-1}$ ) pertaining to meteorological data

selected was used as the output of the AI techniques. Data set were divided to three parts after randomization for ANN, including training data set, cross validation data set, and test data set and were divided to two parts for ANFIS models, including training data set and test data set.

## Intelligent Techniques for Modeling GSR

### Development of ANN Models

Remarkable development of ANN techniques in research activities in the past two decades is the result of high interest in using them for forecasting purposes. These powerful models can also be set up in various arrangements to perform various functions consisting of classification, pattern recognition, data mining, and process modeling. ANN is a network of densely interconnected elements called neurons. Neurons are connected to each other with different weights which determine the robustness of ANN models. A feed forward Back Propagation (BP) MultiLayered Perceptron (MLP) structure is commonly used due to its advantages including: easy and fast application, almost little memory requirement, and extraordinary



**Figure 1.** (a) Daily evolution of Global Solar Radiation (GSR), extraterrestrial global irradiation ( $R_{\text{a}}$ ), and clear-sky Radiation ( $R_{\text{so}}$ ); (b) Monthly mean sunshine duration for selected station (Isfahan Province).

approximation capability, which would be difficult or even impossible for conventional algorithmic methods (Pahlavan *et al.*, 2012).

For illustration purposes, a network having one hidden layer (with a hyperbolic tangent sigmoid activation function) and one output layer (linear function) is drawn in Figure 2.

The bias parameters,  $b_j^{(h)}$  and  $b^{(o)}$ , are to make networks more flexible. The general expression for a feed-forward (FF) operation can compactly be cast into (Taghadomi-Saberi *et al.*, 2014a):

$$p.GSR = \sum_{j=1}^m w_j^{(o)} f \left( \sum_{i=1}^n w_{ji}^{(h)} O_i + b_j^{(h)} \right) + b^{(o)} \quad (1)$$

Where,  $p.GSR$  is the predicted value of the GSR in the network, and

$$O_i = f(net_i) = \text{tansig}(net_i) = \frac{2}{1+e^{-2net_i}} - 1, \quad (2)$$

for hidden neurons, and

$$O_j = f(net_j) = \text{purelin}(net_j) = net_j, \quad (3)$$

for output neurons. The outputs of the hidden layer are summed linearly to produce the purposed GSR estimates.

There are a number of procedures for error minimization in the feed-forward networks, including Gradient Descent (GD), Levenberg-Marquardt (LM), Quasi-Newton (BFGS) and Conjugate Gradient (CG). It is unavoidable to select an algorithm that provides the best fit to the data. The LM algorithm was designed to approach second-order training speed without having to

compute the Hessian matrix. As the performance function has the form of a sum of squares, the Hessian matrix can be approximated as follows (Omid *et al.*, 2010):

$$H = J^T J \quad (4)$$

And the Gradient can be computed as:

$$G = J^T e \quad (5)$$

Where,  $J$  is the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases, and  $e$  is a vector of network errors. The LM algorithm uses this approximation to the Hessian matrix in the following Newton-like weight update (Omid *et al.*, 2010):

$$w_{k+1} = w_k - [J^T J + \mu I]^{-1} J^T e \quad (6)$$

Where,  $w$  indicates the weights of neural network, and  $\mu$  a scalar that controls the learning process. Note that the above expression approximates GD with a small step size when parameter  $\mu$  is large while the algorithm approximates the Newton's method for a small  $\mu$ . By adaptively adjusting  $\mu$ , the LM can maneuver between its two extremes i.e. the GD and the Newton's algorithm (Omid *et al.*, 2010).

In this paper, ANN as implemented in MATLAB, was used for modeling the relationship between the meteorological data [day of year (1-365), sunshine duration, daylight hours, clear-sky solar radiation, minimum and maximum temperature, etc] and corresponding GSR. LM algorithm was used to train the networks. The routine of

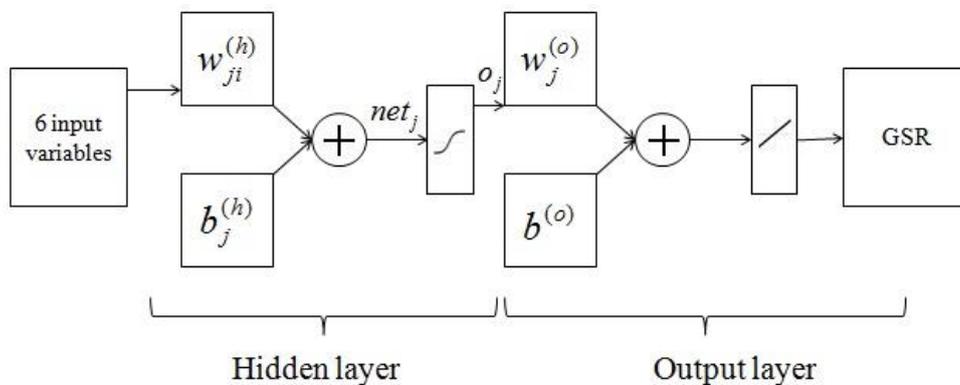


Figure 2. Structure of artificial neural network.

ANN generation was programmed in MATLAB. Several ANNs, 480 ANN topologies, were designed and tested with one and two hidden layers and variable number of neurons from 5 to 20 in each layer in every run.

**Development of ANFIS Models**

In ANFIS, an ANN learning algorithm is applied to construct a set of fuzzy if-then rules with proper Membership Functions (MFs) from specified input-output pairs. Two methods are used for updating MFs in the training phase (Yalcin *et al.*, 2011):

- (1) Back Propagation (BP) for all parameters (a gradient descent method),
- (2) A hybrid method including BP and least squares estimation; BP for parameters associated with input membership and least squares estimation for parameters associated with output MF.

The functionality of nodes in ANFIS, as a five-layered feed-forward neural structure can be summarized as is explained in the following section (Figure 3) (Soltani *et al.*, 2010; Bektas Ekici and Aksoy, 2011):

Layer 1: Every node *i* in this layer is an adaptive node with a node function.

$$O_{1i} = \mu_{A_i}(x), \text{ for } i = 1, 2 \text{ \& } O_{2i} = \mu_{B_i}(y), \text{ for } i = 1, 2 \tag{7}$$

Where, *x* and *y* are inputs to *i*<sup>th</sup> node, and *A<sub>i</sub>* and *B<sub>i</sub>* are linguistic labels for inputs.  $\mu_{A_i}(x)$  and  $\mu_{B_i}(y)$  can adopt any fuzzy MF. For instance, if the Gaussian MF is employed,  $\mu_{A_i}(x)$  is given by:

$$\mu_{A_i}(x) = \exp\left(-0.5 \frac{(x_i - c_i)^2}{\sigma^2}\right) \tag{8}$$

Where,  $\sigma$  and  $c_i$  are the parameters set. These parameters in this layer are referred to as premise parameters.

Layer 2: In this layer, the firing strength of each rule is calculated by mathematical multiplication (Nodes are fixed and labeled with M).

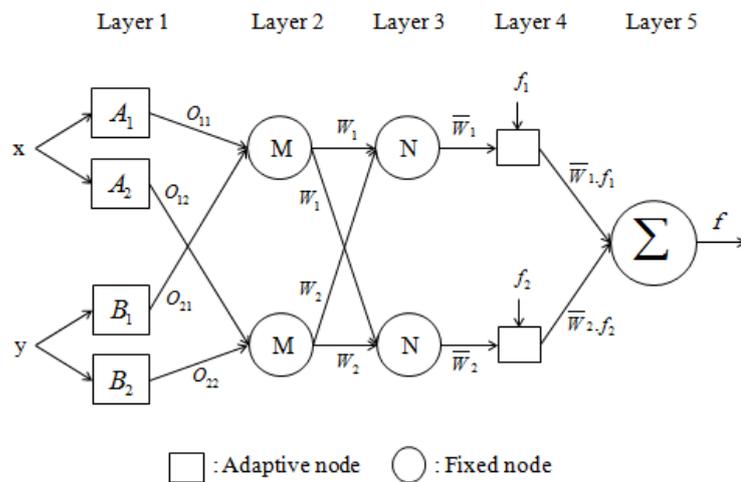
$$W_i = \mu_{A_i}(x) \cdot \mu_{B_i}(y), \quad i = 1, 2 \tag{9}$$

Layer 3: In this layer, the normalization of the firing strengths is performed. The *i*<sup>th</sup> node calculates the ratio of the *i*<sup>th</sup> rule's firing strength to all rules firing strength (Nodes are fixed and labeled with N).

$$\bar{W}_i = \frac{W_i}{W_1 + W_2}, \quad i = 1, 2 \tag{10}$$

Layer 4: Nodes are adaptive with a node function

$$\bar{W}_i \cdot f_i = W_i \cdot (p_i x + q_i y + r_i), \quad i = 1, 2 \tag{11}$$



**Figure 3.** Structure of ANFIS network.



\* Rule 1: If  $x$  is  $A_1$  and  $y$  is  $B_1$  then  $f_1 = p_1x + q_1y + r_1$

\* Rule 2: If  $x$  is  $A_2$  and  $y$  is  $B_2$  then  $f_2 = p_2x + q_2y + r_2$

Where,  $W_i$  is the output of Layer 3 and  $\{p_i, q_i, r_i\}$  is the parameter set. Parameters in this layer will be referred to as consequent parameters.

Layer 5: The single node is fixed with output equal to the sum of all the rules' outputs.

### Parameter Selection

Although relative humidity and precipitation are the most important meteorological data, they were firstly omitted from the data set due to their unfavorable effect on solar radiation prediction models. As it can be seen in Figures 1(a) and 4, these two features do not follow the same behavior as GSR and other useful meteorological parameters. Ramedani *et al.* (2013) also reported such unfavorable effect for these parameters on radiation prediction. Consequently, their deletion led to a better data set for modeling. In order to determine the best effective features, different sets of input variables were used in ANN models. Different selections of input variable are shown in Table 1.

### Accuracy Assessment and Calibration

Assessing the accuracy and performance of ANFIS and ANN models, the correlation coefficient (R), Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) were used. These statistical criteria are

defined in Equations (12)-(14) (Taghadomi-Saberi *et al.*, 2014b).

$$R = \sqrt{\frac{\left(\sum_{i=1}^n (P_i - \bar{P}_i)(O_i - \bar{O}_i)\right)^2}{\sum_{i=1}^n (P_i - \bar{P}_i)^2 \sum_{i=1}^n (O_i - \bar{O}_i)^2}} \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_i - O_i)^2}{n}} \tag{13}$$

$$MAE = \frac{\sum_{i=1}^n |P_i - O_i|}{n} \tag{14}$$

Where,  $P_i$  is the predicted value,  $O_i$  is the observed value,  $\bar{P}_i$  is the average value for  $P_i$ ,  $\bar{O}_i$  is the average value for  $O_i$  and  $n$  is the number of observations. As these errors are independent, they can be used step by step. It means the  $R$  and  $RMSE$  criteria were considered at first (for selecting the best configuration) before the other one (MAE). In other words, if two models have similar performances based on  $R$  and  $RMSE$ , we refer to  $MAE$  and compare this criterion for the two models to find the optimum configuration.

## RESULTS AND DISCUSSION

### Modeling by ANNs

At first, data were divided into three sets: 70, 10, and 20% for training, validation, and testing, respectively. To prevent overtraining, validation set was used. Overtraining occurs when the validation error starts increasing while the training error is still decreasing.

**Table 1.** Different sets of input variable to detect the best set.

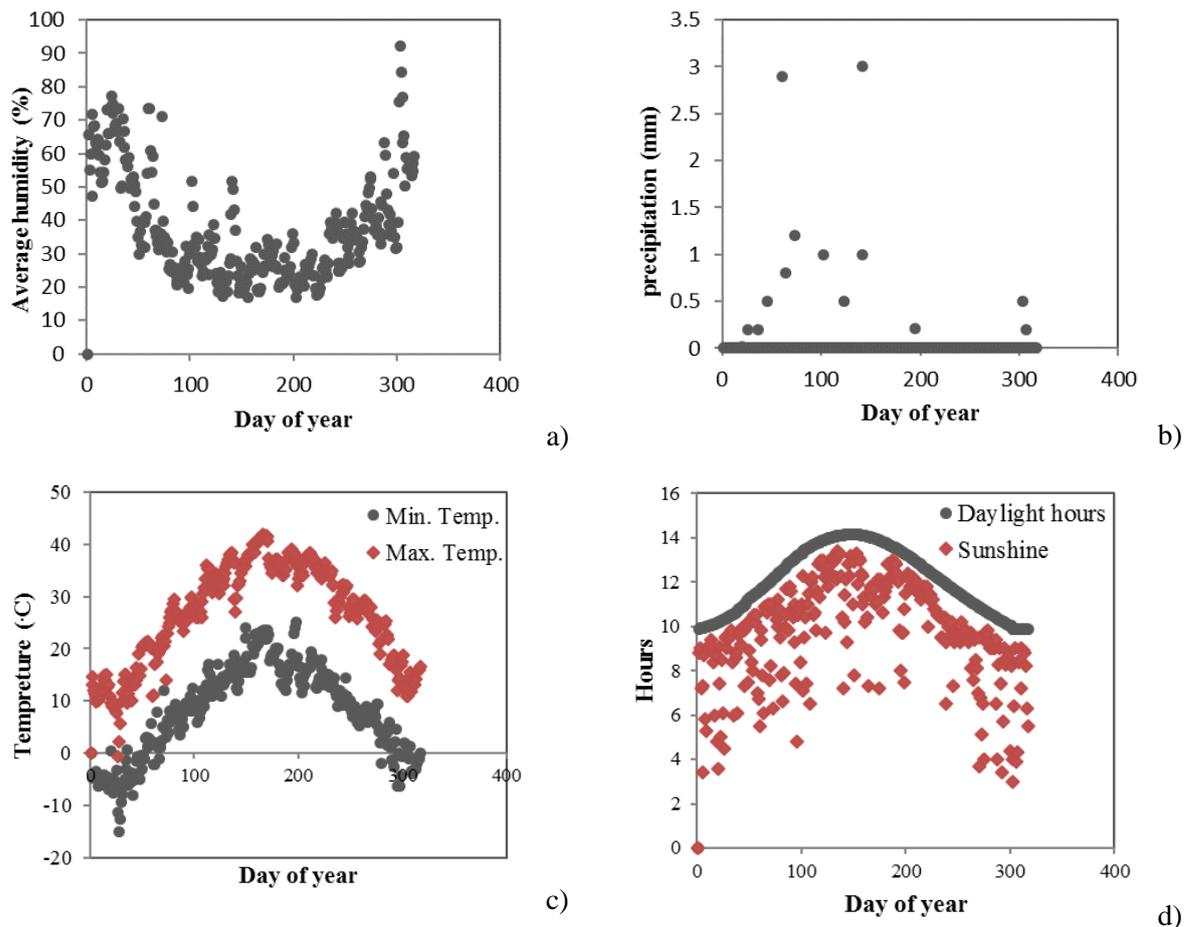
ANN type	Input variable
1	Day, sunshine, min temperature, max temperature, $N, R_{so}$
2	Day, sunshine, average temperature, $N, R_{so}, R_a$
3	Day, sunshine, max temperature, $N, R_{so}$
4	Day, sunshine, min temperature, $N, R_{so}$
5	Day, min temperature, max temperature, $N, R_{so}$
6	Day, sunshine, min temperature, max temperature, $R_{so}$
7	Day, sunshine, min temperature, max temperature, $N, R_a$

Several ANNs were designed, trained and generalized by using the Neural Network Toolbox of MATLAB software for modeling GSR. LM algorithm was chosen to build the prediction models; hyperbolic tangent sigmoid ('tansig') and Linear ('purelin') transfer functions were used for hidden and output layer neurons, respectively.

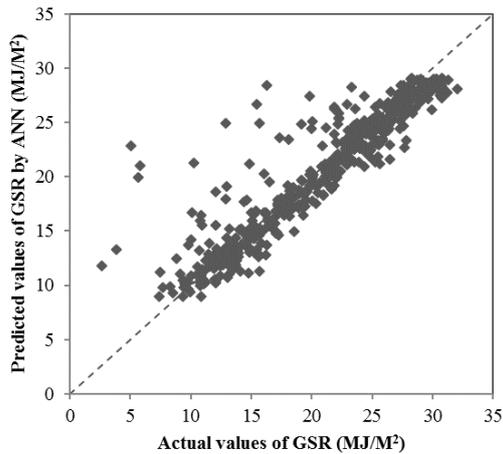
Three models and their performance characteristics are illustrated in Table 2 as the best ones in any configuration. Among these, one hidden layer network had the best performance, without overtraining with 'LM' and 'tansig' as training and transfer function, respectively, and 6-5-1 architecture, i.e. the best model consisted of an input layer with 6 input variables (number of day, sunshine duration, minimum temperature, maximum

temperature, daylight hours,  $R_{so}$ ), one hidden layer with five neurons, and an output layer with five neurons, highlighted in Table 2. This ANN had the highest correlation coefficient (0.922) (Figure 5). The high value of correlation coefficient and the low values of MAE and RMSE (see Table 2) indicate that the ANN predicted GSR by 6-5-1 architecture tend to follow the corresponding actual GSR.

ANN has been also used for predication of GSR in the main cities in the UAE, namely, Abu Dhabi, Al-Ain, and Dubai (Assi *et al.*, 2013). In this study, different combinations of inputs were used to develop these models,



**Figure 4.** Daily evolution of: (a) Average humidity; (b) Precipitation; (c) Minimum and maximum temperature, and (d) Dalight hours and sunshine duration in 2001 to represent how they change during a typical year in this region.



**Figure 5.** Correlation between actual and predicted values of GSR by ANN.

including: the maximum temperature (°C), mean wind speed (knot), sunshine hours, and mean relative humidity (%). Among them, the best performance criteria were reported for an MLP network with 4-20-25-30-1 architecture using all four inputs. It means

that 1,435 parameters were updated during training, which is really high compared to our optimum network (40 parameters). Parsimonious models (limited number of neurons or hidden layer) are more transparent, and lead to increased trust, reflection, and insight. Simple models are more accurate than the more complex ones, especially for operational works involving one or a few decision makers (Katsikopoulos *et al.*, 2017). Consequently, introducing a simpler ANN in this study can be an advantage over previous study.

### Modeling by ANFIS

There are many parameters that can be adjusted to obtain better results in ANFIS. These parameters include the number and type of MF for each input (trapmf, gbellmf, pi, etc.), the output MF type (linear or constant), the training epoch number, the

**Table 2.** The best models of any configuration and their performance characteristics.

Inputs	Topology	R	RMSE	MAE
Day, sunshine, min temperature, max temperature, $N, R_{so}$	6-5-1	0.9222	2.4914	1.5326
	6-16-1	0.9219	2.4979	1.5515
	6-18-1	0.9170	2.5804	1.6379
Day, sunshine, average temperature, $N, R_{so}, R_a$	6-5-1	0.9110	2.6780	1.6425
	6-8-1	0.9103	2.6737	1.5963
	6-11-1	0.9099	2.6805	1.6199
Day, sunshine, max temperature, $N, R_{so}$	5-11-1	0.9128	2.6752	1.7088
	5-13-1	0.9126	2.6348	1.5387
	5-15-1	0.9136	2.6221	1.5406
Day, sunshine, min temperature, $N, R_{so}$	5-5-1	0.9109	2.6665	1.6161
	5-10-1	0.9106	2.6717	1.6286
	5-13-1	0.9125	2.6497	1.6508
Day, min temperature, max temperature, $N, R_{so}$	5-7-1	0.8847	3.0058	2.0136
	5-14-1	0.8863	2.9880	2.0024
	5-20-1	0.8844	3.0121	2.0378
Day, sunshine, min temperature, max temperature, $R_{so}$	5-10-1	0.9123	2.6428	1.5788
	5-13-1	0.9127	2.6340	1.5346
	5-14-1	0.9129	2.6331	1.5967
Day, sunshine, min temperature, max temperature, $N, R_a$	6-5-1	0.9130	2.6372	1.6129
	6-7-1	0.9132	2.6336	1.5933
	6-10-1	0.9138	2.6200	1.5649
Day, sunshine, min temperature, max temperature, $N, R_{so}$	6-9-20-1	0.9135	2.6350	1.5529
	6-7-6-1	0.9130	2.6306	1.5931
	6-13-9-1	0.9129	2.6411	1.6431

training error goal, the initial step size, and the step size decrease and increase rate. Accordingly, the ANFIS network was designed; this process was conducted with 'genfis1' command. The training process was proceeded with BP method and epoch number of 100. After dividing the data set into training set (80%) and test set (20%), ANFIS model was setup for forecasting GSR by using parameters as listed below:

- Initial FIS generation method= 'Grid partition'
- Number of MFs= 2
- Input MFs type= 'trimf', 'trapmf', 'gbellmf', 'gaussmf', 'gauss2mf', 'pimf', 'psigmf' and 'dsigmf'
- Output MF type= 'Linear'
- Step size= Adaptive (Initial= 0.04, Decrease rate= 0.9, Increase rate= 1.1)
- Epoch number: 100
- Learning algorithm: Hybrid

Different structures were investigated to find the best ANFIS model. Best selection for each parameter was made based on the performance criteria. In addition to the parameter selection, test data were used to detect overtraining of the training data set. To perform fuzzy inference calculations, 'evalfis' command was used. A summary of the main results of eight models is given in Table 3. ANFIS model with 'tri' MF and correlation coefficient of 0.891 had the best performance for GSR prediction (Figure 6).

Comparison of the results of the two techniques for modeling GSR in Isfahan, Iran, shows that both techniques are acceptable for this purpose. By considering *R*, *RMSE*, and *MAE* criteria, ANN showed better results than ANFIS. The performance

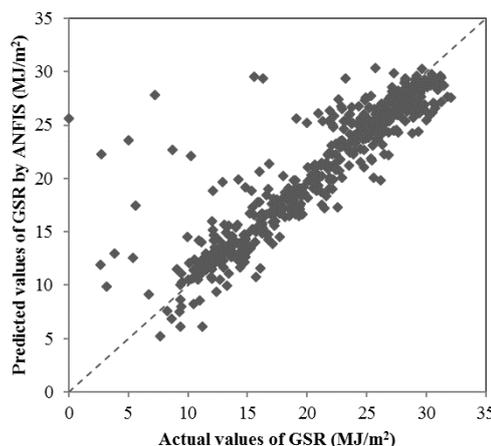
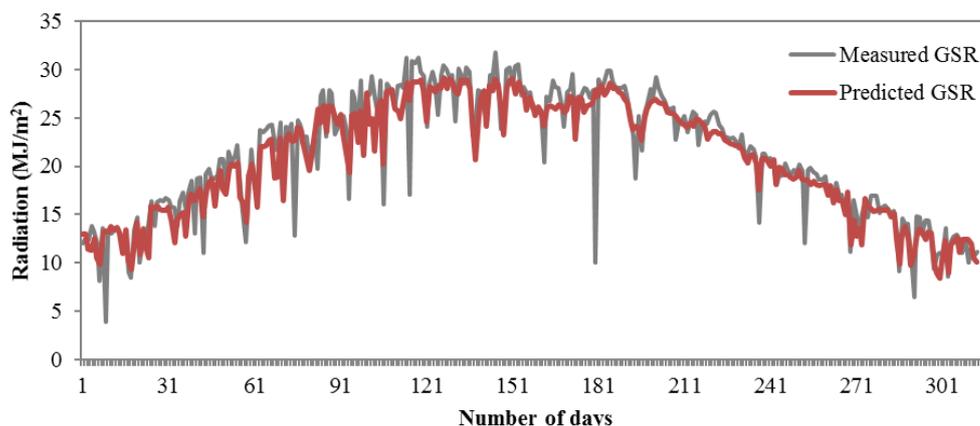


Figure 6. Correlation between actual and predicted values of GSR by ANFIS.

of proposed ANN model to estimate GSR is represented in Figure 7. As mentioned in the introduction section, there are some satisfactory applications of ANN for solar-related projects (Mubiru and Banda 2008; Jiang 2009; Mellit and Pavan 2010; Hernandez *et al.*, 2012). Appraisal research on ANN and ANFIS revealed different results in various cases. Mollazade *et al.* (2012) obtained better correlation coefficients for ANNs among different techniques of data mining for grading raisins based on visual features. In another work, Taghadomi-Saberi *et al.* (2014b) concluded that ANN was more efficient than ANFIS for modeling some quality features of sweet cherry such as antioxidant activity and anthocyanin content. However, there are some cases in which ANFIS had better performance than ANN. For instance, Yalcin *et al.* (2011) concluded that ANFIS performs

Table 3. Performance characteristics of ANFIS models with different membership functions.

MF type	<i>R</i>	<i>RMSE</i>	<i>MAE</i>
<i>dsigmf</i>	0.8697	3.2917	1.8605
<i>gauss2mf</i>	0.8793	3.1601	1.8230
<i>gaussmf</i>	0.8853	3.0805	1.7817
<i>gbellmf</i>	0.8839	3.1007	1.7638
<i>pimf</i>	0.8518	3.5115	1.9285
<i>psigmf</i>	0.8690	3.3002	1.8452
<i>trapmf</i>	0.8485	3.5604	2.0351
<i>trimf</i>	0.8906	3.0130	1.7108



**Figure 7.** The performance of proposed ANN model to estimate GSR in 2001 to represent how it predicts GSR.

better than ANN for prediction of the effect of natural antioxidant compounds on hazelnut oil oxidation by inspecting the mentioned criteria. It is the nature of the data that affects the AI technique results, nonetheless, it is possible to modify the performance of any AI technique by applying more preprocessing on the raw data, changing the number of inputs by using feature selection techniques or even choosing attributes other than those used in this paper. Generally, AI techniques are good devices to prognosticate the accessibility of solar energy in various climate conditions. This knowledge can be applied to manage solar facility and/or improve its performance to the acceptable level.

Finally, for small datasets, we recommend a more rigorous testing scheme such as k-fold cross validation. This suggestion can be considered and explored in future research in the light of the present results. This technique may be used in combination with other AI techniques, too.

## CONCLUSIONS

As the perpetual source of natural energy, solar radiation has a large number of uses because of its abundance and accessibility. Moreover, this type of energy can be an

efficient alternative to the problems caused by the dependence on fossil fuels and increasing carbon emissions. Ongoing concerns about climate change and the aim of many countries to become more independent of energy imports will likely lead to further increase in the share of renewable energy sources in the electricity supply system. Undoubtedly, accurate estimation of the solar radiation is necessary for an optimal design of a solar system. Therefore, accurate model development for estimating solar radiation from the available data is of great importance. The cost of high-tech equipment to measure the GSR is considerable in most cases, too.

This paper presented a low cost and rapid way to estimate GSR by using two common AI techniques in MATLAB software. BP-ANNs using 'trainlm' and 'tansig' as training algorithm and transfer function were used. Networks with 6-5-1 architecture had the best results for modelling. This ANN had the highest correlation coefficient (0.922) and low values of *MAE* (1.53) and *RMSE* (2.49). ANFIS model with 'tri' MF and correlation coefficient of 0.891 had the best performance for estimating GSR among other ANFISs. Evaluation of actual and modelled values suggested that this system can be used for estimation of GSR effectively.

## ACKNOWLEDGEMENTS

Gratitude is owed to Dr. Mohammad R. Sabzalian at Isfahan University of Technology for his advice and contribution. The author dedicates this research article to Dr. Seyed Jalil Razavi who sadly passed away in October 2017.

## REFERENCES

1. Akhyani, M., Chegini, V. and Aliakbari Bidokhi, A. 2015. An Appraisal of the Power Density of Current Profile in the Persian Gulf and the Gulf of Oman Using Numerical Simulation. *Renew. Energ.*, **74**: 307-317.
2. Assi, A. H., Al-Shamisi, M. H., Hejase, H. A. N. and Haddad, A. 2013. Prediction of Global Solar Radiation in UAE Using Artificial Neural Networks. *International Conference on Renewable Energy Research and Applications (ICRERA)*, DOI.10.1109/ICRERA.2013.6749750.
3. Bektas Ekici, B. and Aksoy, U. T. 2011. Prediction of Building Energy Needs in Early Stage of Design by Using ANFIS. *Expert Syst. Appl.*, **38**: 5352–5358.
4. Hernandez, J.A., Rivera, W., Colorado, D. and Moreno-Quintanar, G. 2012. Optimal COP Prediction of a Solar Intermittent Refrigeration System for Ice Production by Means of Direct and Inverse Artificial Neural Networks. *Sol. Energ.*, **86**: 1108–1117.
5. Islamic Republic of Iran Meteorological Office (IRIMO) Data Center. 2015. *Meteorological Data of 1994–2014*. Isfahan, Iran.
6. Jiang, Y. 2009. Computation of Monthly Mean Daily Global Solar Radiation in China Using Artificial Neural Network and Comparison with Other Empirical Models. *Energy*, **34**: 1276–1283.
7. Katsikopoulos, K. V., Durbachm, I. N. and Stewart, T. J. 2017. When Should We Use Simple Decision Models? A Synthesis of Various Research Strands. *Omega*, **81**: 17-25
8. Khoshnevisan, B., Rafiee, S., Iqbal, J., Shamshirband, Sh., Omid, M., Badrul Anuar, N. and Abdul Wahab, A. W. 2015. A Comparative Study between Artificial Neural Networks and Adaptive Neuro-Fuzzy Inference Systems for Modeling Energy Consumption in Greenhouse Tomato Production: A Case Study in Isfahan Province. *J. Agr. Sci. Tech.*, **17**: 49-62.
9. Klessmann, C., Rathmann, M., de Jager, D., Gazzo, A., Resch, G. and Busch, S. 2013. Policy Options for Reducing the Costs of Reaching the European Renewables Target. *Renew. Energ.*, **57**: 390-403.
10. Kumar, R., Aggarwal, R. K. and Sharma, J. D. 2013a. New Regression Model to Estimate Global Solar Radiation Using Artificial Neural Network. *Adv. Energ. Eng.*, **1(3)**: 66-73.
11. Kumar, R., Aggarwal, R. K. and Sharma, J. D. 2013b. Energy Analysis of a Building Using Artificial Neural Network: A Review. *Energ. Build.*, **65**: 352-358.
12. Lee, Ch. and Zhong, J. 2015. Financing and Risk Management of Renewable Energy Projects with a Hybrid Bond. *Renew. Energ.*, **75**: 779-787.
13. Mellit, A. and Pavan, M.A. 2010. A 24-h Forecast of Solar Irradiance Using Artificial Neural Networks: Application for Performance Prediction of a Grid-Connected PV Plant at Trieste, Italy. *Sol. Energ.*, **84(5)**: 807–821.
14. Mollazade, K., Omid, M. and Arefi, A. 2012. Comparing Data Mining Classifiers for Grading Raisins Based on Visual Features. *Comput. Electron. Agr.*, **84**: 124–131.
15. Mostafavi, E. S., Saeidi Ramiyani, S., Sarvar, R., Izadi Moud, H. and Mousavi, S. M. 2013. A Hybrid Computational Approach to Estimate Solar Global Radiation: An Empirical Evidence from Iran. *Energy*, **49**: 204-210.
16. Mubiru, J. and Banda, E. J. K. B. 2008. Estimation of Monthly Average Daily Global Solar Irradiation Using Artificial Neural Networks. *Sol. Energ.*, **82(2)**: 181–187.
17. Omid, M., Mahmoudi, A. and Omid, M. H. 2010. Development of Pistachio Sorting System Using Principal Component Analysis (PCA) Assisted Artificial Neural Network (ANN) of Impact Acoustics. *Expert Syst. Appl.*, **37**: 7205–7212.
18. Osorio, G. J., Matias, J. C. O. and Catalao, J. P. S. 2015. Short-Term Wind Power Forecasting Using Adaptive Neuro-Fuzzy Inference System Combined with Evolutionary Particle Swarm Optimization, Wavelet Transform and Mutual Information. *Renew. Energ.*, **75**: 301-307.



19. Pahlavan, R., Omid, M. and Akram, A. 2012. Application of Data Envelopment Analysis for Performance Assessment and Energy Efficiency Improvement Opportunities in Greenhouses Cucumber Production. *J. Agr. Sci. Tech.*, **14**: 1465-1475.
20. Pahlavan, R., Omid, M. and Akram, A. 2012. Energy Input-Output Analysis and Application of Artificial Neural Networks for Predicting Greenhouse Basil Production. *Energy*, **37**: 171-176.
21. Pahlavan, R., Omid, M. and Akram, A. 2012. The Relationship between Energy Inputs and Crop Yield in Greenhouse Basil Production. *J. Agr. Sci. Tech.*, **14**: 1243-1253.
22. Ramedani, Z., Omid, M. and Keyhani, A. 2013. Modeling Solar Energy Potential in Tehran Province Using Artificial Neural Networks. *Int. J. Green Energ.*, **10(4)**: 427-441.
23. Ramedani, Z., Omid, M., Keyhani, A., Shamsirband, Sh. and Khoshnevisan, B. 2014. Potential of Radial Basis Function Based Support Vector Regression for Global Solar Radiation Prediction. *Renew. Sustain. Energ. Rev.*, **39**: 1005-1011.
24. Rashidi, M., Rameshat, M. A. and Gharib, H. 2012. Air Pollution and Death Due to Cardiovascular Diseases: A Case Study of Isfahan Province of Iran. In: "Air Pollution : A Comprehensive Perspective", (Ed.): Haryanto, B. Available from: <http://www.intechopen.com/books>
25. Richard, G., Allen, L. S., Pereira, D. R. and Martin, S. 2006. *FAO Irrigation and Drainage. Crop Evapotranspiration: Guidelines for Computing Crop Water Requirements*. Paper No. 56, Food and Agriculture Organization. [www.fao.org](http://www.fao.org).
26. Soltani, F., Kerachian, R. and Shirangi, E. 2010. Developing Operating Rules for Reservoirs Considering the Water Quality Issues: Application of ANFIS-Based Surrogate Models. *Expert Syst. Appl.*, **37**: 6639-6645.
27. Taghadomi-Saberi, S., Omid, M. and Emam-Djomeh, Z. 2014a. Estimating Some Physical Properties of Sour and Sweet Cherries Based on Combined Image Processing and AI Techniques. *Int. J. Food Eng.*, **10(3)**: 403-415.
28. Taghadomi-Saberi, S., Omid, M., Emam-Djomeh, Z. and Ahmadi, H. 2014b. Evaluating the Potential of Artificial Neural Network and Neuro-Fuzzy Techniques for Estimating Antioxidant Activity and Anthocyanin Content of Sweet Cherry during Ripening by Using Image Processing. *J. Sci. Food Agr.*, **94**: 95-101.
29. Weitemeyer, S., Kleinhans, D., Vogt, T. and Agert, C. 2015. Integration of Renewable Energy Sources in Future Power Systems: The Role of Storage. *Renew. Energ.*, **75**: 14-20.
30. Yalcin, H., Ozturk, I., Karaman, S., Kisi, O., Sagdic, O. and Kayacier, A. 2011. Prediction of Effect of Natural Antioxidant Compounds on Hazelnut Oil Oxidation by Adaptive Neuro-Fuzzy Inference System and Artificial Neural Network. *J. Food Sci.*, **76**: 1112-1120.

## ارزیابی پتانسیل استفاده از تکنیک های شبکه های عصبی مصنوعی و عصبی-فازی به منظور پیش بینی GSR مطالعه موردی: استان اصفهان، ایران

س. تقدیمی صابری، و س.ج. رضوی

### چکیده

امروزه کاربرد انرژی های پاک، تجدیدپذیر و قابل اطمینان و برنامه ریزی برای کاهش هزینه های کاربرد و افزایش بازده آن ها توجه زیادی را به خود جلب کرده است. این تلاش ها نه تنها از نقطه نظر مواجهه با تغییرات آب و هوایی، آلودگی آب و هوا مؤثر و مفید است، بلکه برای ارتقای وضعیت بهره وری از انرژی

نیز مؤثر و مفید واقع می‌شود. به منظور طراحی یک استراتژی مدیریت انرژی برای یک سامانه خورشیدی، ناگزیر باید از دسترسی به انرژی خورشیدی، جذاب‌ترین و فراوان‌ترین فرم از انرژی‌های پاک، آگاهی داشت. در این مقاله به منظور پیش‌بینی تابش خورشیدی جهانی (GSR) در استان اصفهان از دو تکنیک کاربرد هوش مصنوعی، شبکه‌های عصبی مصنوعی و انفیس، استفاده شده است. از مجموعه داده‌های هواشناسی مختلف با ترکیب متفاوت داده‌ها استفاده شد تا بهترین مجموعه ورودی تعیین شود. رطوبت نسبی و میزان بارش تأثیر نامطلوبی روی پیش‌بینی تابش داشتند. در حالیکه شماره روز (۳۶۵-۱)، طول دوره تابش، دمای بیشینه و کمینه، ساعت روشنایی روز و میزان تابش آسمان- صاف پارامترهای مؤثری در تخمین GSR ارزیابی شدند. با استفاده از پارامترهای مذکور به عنوان ورودی، یک شبکه با توپولوژی ۱-۵-۶ بهترین عملکرد بدون بیش‌برازش را نشان داد. در بین مدل‌های انفیس نیز، تابع عضویت «مثلی» بهترین عملکرد را از میان توابع دیگر نشان داد. ضرایب همستگی و خطاهای منتج نشان داد که به طور کلی عملکرد شبکه‌های عصبی مصنوعی برای هدف مورد نظر از مدل‌های انفیس بهتر است.