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A Novel Intelligent Water Drops Optimization Approach for Estimating Global Solar Radiation

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ABSTRACT

Measurement of the solar radiance requires utilization of expensive devices. To address this issue, estimator models are used to facilitate the measurement process. In this paper, a new method based on the empirical equations is introduced to estimate the monthly average of daily global solar radiation on a horizontal surface. The proposed method takes advantages of an intelligent water drops algorithm as a swarm-based nature-inspired optimization technique. This algorithm has been implemented in the MATLAB software. The best obtained coefficients of linear and nonlinear empirical models and global solar radiation are employed for the measurement of the six different climate regions of Iran. Performance of this approach has been compared to the other existing techniques. The result reveals the superiority of the proposed method in term of accuracy for estimating the monthly average daily global solar radiation.

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1. INTRODUCTION

The energy from the sun propagates in electromagnetic waveform. However, half of the energy is reflected and scattered to the atmosphere, the rest is directed and diffused to hit the Earth's surface as shown in Figure 1.

Measurement of global radiation at Earth's surface is difficult because of high instrumentation cost and limited data record. Therefore, proper estimation of solar radiation becomes important and essential for the design and development of applications based on solar energy. A number of mathematical and regression models were developed by the researchers for the estimation of solar energy. These models are only applicable for cloudless sky [1-5].

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There are number of mathematical and regression models available in the literature for the estimation of solar energy at Earth's surface. The main advantages of empirical models are their simplicity and no need for training and etc. However, the results of these models are not satisfactory. As there are certain numbers of cloudy days in a year; therefore it becomes important to incorporate these days in the model. This fact clears the need for intelligent models for the accurate estimation of solar energy. These intelligent models can incorporate the non-linearly in the system. These models are based on fuzzy logic, artificial neural networks, and evolutionary computation and a combination of them. There are certain limitations in intelligent models, particularly ANN based models. ANN models have high complexity due to prior training requirements. However, these models are more accurate for the estimation of solar radiation than the empirical models [5].

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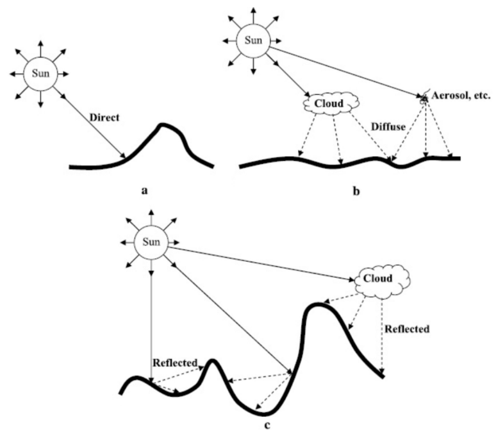

Figure 1. Solar radiation divisions: **(a)** direct, **(b)** diffuse and **(c)** reflected.

In the proposed work, the Intelligent Water Drops (IWD) Algorithm has been used to estimate the monthly average daily Global Solar Radiation (GSR) on horizontal surface for six different climatic stations of Iran based on the different linear and nonlinear empirical equations. In the proposed approach, the best coefficients of the empirical equations are found by using the IWD algorithm to estimate the monthly average daily GSR based on the minimization of an objective function. Obtained results are evaluated through a validation dataset. The proposed approach doesn't require a difficult training stage and can estimate the solar radiation with a high accuracy compared to the other empirical and intelligent models.

2. EMPIRICAL EQUATIONS FOR THE GSR ESTIMATION

Many empirical models have been presented by the researchers for the estimation of global and diffuse solar radiation. These empirical models are based on meteorological parameters. The meteorological parameters include clearness index, sunshine hours, temperature, wind speed, and relative humidity, etc.

2. 1. Linear Empirical Equations Numbers of empirical models are available in the literature for the estimation of solar radiation under cloudless sky. In 1924, the Angstrom proposed a relation between solar radiation and sunshine hours [6]. Later, this model was modified by Prescott and known as Angstrom-Prescott model which can be expressed as a linear regression expression:

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

where H is the global solar radiation (GSR), H_o denotes the extraterrestrial solar radiation, S represents the actual sunshine hours, S_o is the maximum possible sunshine duration, a and b are the empirical coefficients.

After Angstrom-Prescott model, researchers developed other empirical models based on sunshine hours, relative humidity, wind speed, temperature, etc. Swartman and Ogunlade [7], and Abdallah [8] proposed linear models which are defined using Equations (2) and (3), respectively:

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

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

where RH is the mean relative humidity, T is the daily mean air temperature, and a, b, c and d are the empirical coefficients.

2. 2. Nonlinear Empirical Equations The empirical equation provides the relationship between solar radiation with meteorological parameters. These parameters are varying in nature i.e. nonlinear, therefore there is need to develop nonlinear models.

Number of nonlinear models were developed by researchers and are available in literatures; such as the non- linear models developed by Ogelman et al. and Akinoglu and Ecevit [9, 10] which is defined as follows:

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

Bahel et al. proposed the higher-order polynomial nonlinear model for estimating the GSR [11]:

$$H = H_O(a + b(\frac{S}{S_O}) + c(\frac{S}{S_O})^2) + d(\frac{S}{S_O})^3 \quad (5)$$

Almorox and Hontoria suggested the following exponential relationship between solar radiation and sunshine hours [12]:

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

Bakirik developed the following model for the GSR estimation [13]:

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

A logarithmic equation for the SI estimation was proposed by Ampratwum and Dorvol [14]:

$$\frac{H}{H_O} = a + b\log(\frac{S}{S_O}) \quad (8)$$

3. INTELLIGENT WATER DROPS (IWD) AND ITS OVERALL PROGRESS

The IWD algorithm emulates the features of water drops passing through the obstacles of the environment. This algorithm uses a population of water drops to construct paths and then obtains the optimal or near-optimal path among all candidate paths over time. The environment represents the optimization problem needed to be solved. A river of the IWDs looks for an optimal route for the given problem. Hosseini [15] presented the basics of the IWD algorithm. He applied it to solve different optimization problems. As described in this work [15], an IWD model consists of two important parameters:

- The amount of soil it carries or its soil load, "$soil^{IWD}$".
- The velocity of the movement, "vel^{IWD}".

The values of these two parameters may change as the IWD flows in its environment from the source toward a destination. An IWD moves in discrete finite-length steps and updates its velocity by an amount Δvel^{IWD} whenever its position changes from point i to point j as follows:

$$\Delta vel^{IWD} = \frac{a_v}{b_v + c_v[soil(i,j)]^2} \tag{9}$$

where $soil(i, j)$ is the soil load on the edge between two points i and j; av, bv and cv are pre-defined positive parameters for the IWD algorithm. The relationship between velocity and the soil load of the edge is expressed using av and cv, meanwhile bv is a small number used to prevent the singularity problem. Equation (9) indicates that the velocity rate, Δvel^{IWD} depends on the load of soil on the edge, that is, the more the soil load of the edge is, the more is its resistance to the water flow that results in a smaller increment in velocity and vice versa. Thus, the velocity at time $(t + 1)$, vel_{t+1}^{IWD} is given by:

$$vel_{t+1}^{IWD} = vel_t^{IWD} + \Delta vel^{IWD} \tag{10}$$

where vel_t^{IWD} is the velocity of the IWD at time t.

The amount of soil removed from the bed of edge (i, j) is inversely proportional in a non-linear manner to the time needed for the IWD to move from point i to point j and can be computed using Equation (11):

$$\Delta soil(i, j) = \frac{a_s}{b_s + c_s[time(i, j; vel^{IWD})]^2} \tag{11}$$

where, as, bs and cs are pre-defined positive parameters for the IWD algorithm. The as and cs define the relationship between the amount of soil and the IWD duration to move through the *edge* (i, j), and bs is a small number used to avoid the singularity problem. Meanwhile, the duration of time is calculated by the simple laws of physics for linear motion. The time spent by the IWD to move from point i to j with the velocity vel^{IWD} is as follows:

$$time(i, j; vel^{IWD}) = \frac{HUD(i, j)}{\max(\varepsilon_v; vel^{IWD})} \tag{12}$$

$$soil(i,j)_{(t+1)} = (1-\rho_n)(soil(i,j)_{(t)} - \rho_n \Delta soil(i,j) \tag{13}$$

$$soil^{IWD}{}_{(t+1)} = soil^{IWD}{}_{(t)} + \Delta soil(i, j) \tag{14}$$

where ρ_n is the local soil updating parameter, which is chosen from [0, 1], and $\Delta soil(i, j)$ is defined in Equation (11). The behavior of an IWD in edge selection process is defined using a probability measure, $p(i, j; IWD)$, which is defined as a inversely proportional of the soil load on the available edges.

$$p(i, j; IWD) = \frac{f(soil(i, j))}{\sum_{k \notin v_c(IWD)} f(soil(i, k))} \tag{15}$$

where $f(soil(i,k)) = (1 + \varepsilon_s + g(soil(i, j)))$.

The constant ε_s is a small positive number to prevent singularity. The set $vc(IWD)$ denotes the group of nodes that must not been visited to satisfy the constraints of the problem. The function $g(soil(i, j))$ is used to shift the $soil(i, j)$ of the edge connecting point i and point j toward a positive value and is described as bellows:

$$g(soil(i, j)) = \begin{cases} soil(i,j) & if: \min_{l \notin v_c(IWD)} (soil(i,l)) \geq 0 \\ soil(i,j) - \min_{l \notin v_c(IWD)} (soil(i,l)) & otherwise \end{cases} \tag{16}$$

The function min() returns the minimum value of its arguments. In order to decide about the next location to move, a random number is generated (using a uniform random distribution) to be compared with the probability measure. In order to evaluate the quality or fitness of the solutions, an objective or quality function is employed. The function q represents the quality of solution and its argument, T^{IWD}, is a candidate solution found by an IWD. An iteration is completed whenever all the IWDs construct their solutions. Then the best solution of the current iteration, T^{IB}, is computed as follows:

$$T^{IB} = \arg\max_{\forall IWDs} q(T^{IWD}) \tag{17}$$

Therefore, the best solution of the current iteration, T^{IB}, is the one with the highest quality between all the candidate solutions, T^{IWD}.

Equation (13) updates the soil load on an edge whenever an IWD traverses through a particular path using soil load of the edge and the velocity. The soil load is updated in Equation (13) using local information at edge of the tree. Thus, the algorithm may get trapped in a local optimum. In order to improve the probability of finding the global optimum, the amount of soil on the best solution of the current iteration is updated according to the fitness of the solution whenever an iteration is completed and the overall knowledge of the solution is acquired. Equation (17) is used to update the *soil(i, j)* belonging to the best solution T^{IB} of the current iteration.

$$soil(i,j) = (1+\rho_{IWD})soil(i,j) - \rho_{IWD}\frac{1}{N_{IB}-1}soil_{IB}^{IWD}, \quad \forall (i,j) \in T^{IB} \tag{18}$$

where $soil_{IB}^{IWD}$ represents the soil load of the best IWD in the current iteration, N_{IB} is the number of nodes in the solution T^{IB} and ρ_{IWD} is the global soil updating parameter chosen from [0, 1]. The first term on the right-hand side of Equation (18) is the amount of soil remained from the previous iteration. Meanwhile, the other term in Equation (18) represents the quality of the current solution, obtained by the IWD. This way of updating soil load guides the IWDs to search near good solutions with the expectation of finding the global optimum. At the end of each iteration of the algorithm, the overall best solution T^{TB} is updated using the information of the best solution of the current iteration, T^{IB}, as follows:

$$T^{TB} = \begin{cases} T^{TB} & if \quad q(T^{TB}) \geq q(T^{IB}) \\ T^{IB} & otherwise \end{cases} \tag{19}$$

Thus, it is guaranteed that T^{IB} holds the best solution obtained so far by the IWD algorithm.

Figure 2 represents the flowchart of the main processes of the IWD algorithm.

4. THE PROPOSED METHODOLOGY BASED ON INTELLIGENT WATER DROPS OPTIMIZATION AND EMPIRICAL MODELS

In this paper, the intelligent water drop algorithm has been used to find the coefficients of empirical models and estimate the GSR using a measured dataset. The detail of this method is summarized in the following steps:

Step 1: Split the Dataset into Two Groups: The dataset was divided into two different parts: installation, and validation datasets. The limit checks were carried out on the monthly mean daily GSR and monthly mean daily sunshine duration to make sure that the data are homogeneous. Also, the variations of monthly mean daily GSR are caused only by climatic influences and not by any other sources of errors [16]. In this study, the number of valid data for each region was calculated from the following equation:

$$N_v = N_t - N_l \tag{20}$$

where, N_v is the number of valid data, N_t is the number of total available data in the period, and N_l is the number of data in the period out of limit.

Step 2: Calculate the Required Ratios Using Measured Data: The values of $\frac{H}{H_o}$ (the fraction of possible monthly average daily GSR) and $\frac{S}{S_o}$ (the fraction of possible monthly average daily sunshine duration) are calculated using measured data, in both installation and validation datasets.

Step 3: Estimation of Empirical Coefficients for the GSR: The installation dataset in step 2 is used in intelligent water drop algorithm to find the candidates of the best coefficients for the empirical equations by minimizing the fitness function in Equation (21).

$$F = \sum_{i=1}^{m}(Y_i - X_i)^2 \tag{21}$$

where, $Y_i = (\frac{H}{H_o})ci$ and $X_i = (\frac{H}{H_o})ei$ are the computed and estimated fraction of possible monthly average daily GSR, respectively for the ith observation, H is the GSR, H_o denotes the extraterrestrial solar radiation and, m illustrates the cumulative observations (calculation of the extraterrestrial solar radiation (H_o) has been discussed elsewhere [17]).

The IWD process continues until the stopping criterion is satisfied.

Step 4: Validation of Results: After each run of the program, the obtained results of the IWD are validated using calculated values in the validation period. If the GSR values based on the obtained empirical coefficients using the IWD are in good agreement with the calculated GSR values in the validation period (at least 80% agreement), thus the obtained empirical coefficients are chosen, otherwise this process is repeated from step 3.

The accuracy of obtained empirical coefficients has been investigated using two statistical indicators, absolute fraction of variance (R^2) and Root Mean

Square Error (RMSE). The R^2 and RMSE are described by Equations (22) and (23), respectively, as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{\sum_{i=1}^{m}(Y_i)^2} \quad (22)$$

$$RMSE = \left[\frac{\sum_{i=1}^{m}(X_i - Y_i)^2}{m}\right]^{0.5} \quad (23)$$

(X_i, Y_i and m are defined in Equation (21)).

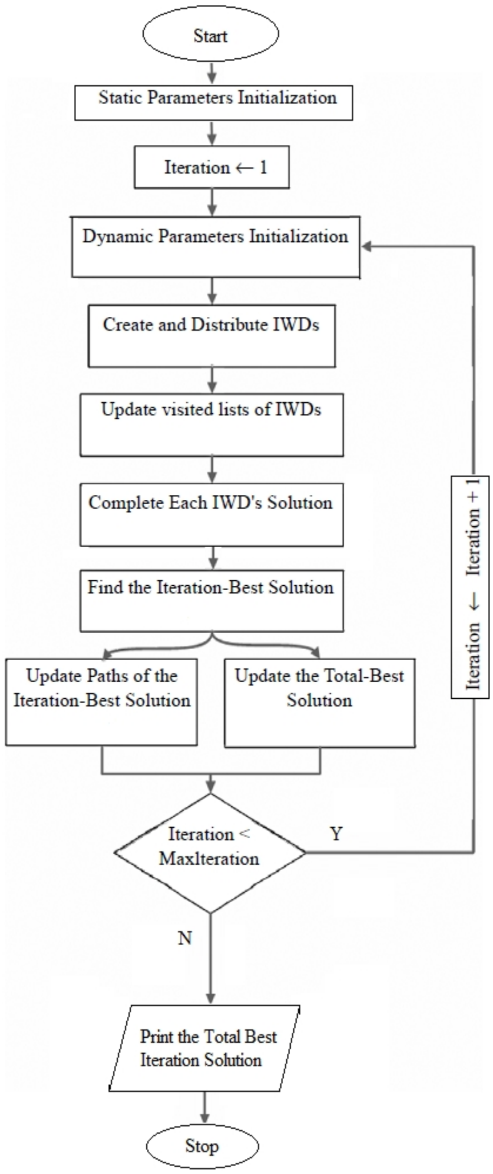

Figure 2. The flowchart of the main process of the IWD algorithm

5. EVALUATION OF RESULTS AND DISCUSSION

In this study, the proposed approach based on the IWD was implemented in the MATLAB software.The parameters for the IWD algorithm are selected as follows (based on trial and error): *as*=1, *bs*=0.01, *cs*=1 *av*=1, *bv*=0.01, *cv*=1, $q(T^{IWD}) = -\infty$, *MaxIter*=300, *Itercount*=1, $\rho_n = 0.88$, $\rho_{IWD} = -0.85$. The initial soil on each path is denoted by *Initsoil* and the initial velocity is denoted by *Initvel*. Both parameters are selected by the user. In this study, *Initsoil*=1200 and *Initvel*=4 are selected. For evaluation purpose, the proposed method was employed for estimation of the monthly average daily GSR on horizontal surface for six different climate cities of Iran. These sample cities are Esfahan, Hamadan, Kerman, Mashhad, Khoorbiabanak and Orumieh. All required information were provided by Meteorological Office in Iran. Since these data are presented in the literature [1], they have not been mentioned in this article. The H/H_o and S/S_o values were calculated separately for both installation and validation data series for all six cities. Among the equations presented in Section 2, two linear and two nonlinear empirical models were selected to evaluate the performance of the proposed technique to find the best empirical coefficients and the GSR estimation on sample cities. Linear empirical equations included Angstrom-Prescott (Equation (1)) and Abdallah (Equation (3)) which hereafter are considered as Model 1 and Model 2, respectively. The nonlinear empirical equations are: Akinoglu and Ecevit (Equation (4)) and Ampratwum and Dorvol (Equation (8)) that hereafter are considered as Model 3 and Model 4, respectively.

The IWD algorithm was programmed in the MATLAB software based on the procedures described in Sections 3 and 4. The program is applicable for all cities. Table 1 includes the obtained coefficients of *a*, *b*, *c*, and *d* for four tested empirical models on the six sample cities using the IWD algorithm. Similar data were used to ensure a fair comparison between the performance of the IWD, Bees Algorithm (BA), the SRTs, and the ANN on the GSR modeling. The empirical coefficients for four selected empirical models (Models 1 to 4) were separately calculated for six sample cities using the IWD, BA and SRTs (Least absolute deviations method). Also an ANN model trained using the Levenberg–Marquardt algorithm with sigmoid and linear transfer functions in the hidden and output layers, respectively, was designed in the neural network toolbox of the MATLAB. The obtained RMSE and R^2 values for the GSR values using different above models based on the IWD, BA, the SRTs, and the ANN are shown in Table 2. The results reveal the superiority of combination of the IWD and linear Angstrom model (IWD & Model 1) rather than other models for the solar radiation estimation with R^2 greater than 0.98 and the RMSE smaller than 0.0094 on six sample cities. Among all sample cities, the best result was obtained for Esfahan with R^2 = 0.9998, and the RMSE = 0.0002 for combination of IWD and Angstrom model, and the worst was obtained for Orumieh with R^2=0.8387, and RMSE=0.2610 based on the SRTs and the Abdallah model. By computing the average of the R^2 and the RMSE measures for all testing models on six sample cities from Table 2, the following results can be concluded:

❖ Combination of the IWD with all linear and nonlinear tested empirical models generates acceptable results with $R^2_{average}$ > 0.988, and $RMSE_{average}$ < 0.003 for all sample cities.

❖ Among the IWD, BA, SRTs, and ANN models, the best result was obtained from the IWD and Angstrom model (IWD & Model 1) with $R^2_{average}$=0.996, and $RMSE_{average}$=0.0007, and the worst result was reported for the SRTs and Abdallah model (SRTs & Model 2) with $R^2_{average}$=0.880, $RMSE_{average}$=0083.

TABLE 1. The obtained empirical coefficients using the IWD algorithm

City name	Empirical model	a, b, c, d
Esfahan	Model 1	0.4108, 0.3740
	Model 2	0.0629, 0.3559, 0.2284, 0.0952
	Model 3	0.5106, -0.0194, 0.1836
	Model 4	0.7104, 0.2134
Hamadan	Model 1	0.3473, 0.3104
	Model 2	0.2251, 0.1376, 0.3198, 0.2752
	Model 3	0.48032, 0.1264, 0.3418
	Model 4	0.7416, 0.2582
Kerman	Model 1	0.3153, 0.4833
	Model 2	0.1687, 0.1845, 0.2013, 0.2574
	Model 3	0.2366, 0.7942, -0.1791
	Model 4	0.8492, 0.3755
Mashhad	Model 1	0.3159, 0.2942
	Model 2	0.3247, 0.3831, 0.2796, 0.3245
	Model 3	0.9182, 1.137, 1.001
	Model 4	0.6592, 0.0935
Orumieh	Model 1	0.3604, 0.3256
	Model 2	0.1847, -0.1705, 0.1935, 0.1726
	Model 3	0.6774, 0.4839, 0.3251
	Model 4	0.4635, -0.7055
Khoor-biabanak	Model 1	0.3942, 0.4186
	Model 2	0.4367, 0.3154, 0.4329, -0.4248
	Model 3	0.3415, 0.3530, 0.0716
	Model 4	0.7618, 0.2925

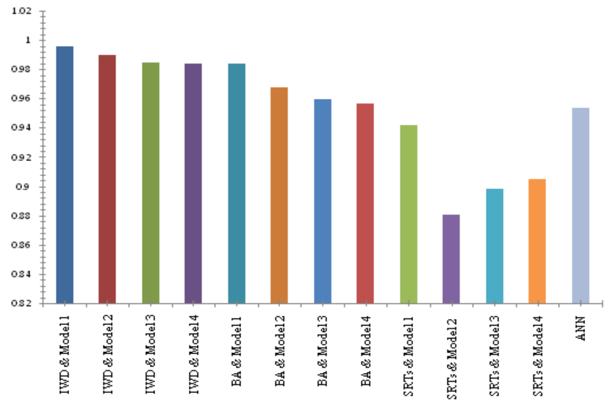

Figure 3. Comparison between $R^2_{average}$ values for different test methods

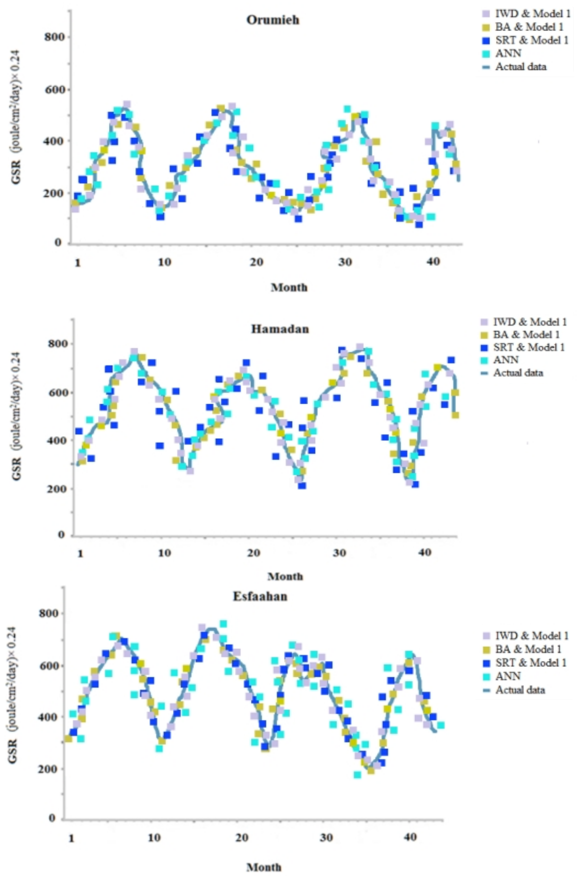

Figure 4. Comparison between actual values compared to the IWD, BA, SRT (based on Angstrom model), and ANN values of monthly average daily GSR for six sample cities

❖ After the IWD algorithm, the best results were obtained based on the BA and Angstrom model with $R^2_{average}$ > 0.98, and $RMSE_{average}$ < 0.01 for all six sample cities.

TABLE 2. Accuracy results using the R^2 and the RMSE indicators

City	Technique	R2 value	RMSE value
Esfahan	IWD & Model 1, 2, 3, and 4	0.9998,0.9991,0.9922,0.9913	0.0002, 0.0004, 0.0010, 0.0007
	BA & Model 1, 2, 3, and 4	0.9931,0.9807,0.9604,0.9520	0.0009, 0.0021, 0.0144, 0.0057
	SRTs & Model 1, 2, 3, and 4	0.9913,0.8635,0.8726,0.9278	0.0135, 0.1046, 0.1012, 0.0481
	ANN	0.9377	0.0108
Hamadan	IWD & Model 1, 2, 3, and 4	0.9925,0.9876,0.9817,0.9833	0.0008,0.0064, 0.0045, 0.0093
	BA & Model 1, 2, 3, and 4	0.9912,0.9417,0.9699,0.9835	0.0011,0.0364, 0.0047, 0.0019
	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
Kerman	IWD & Model 1, 2, 3, and 4	0.9970,0.9910,0.9881,0.9815	0.0005,0.0005,0.0068,0.0070
	BA & Model 1, 2, 3, and 4	0.9872,0.9751,0.9411,0.9407	0.0083,0.0136,0.0063,0.0071
	SRTs & Model 1, 2, 3, and 4	0.9864,0.8934,0.9318,0.8916	0.0066,0.0267,0.0189,0.0164
	ANN	0.9409	0.0282
Mashhad	IWD & Model 1, 2, 3, and 4	0.9986,0.9962,0.9812,0.9884	0.0004,0.0006,0.0042,0.0035
	BA & Model 1, 2, 3, and 4	0.9786,0.9639,0.9618,0.9484	0.0175,0.0294,0.0092,0.0205
	SRTs & Model 1, 2, 3, and 4	0.8815,0.8753,0.8836,0.8719	0.0518,0.0710,0.0303,0.0615
	ANN	0.9639	0.0189
Orumieh	IWD & Model 1, 2, 3, and 4	0.9884,0.9839,0.9818,0.9801	0.0017,0.0061,0.0067,0.0089
	BA & Model 1, 2, 3, and 4	0.9651,0.9587,0.9418,0.9445	0.0256,0.0261,0.0167,0.0211
	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
Khoorbiabanak	IWD & Model 1, 2, 3, and 4	0.9950,0.9802,0.9843,0.9807	0.0009,0.0012,0.0056,0.0037
	BA & Model 1, 2, 3, and 4	0.9908,0.9852,0.9843,0.9707	0.0014,0.0017,0.0056,0.0189
	SRTs & Model 1, 2, 3, and 4	0.9463,0.9303,0.8945,0.8974	0.0038,0.0012,0.0182,0.0143
	ANN	0.9532	0.0058

❖ The performance of the ANN with $R^2_{average}$=0.953, and the $RMSE_{average}$=0.013 is better than the SRTs, which is very close to the IWD and BA results, while the IWD and BA don't need a complex training stage same as the ANN.

The $R^2_{average}$ values for testing methods have been compared in Figure 3. Figure 4 shows the comparisons between GSR estimations obtained by IWD and Angstrom model (IWD & Model 1), BA and Angstrom model (BA & Model 1), SRT and Angstrom model (SRTs & Model 1), and ANN with actual data for all six sample cities. As can be seen from this figure, among all compared methods, the IWD results are closer to the corresponding actual data values for all tested cities.

6. CONCLUSION

This study proposed a new technique for estimation of the monthly average daily global solar radiation on horizontal surface using a combination of intelligent water drops algorithm with linear and nonlinear empirical equations. For performance evaluation, the proposed algorithm was tested on six different climate cities of Iran using two linear and two nonlinear empirical equations. The results produced by the proposed technique were compared to the bees algorithm, statistical regression and artificial neural network techniques using two statistical indicators: absolute fraction of variance and root mean square of the error. The comparison results reveal the superiority of combination intelligent water drops algorithm and linear Angstrom model compared to other models for solar radiation estimation for all sample cities. Among all compared methods for sample cities, the best result was obtained for Esfahan based on combination of the IWD and Angstrom model, and the worst results was achieved for Orumieh based on statistical regression techniques for Abdallah model. After the IWD algorithm, the best results are obtained based on the BA and Angstrom model for all six sample cities. Also the performance of artificial neural network is better than statistical regression technique, and is close to bees and intelligent water drops algorithms results, but it requires a complex training stage.

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