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Estimation of Global Solar Irradiance Using a Novel Combination of Ant Colony Optimization and Empirical Models

Afshin Lashkar Ara[a], Rahil Hosseini[b], Hajar Bagheri Tolabi[c] *

[a]*Department of Electrical Engineering, Dezful Branch, Islamic Azad University, Dezful, Iran*
[b]*Department of Computer Engineering, Shahr-e-Qods Branch, Islamic Azad University, Tehran, Iran*
[c]*Department of Electrical Engineering, Khorramabad Branch, Islamic Azad University, Khorramabad, Iran*

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ABSTRACT

In this paper, a novel approach for estimation of global solar irradiance is proposed based on a combination of empirical correlation and ant colony optimization. Empirical correlation has been used to estimate monthly average of daily global solar irradiance on a horizontal surface. The Ant Colony Optimization (ACO) algorithm has been applied as a swarm-intelligence technique to tune the coefficients of linear and nonlinear empirical models. The performance of the models is investigated for estimation of global solar irradiance at different climatic regions of Iran based on statistical indicators like coefficient of determination (R^2) and root mean square error (RMSE). The results obtained from the proposed model are superior in comparison with the other well established models.

1. INTRODUCTION

Solar Irradiance (SI) is one of the important parameters for designing solar systems. In developing countries, the Global Solar Irradiance (GSI) measurements are usually reported based on measurements made at small number of solar observation stations. Hence, to alleviate the problems, mathematical models are used to accurately estimate the GSI [1].

Numerous studies have been conducted to estimate the SI based on available data such as temperature, moisture, elevation, solar irradiance hours, cloudiness, wind speed, etc. [1-4]. These approaches can be categorized in two categories, empirical models and intelligent models [1].

The main advantage of the empirical models is their simplicity. However, they suffer from low models. Intelligent models like ANN (Artificial Neural Network) have high complexity during training process, but these methods have higher accuracy for the SI estimation in comparison to the empirical based models. As an empirical based model, Angstrom [1, 2] proposed the first relation for the GSI prediction using sunshine hours. Prescott [1] improved Angstrom model. For intelligent models, Edalati and colleagues [2] offered an ANN model for prediction of the SI data.

In this study, the Ant Colony Optimization (ACO) Algorithm was used to estimate the monthly average daily GSI for various climate cities of Iran, based on minimization of a fitness function.

In the proposed approach, the optimized coefficients of the empirical equations (both linear and nonlinear empirical models) are estimated by using the ant colony optimization algorithm to evaluate the monthly average daily GSI. Obtained results are evaluated through a validation data series. The proposed approach doesn't need a difficult training and can estimate the solar irradiance with a higher accuracy compared to the empirical and intelligent models.

The remainder of this paper is organized in the following manner. The linear and nonlinear empirical equations are discussed in section 2. The concept of Ant Colony Optimization and its overall progress are reviewed in section 3. The proposed methodology to find the optimal empirical coefficients and the SI estimation based on the Ant Colony Optimization are investigated in section 4. Results and discussions are presented in section 5. A conclusion followed by references is presented in section 6.

*Corresponding Author's Email: hajar.bagheri1@gmail.com (H. Bagheri Tolabi)

2. EMPIRICAL EQUATIONS FOR SI ESTIMATION

Various studies have been reported which have defined empirical equations to estimate the SI estimating by using meteorological information [1]. These equations are based on the proposed equations that use the information such as cloudiness, sunshine hours, and temperature. These mathematical equations can be classified into two categories: 1) linear (proposed by Angstrom [1, 2]), and 2) nonlinear. Prescott [1] modified the Angstrom's model using the linear regression as follows:

$$\frac{H}{H_o} = a + b(\frac{S}{S_o}) \tag{1}$$

where H is the GSI, H_o is extraterrestrial solar irradiance, S is the actual sunshine hours, S_o is maximum sunshine duration, and a and b are the empirical coefficients.

Other linear models were proposed with more meteorological parameters. Swartman and Ogunlade [1] proposed another linear model using more meteorological parameters, also Abdallah suggested following linear models:

$$H = a + b(\frac{S}{S_o}) + cRH \tag{2}$$

$$\frac{H}{H_o} = a + b(\frac{S}{S_o}) + cRH + dT \tag{3}$$

where, T is the daily mean air temperature, RH is the relative humidity and a, b, c, and d are the empirical coefficients. Ogelman et al. (1984), Akinoglu and Ecevit (1990) have added a nonlinear part to the Angstrom model as follows:

$$\frac{H}{H_o} = a + b(\frac{S}{S_o}) + c(\frac{S}{S_o})^2 \tag{4}$$

A third order polynomial model for the GSI prediction was presented by Bahel et al. as follows:

$$H = H_o(a + b(\frac{S}{S_o}) + c(\frac{S}{S_o})^2) + d(\frac{S}{S_o})^3 \tag{5}$$

A nonlinear exponential model using the solar irradiance and sunshine hours was proposed by Almorox and Hontoria as follows:

$$H = a + b\exp(\frac{S}{S_o}) \tag{6}$$

A GSI prediction model was suggested by Bakirik as follows:

$$H = a + b(\frac{S}{S_o}) + c\exp(\frac{S}{S_o}) \tag{7}$$

Ampratwum and Dorvol preposed a logarithmic model as follows:

$$\frac{H}{H_o} = a + b\log(\frac{S}{S_o}) \tag{8}$$

All the above equations are classified in [1].

3. ANT COLONY OPTIMIZATION (ACO) ALGORITHM

The Ant Colony Optimization (ACO), proposed by Dorigo et al., is a solution for combinational problems [5]. The ACO is a swarm intelligence technique. Its main idea is originally inspired from the biological behavior of the ants and specifically the way that they communicate with each other for finding food. This inspiration is related to ability of ants for finding the short paths in their movement from and to their nests when searching for food [5]. However, ants communicate with each other through pheromones. Fig. 1 represents a simple example of ants' behavior. There are two ants in this figure that start at the same time and leave their nest in different directions looking for the food. As they move forward, they build a pheromone trail that evaporates slowly which is recognizable by other ants. If no pheromone initially exists outside the nest, the ants' paths are randomly initiated. Let us consider an example in which ant 1 finds food source 1 while ant 2 is still searching randomly. Then ant 1 picks up some of the food and goes back toward the nest by tracing its own pheromone trail, putting additional pheromone on its way back. The Ant 1 arrives at the nest almost at the same time as the ant 2 finds food source 2. When the next group of ants leaves the nest looking for food, they detect twice as much pheromone on the path toward food source 1 than on the path toward food source 2. Thus, the probability that the ants take path to food source 1 is higher than the other paths. As ants further travel, they lay more pheromone on the path. This means that the ants efficiently collect and bring food source 1 to the nest. When food source 1 is over, the rest of ants return to the nest without any food, but some of them randomly continue beyond food source 1, and find new sources of food, such as the remains at food source 2 [5].

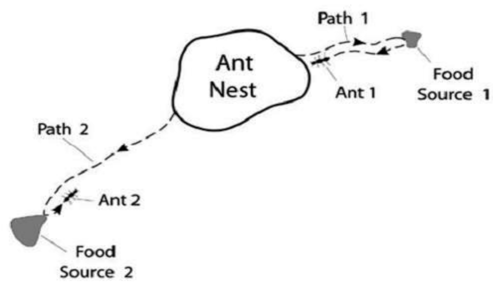

Figure 1. Illustration of ants movement searching for food

The ACO algorithms attempt to exploit the efficiency of ant travelling behavior by creating a similar environment of possible paths, and simulating the ants' movements along these paths. Each ant chooses a different path which may lead to different solutions in the problems search space, simulating the idea of depositing pheromone on each ant's passes through a path. This strategy improves the ACO algorithms by avoiding traps in local optima [5].

3.1. The ACO Procedure

An ACO algorithm can be applied to an optimization problem using the following steps [5]:

- Representation of the problem: the problem must be described using a graph including a set of nodes and edges between nodes.
- Heuristic desirability (η) of the edges: A desirable heuristic indicator of goodness of paths from one node to every other connected node in the graph.
- Solution construction: A mechanism to efficiently construct solutions.
- Pheromone updating rule: A suitable method of updating the pheromone levels on edges is required with a corresponding evaporation rule such as selecting the best ants and updating the paths they chose.
- Probability of transition: The rule determines the probability of an ant traversing from one node in the graph to the next.

A suitable heuristic fitness of traversing could be any evaluation function. The probabilistic transition rule which is a combination of the heuristic desirability of traversal and edge pheromone levels, denotes the probability of an ant at feature *i* deciding to travel to feature *j* at time *t*:

$$P^k{}_{i,j}(t) = \begin{cases} \dfrac{\left[\tau_{i,j}\right]^{\alpha}\left[\eta_{i,j}\right]^{\beta}}{\sum_{i\in T}\left[\tau_{i,j}\right]^{\alpha}\left[\eta_{i,j}\right]^{\beta}} & if \quad i,j \in T, \\ 0 & otherwise \end{cases} \tag{9}$$

where, k is the kth ant, $\alpha > 0$ and $\beta > 0$ determine the relative effect of the pheromone trail and the heuristic desirability in which α and β are determined experimentally, $\tau_{i,j}$ is the value of pheromone for the *ij*th path of the ACO algorithm, $\eta_{i,j}$ is heuristic desirability for the *ij*th path of the algorithm, and T represents the total number of paths not yet visited by the ant.

As seen in Equation 9, the probability of transition is determined using the pheromone and heuristics of the trail which is related to the cost of the *ij*th path. This path is acceptable when a higher probability is obtained as a result of high quantity of pheromone or heuristic desirability [5]. Therefore, the ant that traverses through the *ij*th path has to produce higher pheromones amount to increase the probability of selecting current path in the next iteration. After all ants return to the nest, the pheromone level is updated as follows:

$$\tau_{i,j}(t+1) = (1-\rho)\cdot\tau_{i,j}(t) + \sum_{k=1}^{m}\Delta\tau_{i,j}^{k}(t) \tag{10}$$

where, $\rho \in (0,1)$ is the evaporation rate of pheromone trail, and m is number of ants. The role of ρ is to avoid unlimited congestion of the pheromone trails which leads to forget previous wrong decisions. For the paths not chosen by the ants, the pheromone strength is exponentially decreased in each iteration. The $\Delta\tau_{i,j}^{k}(t)$ denotes the *k*th ant pheromone deposits on the paths defined as follows [5]:

$$\Delta\tau_{i,j}^{k}(t) = \begin{cases} 1/L^k(t) & if \quad path \ ij \ is \ used \ by \ ant \ k, \\ 0 & otherwise \end{cases} \tag{11}$$

where $L^k(t)$ denotes the length of the tour for the *k*th ant. According to Equation 11, the shortest ant's tour receives more pheromone. The steps of the standard ACO algorithm are shown in Fig. 2 as described below [5]:

(a) Read the input data;
(b) Initialize the system parameters;
(c) Creating the graph for each ant including nodes and edges;
(d) Update the list of feasible operation and probability values to schedule ants next operation; and
(e) If ants reached food node, select the best solution, update the pheromones, and control the stopping criterion [5].

4. THE PROPRSED SI ESTIMATION METHOD BASED ON EMPIRICAL EQUATIONS AND THE ACO ALGORITHMSI

In the proposed method of this study, the ACO algorithm exploration capability was used for finding the optimize coefficients in the empirical (linear and non-linear) models and estimating the GSI according to the input dataset. The steps of the proposed method are described as follows:

Step 1: Split the input dataset (measures) into training and validation sets- The dataset including input measures collected from meteorological department was divided into two categories: 1) training data set for installation, and 2) validation data series. In this study, for Esfahan city, 111 months are considered for installation data from 1985 until 2001, and 45 months for validation purpose.

Step 2: Compute the fractions for training and validation datasets; The fractions of possible monthly average daily GSI and sunshine duration, i.e., $\frac{H}{H_o}$ and $\frac{S}{S_o}$ are computed for installation and validation datasets.

Step 3: Estimate the empirical coefficients using the ACO algorithm; The obtained results in Step 2, are used in the ACO algorithm to find the optimize candidates of the coefficients of the empirical equations. The minimization fitness function is defined as follows and is illustrated in Fig. 3:

$$F = \sum_{i=1}^{m} (Y_i - X_i)^2 \tag{12}$$

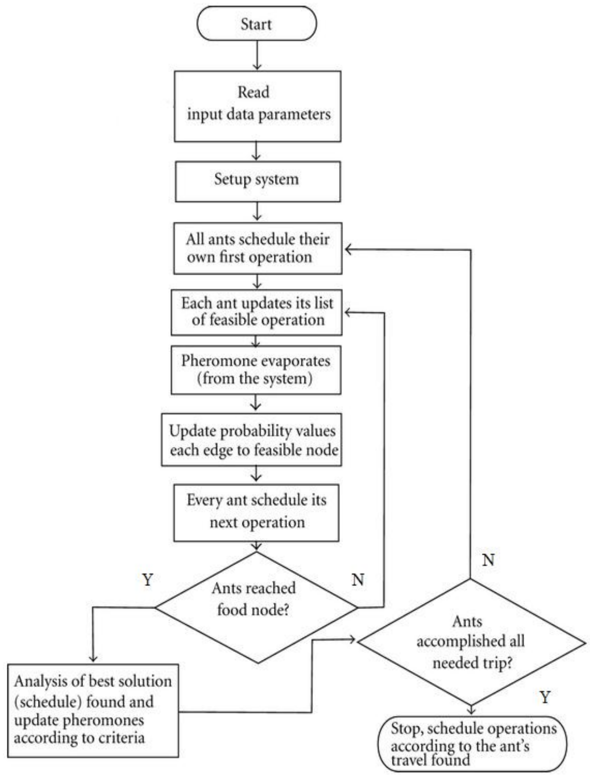

Figure 2. The flowchart of the standard ACO algorithm

where, $Y_i = (\frac{H}{H_o})ci$ and $X_i = (\frac{H}{H_o})ei$ are the computed and estimated fractions of possible monthly average daily GSI, respectively for the *i*th sample, H is the GSI, H_o is extraterrestrial solar irradiance, and m illustrates the cumulative observations (details of extraterrestrial solar irradiance [H_o] calculation is provided in [1]). The ACO algorithm stops when the stopping criterion is satisfied.

Step 4: Validation of the results; For each run of the algorithm, the optimized empirical coefficients reported by the ACO are validated using the validation dataset. If the GSI measures using empirical coefficients obtained from the ACO algorithm agree with the estimated GSI computed values using the validation series (the minimum requirement of 80% is considered in this study), the optimize empirical coefficients are selected, and otherwise thee algorithm goes to Step 3.

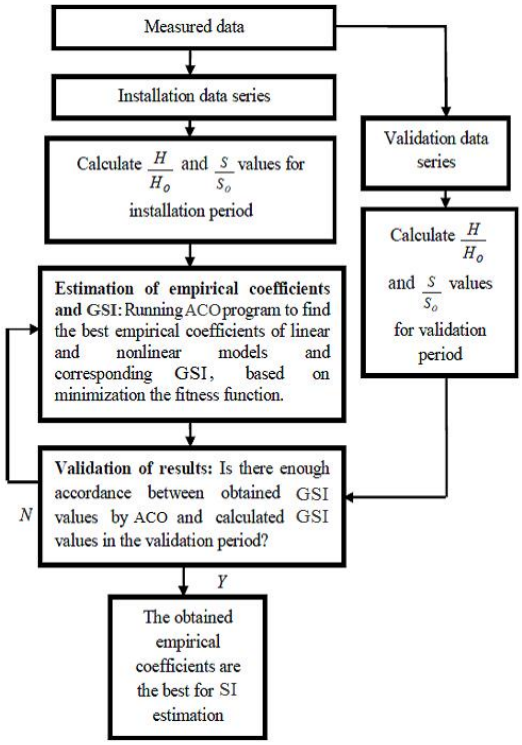

Figure 3. General flowchart of the SI estimation using combination of the ACO and empirical equations

Accuracy of the obtained empirical coefficients was investigated in terms of the coefficients of determination (R^2) and Root Mean Square Error (RMSE). The values of R^2 and the RMSE were computed using Equations 13 and 14, respectively:

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(X_i)^2} \tag{13}$$

$$RMSE = \sqrt{\sum_{i=1}^{m}(X_i - Y_i)^2 \Big/ m} \tag{14}$$

5. RESULTS AND DISCUSSION

The proposed ACO algorithm was implemented in MATLAB software and applied for estimation of the monthly average daily GSI on horizontal surface for four different climatic stations (Esfahan, Hamadan, Tabriz, and Orumieh) in Iran. The geographical features of these stations are shown in Fig. 4. The input features such as minimum and maximum temperature, sunshine hours, relative moisture, elevation etc., were collected from Iran Meteorological department. Table 1. represents the geographical data including longitude and latitude of four stations considered in this study. The range of installation and validation datasets is shown in Table 1. The method proposed in [6] was used to check the accuracy of the measurements. The $\frac{H}{H_o}$ and $\frac{S}{S_o}$ were separately computed for installation and validation datasets for all four stations. Tables 2. & 3. show the $\frac{H}{H_o}$ and $\frac{S}{S_o}$ for sixteen sample months of Hamadan and Tabriz stations, typically. These samples are 1, 11, 21, 31, 41, 51, 61, 71, 81, 91, 101, and 111 months for installation data and 121, 131, 14, and 151 months for validation data series.

Linear empirical equations used in this study include Angstrom-Prescott (Equation 1) and Abdallah (Equation 3), (called Model 1 and Model 2, respectively). Nonlinear empirical equations are proposed in Equation 4 and Equation 8, hereafter defined as Model 3 and Model 4, respectively.

Performance of the ACO is satisfactory using the parameters values shown in Tables 4. & 5. includes the coefficients of a, b, c, and d for four tested empirical models on the four sample cities using the ACO. For comparison purpose, the same datasets were used for performance evaluation of the ACO, the SRTs, and the ANN on the GSI modeling. The empirical coefficients for these models were separately computed for four sample cities using the SRTs (Least absolute deviations method) explained in [1]. An ANN model was trained using the Levenberg–Marquardt algorithm with sigmoid and linear transfer functions in the hidden and output layers, respectively. The ANN model was implemented in neural network toolbox in MATLAB [2, 7].

Table 6. shows the results of R^2 and the RMSE obtained for GSI using different models based on the ACO, the SRT, and the ANN models. The results reveal the superiority of combination of the ACO and linear Angstrom model (ACO & Model 1) compared to other models for the SI estimation with an R^2 greater than 0.96, and the RMSE smaller than 0.0018 on the four stations. Among all sample stations, the best result was obtained using combination of the ACO and Angstrom model (ACO & Model 1) for Esfahan with $R^2 = 0.9961$, and the RMSE = 0.0012, and the worst result was for Orumieh with $R^2= 0.8387$, and RMSE= 0.2610 for the SRT and Abdallah model (SRTs & Model 2).

TABLE 1. Information of four sample stations in Iran

City name	Longitude ° E	Latitude ° N	Altitude (m)	Installation data period	Validation data period
Esfahan	51.67	32.62	1550.4	1985 -2001	2002-2005
Hamadan	48.53	34.87	1741.5	1985 -2001	2002-2005
Orumieh	45.05	37.67	1328.0	1985 -2001	2002-2004
Tbriz	46.28	38.08	1361.0	1987 -2001	2002-2005

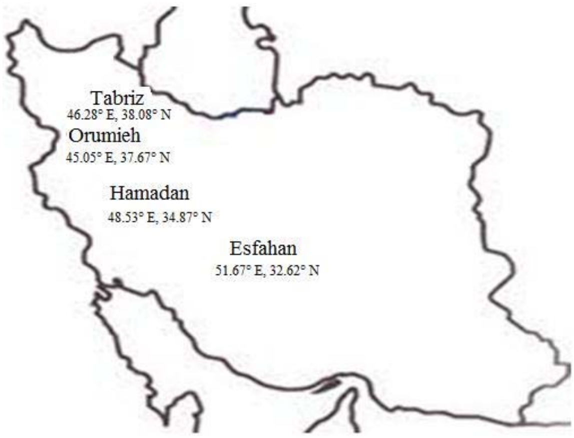

Figure 4. Geographical positions of sample stations in Iran

The $R^2_{average}$ and the $RMSE_{average}$ values for all nine testing methods were estimated and compared to each other, as shown in Fig. 5 The following conclusions have been extracted from Fig. 5:

- The results of the ACO combined with linear and nonlinear empirical models were acceptable with an average R^2 greater than the 0.94, and an average RMSE less than the 0.019 for all chosen stations, which reveals satisfactory performance of the empirical models.

TABLE 2. Sample estimated values of $\frac{H}{H_o}$ and $\frac{S}{S_o}$ for both data types on Hamadan station

Data series	Months	$\frac{H}{H_o}$	$\frac{S}{S_o}$
Installation	1	0.510	0.447
Installation	11	0.485	0.485
Installation	21	0.513	0.512
Installation	31	0.424	0.421
Installation	41	0.423	0.398
Installation	51	0.500	0.423
Installation	61	0.681	0.779
Installation	71	0.554	0.878
Installation	81	0.529	0.891
Installation	91	0.844	0.850
Installation	101	0.759	0.633
Installation	111	0.796	0.774
Validation	121	0.620	0.619
Validation	131	0.597	0.598
Validation	141	0.591	0.678
Validation	151	0.693	0.700

- Comparing the ACO, the SRT, and the ANN methods, the best result was obtained by the ACO and

Angstrom model (ACO & Model 1) with an average R^2=0.974, and an average RMSE=0.001, and the worst result was for the SRT and the Abdallah model with an average R^2=0.872, and an average RMSE=0.104.

TABLE 3. Sample estimated values of $\frac{H}{H_o}$ and $\frac{S}{S_o}$ for both data types on Tabriz station

Data series	Months	$\frac{H}{H_o}$	$\frac{S}{S_o}$
Installation	1	0.419	0.523
Installation	11	0.493	0.212
Installation	21	0.655	0.735
Installation	31	0.873	0.820
Installation	41	0.700	0.791
Installation	51	0.670	0.813
Installation	61	0.715	0.895
Installation	71	0.403	0.319
Installation	81	0.512	0.600
Installation	91	0.697	0.732
Installation	101	0.478	0.600
Installation	111	0.581	0.591
Validation	121	0.400	0.400
Validation	131	0.493	0.641
Validation	141	0.448	0.823
Validation	151	0.500	0.615

▪ Although the results of ANN was worse than the results of the ACO & Model 1, but was better than the other three combined ACO & Models 2, 3, and 4 methods, respectively.

TABLE 4. Parameters used for the ACO algorithm

Pheromone constant	2×10^{-4}
Evaporation factor	0.75
Allowable edge probability	0.05
Total ants	40
Iteration	500

TABLE 5. Obtained empirical coefficients using the ACO

Station name	Empirical model	a, b, c, and d
Esfahan	Model 1	0.37, 0.34
	Model 2	0.07, 0.51, 0.23, 0.14
	Model 3	0.52, -0.02, 0.18
	Model 4	0.68, 0.70
Hamadan	Model 1	0.35, 0.29
	Model 2	0.22, 0.16, 0.36, 0.79
	Model 3	0.20, -0.03, 0.33
	Model 4	0.93, 0.91
Orumieh	Model 1	0.37, 0.41
	Model 2	0.12, -0.26, 0.54, 0.34
	Model 3	0.61, 0.12, 0.29
	Model 4	0.49, -0.09
Tabriz	Model 1	0.56, 0.68
	Model 2	0.28, 0.34, 0.41, 0.10
	Model 3	0.17, 0.84, 0.11
	Model 4	0.55, 0.14

TABLE 6. Accuracy evaluation of the results through R^2 and RMSE indicators

Station name	Method/Approach	R^2	RMSE
Esfahan	ACO & Model 1, 2, 3, and 4	0.9961,0.9735,0.9489,0.9379	0.0012, 0.0014, 0.0134, 0.0168
	SRTs & Model 1, 2, 3, and 4	0.9913,0.8635,0.8726,0.9278	0.0135, s0.1046, 0.1012, 0.0481
	ANN	0.9377	0.0108
Hamadan	ACO & Model 1, 2, 3, and 4	0.9715,0.9681,0.9311,0.9332	0.0013,0.0096, 0.0045, 0.0191
	SRTs & Model 1, 2, 3, and 4	0.9147,0.8817,0.8915,0.9167	0.0715,0.0376,0.0358,0.0169
	ANN	0.9815	0.0012
Orumieh	ACO & Model 1, 2, 3, and 4	0.9667,0.9259,0.9318,0.9301	0.0017,0.0153,0.0185,0.0196
	SRTs & Model 1, 2, 3, and 4	0.9312,0.8387,0.9170,0.9235	0.0173,0.2610,0.0151,0.0287
	ANN	0.9461	0.0179
Tabriz	ACO & Model 1, 2, 3, and 4	0.9644,0.9482,0.9623,0.9620	0.0013,0.0049,.0.0160,0.0172
	SRTs & Model 1, 2, 3, and 4	0.8953,0.9055,0.9147,0.8939	0.0734,0.0167,0.0223,0.1001
	ANN	0.9716	0.0016

▪ The combination results of linear empirical models and ACO had greater average R^2 than combination of nonlinear empirical models with ACO, while this conclusion is inversely for the obtained average RMSE values. It is seen that the performance of the ACO algorithm changes when it is combined to different empirical models. Accordingly, estimation of the solar irradiance using the the linear empirical equations are more appropriate than combination of ACO and nonlinear empirical equations in all sample regions.. The results have been developed and the coefficients of the proposed ACO & model 1 have been calculated for all capital cities of provinces of Iran (except four sample cities for which results are presented in Table 5).

The obtained coefficients are presented in Table 7. Appendix A.

▪ The average performance of the ANN with R^2=0.959, and the RMSE=0.007 was better than the SRTs, and very close to the ACO & Model 2 results with an R^2=0.953, and the RMSE=0.007, while the ACO training process is not as complex as the ANN. Therefore, the ACO algorithm outperforms the artificial neural network.

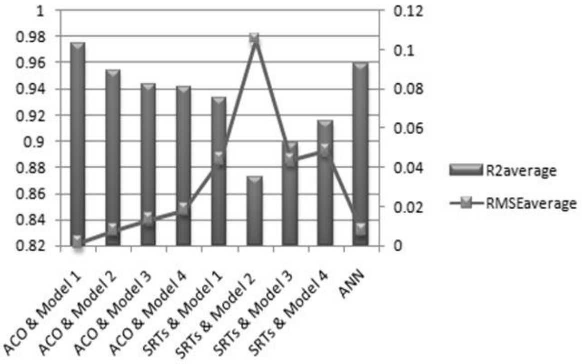

Figure 5. Comparison between average R^2 and average RMSE for nine testing methods

6. CONCLUSION

This paper presents a novel approach for estimating the monthly average of daily global solar irradiance on a horizontal surface. This method takes advantages of the linear and nonlinear empirical equations and ant colony optimization algorithm. For performance evaluation, the proposed algorithm was implemented and tested on different climate stations in Iran using two linear and two nonlinear empirical equations. The objective was to optimize the empirical coefficients for the GSI estimation using installation and validation data series obtained from meteorological department of Iran. The results of the proposed method were compared to the statistical regression and artificial neural network in terms of maximization of the coefficient of determination (R^2) and minimization of the root mean square error (RMSE). The R^2 values of the proposed ACO approach were greater than 0.96 and the RMSE values were smaller than 0.0018 in all sample stations. The best result was reported for Esfahan and the worst results were reported for Orumieh stations. The performance of artificial neural network was better than the statistical regression techniques and was very close to the ACO algorithm. However, the main drawbacks of the conventional neural networks compared to ACO algorithm are high training time, the need for large number of data during training process, unknown defined structure, the relatively large number of rquired hidden nodes, and possibility of getting trapped to local minima. Therefore, the proposed ACO approach has high simplicity and accuracy for the estimation of the GSI compared to its counterparts.

TABLE 7. The obtained coefficients (using combination of ACO & Angstrom Model) for 29 capital cities of provinces of Iran

City Name	a, b (coefficients of the proposed ACO & Angstrom Model)
Karaj	0.42, 0.66
Rasht	0.87, 0.13
Tehran	0.51, 0.17
Gorgan	0.59, 0.92
Rasht	0.43, 0.31
Khorramabad	0.77, 0.92
Sanandej	0.65, 0.89
Kerman	0.40, 0.03
Yazd	0.21, 0.76
Qom	0.19, 0.93
Qazvin	0.83, 0.40
Arak	0.08, 0.38
Ardabil	0.15, 0.27
Bushehr	0.64, 0.35
Shahrekord	0.33, 0.17
Bandar Abbas	0.95, 0.11
Ilam	0.51, 0.80
Kermanshah	0.98, 0.55
Mashhad	0.76, 0.72
Yasooj	0.24, 0.49
Birjand	0.05, 0.58
Ahvaz	0.69, 0.01
Sari	0.78, 0.92
Semnan	0.35, 0.36
Zanjan	0.99, 0.24
Bojnourd	0.14, 0.27
Shiraz	0.52, 0.41

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