Calibration and Validation of the Angstrom-Prescott Model in Solar Radiation Estimation using Optimization Algorithms

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Abstract

The Angstrom-Prescott (A-P) model is widely suggested for estimating solar radiation (R_s) in areas without measured or deficiency of data. The coefficients of this model must be locally calibrated, to calculate evapotranspiration (ET) correctly. The aim of this research was calibration and validation of the coefficients of the A-P model at six meteorological stations across arid and semi-arid regions of Iran. This model was improved by adding the air temperature and relative humidity terms. Besides, the coefficients ('a' and 'b') of the A-P model and improved models was calibrated using some optimization algorithms including Harmony Search (HS) and Shuffled Complex Evolution (SCE). Performance indices, i.e., Root Mean Square Error (RMSE), Mean Bias Error (MBE), and coefficient of determination (R^2) were used to analyze the models ability in estimating R_s . The results indicated that the performance of the A-P model had more precision and less error than improved models in all the stations. In addition, the best results were obtained for the A-P model with the SCE algorithm. The RMSE varies between 0.82 and 2.67 MJ m⁻² day⁻¹ for the A-P model with the SCE algorithm in the calibration phase. In the SCE algorithm, the values of RMSE had decreased about 4% and 7% for Mashhad and Kerman stations in the calibration phase compared to the HS algorithm, respectively. In other words, the highest decrease of RMSE is related to Kerman station.

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9	Solar radiation	radiation (R_s) in areas without measured or deficiency of data. The coefficients of
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25		phase compared to the HS algorithm, respectively. In other words, the highest
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26 1. Introduction

The solar radiation (R_s) received from the Earth's surface is one of the most important factors 27 affecting the thermal balance of the atmospheric-Earth system. The precise measurement or 28 estimation of R_s is required for accurate design and management in irrigation and water resource 29 planning and management, agriculture, meteorology, climatology, energy engineering, solar 30 energy systems and especially in hydrology (Jahani et al. 2018; Liu et al. 2017; Robaa 2009). 31 One of the major parts of the hydrological cycle is evapotranspiration (ET) process that is 32 widely used for agricultural, irrigation management and water resources planning (Sanikhani 33 et al. 2019). Solar radiation is the main input variable in the calculation of ET (Tabari et al. 34 35 2016; Boscaini et al. 2020). Due to the cost and the maintenance and calibration requirements 36 of the R_s estimating instrument, and missing data or due to instrument failure or other related problems, it might be that the estimates of R_s are not available in several regions (Abraha et al. 37 2008; De Souza et al. 2016; Liu et al. 2001). For this reason, several methods have been 38 presented to estimate R_s based on different types of methods such as satellite remote sensing 39 (Sanchez-Lorenzo et al. 2017; Zhang et al. 2015), machine learning (Ağbulut et al. 2021; ,He 40 et al. 2020; Kisi and Alizamir 2018; Shamshirband et al. 2015), numerical, and artificial 41 intelligence (Jahani and Mohammadi 2018). There are some complexes and difficulties in using 42 43 these methods for R_s estimation including requires many input variables; large datasets; coarse spatial resolution, and the eventuate model may not apply to other areas. Besides, there is no 44 satellite-based database covering the study areas (Mihalakakou et al. 2000; , Şenkal and Kuleli 45 2009; Weiss and Hays 2004). 46

Another kind of method that has been developed and widely used for estimating R_s are empirical models (Fan et al. 2019). These models based on meteorological variables are a substitute to estimate R_s . Besides, these models using the easily accessible meteorological variables, such as sunshine duration, maximum and minimum air temperatures (T_{max} , T_{min}),

cloudiness, relative humidity (RH), and precipitation are attractive for its plainness, efficiency, 51 52 and lower data requirement (Chen et al. 2018). Much preceding research has determinate that the sunshine-based models always outperform other types of models (Besharat et al. 2013; Chen 53 et al. 2004). These models require relatively a few input variables and are easy to apply but it 54 needs to calibrate their coefficients based on location and inputs data. However, the 55 requirements to calibrate empirical models demonstrate that their coefficients are changing with 56 locations. The station dependent coefficients limit the regional application of the empirical 57 models, which is a big challenge for spatial rasterization. To solve this problem, the model 58 coefficients for the regional usage must be calibrated. 59

Many models are developed for estimating R_s. One of the most famous empirical sunshine-60 61 based models is the Angstrom-Prescott (A-P) model. The A-P model has been applied to estimate global solar radiation based on measured sunshine hours. This model is widely used 62 for its simpleness and remarkable performance (Paulescu et al. 2016; Raoof and Mobaser 2019; 63 Sabziparvar and Shetaee 2007). One of the original constraints of the A-P model is that it 64 requires calibration using local estimated Rs data. Where no measured values for global solar 65 radiation are available in some stations, Angstrom prospered values of 0.2, and 0.5, and Prescott 66 0.22, and 0.54 for the empirical coefficients 'a' and 'b', respectively (Chen et al. 2013). Given 67 its simpleness and premiere performance compared with other empirical models, its reference 68 values for radiation coefficients 'a' and 'b', given by the Food and Agriculture Organization 69 (FAO) Irrigation and Drainage Paper No. 56 (FAO56: a = 0.25, b = 0.5), can be used in cases 70 where R_s data are not available (Allen et al. 1998; Chen et al. 2018; Liu et al 2019). Many 71 research executed in various areas has shown that the use of the given coefficients to estimate 72 R_s yields finite accuracy, and therefore, the coefficients of the A-P model should be calibrated 73 locally (Liu et al. 2017; Sabziparvar et al. 2013; Tabari et al. 2016). FAO56 proposed the A-P 74 model, which is a simple method to estimate the daily global solar radiation. The results of 75

previous researches showed that the application of the FAO pre-defined the A-P coefficients, for a variety of climatic and geographical conditions (without regardless of climate effect) the could challenge the validity of the FAO56-PM method (Liu et al. 2009; Yin et al. 2008). Therefore, many researchers performed a temporal and spatial calibration of 'a' and 'b' (Mousavi et al. 2014; Tabari et al. 2016). In another investigation, Aghashariatmadari et al. (2012) are calibrated the coefficients 'a' and 'b' and examined the variations of these coefficients at different time scales.

83 On the other hand, researchers have attempted to estimate R_s in addition to the sunshine, take 84 advantage of other variables such as air temperature, relative humidity, cloudiness, saturation 85 vapor pressure, and even precipitation (Chang and Zhang 2020; Jamil et al. 2019; Mousavi et 86 al. 2014; Ododo et al. 1998).

Recently many kinds of meta-heuristic algorithms have been used to calibrate a different 87 kind of empirical model in the real problem. Few usages of metaheuristic methods to solve solar 88 energy problems have been reported; the Genetic Algorithm (GA) is one of these methods. Sen 89 et al. (2001) have used GA for the designation of the A-P model coefficients. Harmony Search 90 (HS) is one of the well-known and powerful optimization algorithms (Rahimi et al. 2012), 91 which is emulating the music extemporization process where musicians extemporize their 92 93 instruments' pitches searching for a perfect state of harmony, was developed by (Geem et al. 2001). The HS algorithm has been recently applied to different engineering optimization 94 problems including optimized design of water dispensation network (Abualigah et al. 2020), 95 optimal performance of a multi-reservoir system for hydropower and irrigation (Bashiri-Atrabi 96 et al. 2015; Geem 2007), simulation of irrigation systems (Alshammari and Asumadu 2020;, 97 Čistý 2007), an optimization model for groundwater management objectives (Luo et al. 2020), 98 and recognition of unknown groundwater pollution sources (Ayvaz 2010). To fix the defects of 99 the HS algorithm, the methods such as the Global Harmony Search (GHS) and Improved 100

Harmony Search (IHS) algorithm were developed. Another optimization algorithm that is used
for effective global minimization and calibration of hydrologic models is the Shuffled Complex
Evolution (SCE) algorithm (Duan et al. 1993). Also, this algorithm has been used widely for
the calibration of different rainfall-runoff models (Adeyeri 2020), for the rehabilitation of water
distribution networks (Elshaboury et al. 2020), and optimizing urban water supply Headwork's
systems (Cui and Kuczera 2003).

There has not been much research on the computing R_s by optimization algorithms in Iran, 107 and only one research conducted in Mashhad (Rahimi et al. 2012) examined. This is the first 108 research by optimization algorithms for calibration of the A-P model coefficients in Iran. 109 Through these algorithms, the A-P model coefficients are calibrated faster and more accurately, 110 111 and R_s that is a fundamental input for calculating ET (Cunha et al. 2021), estimated more correctly. Accurate estimation of R_s provides an accurate calculate of ET. The exact calculation 112 of ET is necessary for many applications such as improving water usage, agricultural planning, 113 and effective water resources management, especially in arid and semi-arid climates. 114

This research aims to calibrate and improved the A-P model for estimating R_s at six meteorological stations in arid and semi-arid climates of Iran using the optimization algorithms including HS, IHS, GHS, and SCE. Then to investigate the effect of T and RH variables on the efficiency of the A-P model to estimating R_s , three improved A-P models were developed by adding terms of T_{max} , T_{min} , and mean relative humidity (RH_{mean}) and calibrated using applied optimization algorithms.

121 **2. Material and methods**

122 2.1.Study area

Iran is situated among latitudes of 25°N to 40°N and longitudes of 46°E to 65°E with an area of 1,648,000-km². Most parts of Iran are arid and semi-arid climates. On the other hand, low irrigation efficiency in agricultural fields requires that the amount of ET and water requirement

of plants that require an accurate estimate of the amount of R_s be calculated. In this research six 126 meteorological stations, which are situated at arid and semi-arid climates of Iran, were selected 127 to evaluate the performance of the calibrated A-P model in R_s estimation. The selected stations 128 have arid and semi-arid climates based on the De Martonne climate classification method 129 (Pellicone et al. 2019; Rahimi et al. 2013) from 1992–2017 and reliable long-term data (Fig. 1). 130 The criteria for selection of the meteorological stations were based on the climate sort and the 131 availability of the measured R_s. 132



133 134

Fig. 1. Location of meteorological stations

2.2.Data and quality control 135

Daily meteorological data from six radiation stations were obtained from the Islamic Republic 136 of Iran Meteorological Organization (IRIMO). The geographic and meteorological 137 characteristics of the studied stations are presented in Table 1. In this research, the following 138 meteorological characteristics were used as the inputs of the A-P and the three improved 139 models: T_{max}, T_{min}, RH_{mean}, and R_s (MJ m⁻²day⁻¹), maximum possible daily duration of sunshine 140 141 hours (N), and mean the daily number of sunshine duration (n). Due to the importance of radiation data, the quality control of the observed daily global R_s was carried (Moradi 2009): 142

143	•	If either the fluency index (R_s/R_a) or relative sunshine hours (n/N) were greater than
144		one, the data for that day were deleted from the dataset.
145	•	If R_s was greater than $0.78 \times R_a$, the data for that day were deleted from the dataset.
146	•	If R_s was lower than $0.03 \times R_a$, the data for that day were deleted.
147	•	If there were ten or more days of lost data in the same month, the data for that month
148		was omitted.

149 **Table 1**

150 Geographical and meteorological characteristics for the studied stations

station	Lat.	Lon.	Elev.	Maximum	Minimum	Average	Average R _s	RH	Calibration	climate	Validation
	(°N)	([°] E)	(m)	Temperature	Temperature	sunshine	(MJ m ⁻² day ⁻¹)		period		period
				(° c)	(° c)	(h)		(%)			
Bandar	27.19	56.3	17	47	2.6	8.44	19.01	63.40	1992-2012	Semi-arid	2013-2017
Abbas											
Esfahan	32.46	51.66	1590	43	-19.3	8.6	16.74	35.92	1992-2012	Arid	2013-2017
Kerman	30.15	56.58	1754	41.4	-23.2	8.17	18.77	38.4	1992-2012	Arid	2013-2017
Mashhad	36.16	59.38	999	43.4	-21.37	7.27	16.24	53.98	1992-2012	Semi-arid	2013-2017
Shiraz	29.53	52.58	1486	42.4	-9	8.96	19.78	40.54	1992-2012	Semi-arid	2013-2017
Yazd	31.88	54.35	1222	45.6	-6.7	8.94	19.46	28.81	1992-2012	Arid	2013-2017

151

152 2.3.Models and optimization algorithms

153 2.3.1. Models

154 The A-P model is a model based on the sunshine, and to examine the effect of other

155 meteorological variables, the following models presented in Table 2 were examined.

156 **Table 2**

157 Improved A-P model based on terms of T_{max}, T_{min}, and RH_{mean}

Models			Coefficients	
Model1	Include air temperature	$R_s = [a_1 + b_1(n/N) + c (T_{max^*}T_{min})] R_a$	a ₁ , b ₁ , c	
Model2	Include relative humidity	$\mathbf{R}_{s} = \left[\mathbf{a}_{2} + \mathbf{b}_{2} \left(\mathbf{n}/\mathbf{N}\right) + \mathbf{d} \left(\mathbf{R}\mathbf{H}_{mean}\right)\right] \mathbf{R}_{a}$	a ₂ , b ₂ , d	
Model3	Combined Model 1 and Model 2	$R_{s} = [a_{3}+b_{3}(n/N) + c_{1} (T_{max}-T_{min}) + d_{1}(RH_{mean})] R_{a}$	a_3, b_3, c_1, d_1	

158

159 2.4.Optimization algorithm

160 The optimization algorithms were coded with MATLAB R2018a (9.4.0.813654). These 161 algorithms are applied to find the optimal solution to a given calculational problem that 162 minimizes or maximizes a special function. In this research, optimization algorithms including

163 SCE, IHS, GHS, and HS were used.

- 164 2.4.1. Shuffled Complex Evolution (SCE) algorithm
- 165 The SCE algorithm was expanded at the University of Arizona (Duan et al. 1992). Its strategy
- 166 combines the strengths of the controlled random search (CRS) algorithms with the concept of
- 167 competitive evolution (Holland 1975) and the newly modified concept of complex shuffling.
- 168 The most important steps of the SCE are displayed in Fig. 2.

Initialize k, m and s = km Sample $\{\theta_1, \ldots, \theta_s\}$, where $\theta_i \in \Theta$ Calculate function values $fi = f(X, \theta_i) i = 1, \dots, s$ Sort f_i s.t. $k \leftarrow i$ and $f_1 \le f_2 \le f_k \le f_{k+1} \ldots$ $D0 = \{(\theta_k, f_k), k = 1, ..., s\}$ Construct complexes C_j , j = 1, ..., k s.t. $C_j = \{(\theta_k, f_k) \in D_0 | k = (j - 1)_{m+1}, ..., j_m\}$ While Convergence Criteria do For j = 1: k do Evolve Cj using CCE (Competitive Complex Evolution) end for $\mathbf{D}^{l} \leftarrow \mathbf{D}^{l+1}$ Go to 6 end while

Fig. 2. Pseudo-code of the SCE Algorithm

170 2.4.2. Harmony Search (HS) algorithm

When listening to a beautiful piece of classical music, who has ever wondered if there is any connector between music and finding an optimal solution to a tough design problem such as the water distribution networks or other design problems in engineering? Now for the first time, scientists have found such a fascinating connection by expanding a new algorithm, called HS. Geem et al. first expanded the HS in 2001.

176 • HM=
$$\begin{bmatrix} x_{11} & x_{12} & x_{13} \dots & x_{1n} \\ x_{21} & x_{22} & x_{23} \dots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{HMS1} & x_{HMS2} & x_{HMS3} \dots & x_{HMSn} \end{bmatrix}$$
(1)

177 Harmony memory considering (HMC) rule:

• For this rule, a new random number r_1 is produced within the range [0, 1].

• If
$$r_1 < HMCR$$
, where HMCR is the harmony memory consideration rate, then the first
decision variable in the new vector x_{ij}^{new} is elected randomly from the values in the
present HM as follows:

(2)

• $x_{ii}^{new} = x_{ij}, x_{ij} \in \{x_{1j}, x_{2j}, x_{3j}, ..., x_{HMSj}\}$

183

182

The most important steps of the HS are displayed in Fig. 3

For each i ϵ [1, N] do If U (0, 1) \leq HMCR $\mathbf{x}'_i = \mathbf{x}'_j$, where $\mathbf{j} \sim U$ (1, 2, ..., HMS). If U (0, 1) \leq PAR (pitch adjustment rate) $\mathbf{x}'_i = \mathbf{x}_i \pm \mathbf{r} \times \mathbf{bw}$, where $\mathbf{r} \sim U$ (0, 1) and bw is an arbitrary distance bandwidth. end if else $\mathbf{x}'_i = \mathbf{LB}_i + \mathbf{r} \times (\mathbf{UB}_i \cdot \mathbf{LB}_i)$, (\mathbf{LB}_i and \mathbf{UB}_i are the lower and upper bounds for each decision variable, respectively) end if

184 185

Fig. 3. Pseudo-code of the HS Algorithm

186 2.4.3. Developed Harmony Search (HS) algorithm

The HS is good at recognizing high-performance areas of the solution space in a sensible 187 amount of time but gets difficult to do a local search for numeral usages. To improve the exact 188 situation feature HS algorithm, IHS and GHS usage a new method that increases the precision 189 setting and the convergence rate of HS. The IHS usages a new method to generate new solution 190 vectors that increase the precision and convergence rate of the HS. Omran and Mahdavi (2008) 191 suggested a new variation of HS, called GHS. First, in GHS, a dynamically updating scheme 192 of parameter PAR usage in IHS (Mahdavi et al. 2007) is employed to improve the performance 193 of GHS. Second, GHS modifies the pitch adjustment step of HS to use the best harmonic 194 guidance information in harmony memory (HM). In the altered stage, GHS not only destroys 195 the parameter bandwidth (BW), which is difficult to set because it can take any values in the 196 range of $[0,\infty]$ but also introduces a social term of the best harmony with HS. These two 197 198 methods (IHS, GHS) have been developed to overcome the disadvantages of the original method. 199

200 2.5.Methodology

One of the most popular empirical sunshine-based models is the A-P model. This model has been used to estimate global solar radiation based on measured sunshine hours. The model is as follows: (Angstrom 1924; Prescott 1940):

204 •
$$R_s = R_a[a + b(\frac{n}{N})]$$
 (3)

Where R_s and R_a is daily global solar radiation and daily extraterrestrial solar radiation (MJ m⁻² day⁻¹), respectively, n is the mean daily number of sunshine duration (h), N is the maximum possible daily duration of sunshine hours (h) and 'a' and 'b' are empirical coefficients which must be calibrated based on long-term measured R_s data. R_a data for each day and location were gained from the estimation of geographical parameters including solar declination, solar constant, and the time of the year as shown in the method below (Allen et al. 1998):

•
$$R_a = 37.6 d_r [\omega_s \sin \Theta \sin \delta + \cos \Theta \cos \delta \sin \omega_s]$$
 (4)

Where d_r is the eccentricity correction factor of the Earth's orbit (equation (5)); ω_s is the sunshine hour angle of the sun at sunrise in radians (equation (6)), ϕ is the latitude of the station, and δ is the solar declination angle in radians equation(7):

$$\bullet \qquad d_{r} = 1 + 0.033 \cos \left(J_{s} \frac{360}{365} \right) \tag{5}$$

217 •
$$\omega_{\rm s} = \arccos\left(-\tan\Theta\tan\delta\right)$$
 (6)

$$\bullet \qquad \delta = 0.409 \sin\left(\frac{360}{365} J_s - 1.39\right) \tag{7}$$

The maximum possible average daily length of sunshine hour N can be calculated by Duffie-Beckman 1991 model:

$$221 \quad \bullet \quad N = \frac{2}{15} \omega_s \tag{8}$$

222

223

224 2.6.Performance indicators

The performance indicators discussed in this research were the coefficient of determination (R^2) , Mean Bias Error {MBE (MJ m⁻²day⁻¹)}, Root Mean Square Error {RMSE (MJ m⁻²day⁻¹)}. These indicators were calculated as follows:

228 •
$$\mathbf{R}^2 = \left[\frac{\sum_{i=1}^{m} (R_{estim} - \mu_{estim})(R_{meas} - \mu_{meas})}{\left[\sum_{i=1}^{m} (R_{estim} - \mu_{estim})^2\right]^{0.5} \left[\sum_{i=1}^{m} (R_{meas} - \mu_{meas})^2\right]^{0.5}}\right]^2$$
 (9)

•
$$\mathbf{RMSE} = \left[\frac{1}{M}\sum_{i=1}^{M} (\mathbf{R}_{estim} - \mathbf{R}_{meas})^2\right]^{1/2}$$
 (10)

$$\bullet \qquad \mathbf{MBE} = \frac{1}{M} \sum_{i=1}^{M} (\mathbf{R}_{\text{estim}} - \mathbf{R}_{\text{meas}}) \tag{11}$$

Where M is the total number of estimated values, Restim and Rmeas are, respectively, estimated 231 and measured daily global solar radiation values, μ_{estim} is the average of the daily estimated 232 values and μ_{meas} is the average of the daily measured values. The R² stands for the proportion 233 of variability in a data set that is calculated for by the model. The MBE, RMSE, and the R^2 234 statistical indices were used to evaluate the performance of applied optimization methods and 235 improved the A-P model for R_s estimating. The negative values of MBE represent the difference 236 237 between the estimated data and measured data. If the MBE value is positive, then the estimated values are overestimated and if the MBE value is negative, it means the underestimate of the 238 estimated values. Whatever the MBE value is closer to zero indicates the accuracy of the model 239 and the closeness of the amount of estimation data to the measured data. 240

241 **3. Results and discussion**

The calibrated coefficients for the A-P model and the models obtained with different optimization algorithms, the empirical coefficients (a, b, c, d) for four models, and the RMSE, R^2 , MBE values are shown in Table 3 and Table 4 respectively.

- 245
- 246
- 247

248 Table 3

		A-P	Model		Mod	el1		Mode	el2	Model3			
station	Algorithm	а	b	\mathbf{a}_1	\mathbf{b}_1	c	\mathbf{a}_2	\mathbf{b}_2	d	\mathbf{a}_3	b ₃	\mathbf{c}_1	dı
	SCE	0.38	0.35	0.39	0.31	-0.0015	0.38	0.35	0	0.4	0.35	-0.0019	0
Bandar Abbas	HS	0.38	0.36	0.36	0.35	0.0036	0.47	0.33	-0.0012	0.3	0.38	0.0078	0.0002
	IHS	0.39	0.33	0.39	0.36	-0.0046	0.32	0.37	0.0008	0.29	0.33	0.0058	0.0012
	GHS	0.36	0.37	0.35	0.39	-0.0006	0.39	0.35	-0.0002	0.47	0.20	-0.0016	-0.0003
	SCE	0.15	0.58	0.15	0.58	-0.0004	0.15	0.58	0	0.15	0.58	-0.0004	0
Esfahan	HS	0.13	0.60	0.18	0.60	-0.0076	0.20	0.54	-0.0007	0.1	0.54	0.0152	-0.0008
	IHS	0.16	0.56	0.12	0.64	-0.0021	0.16	0.54	0.0005	0.15	0.57	-0.0006	0.0003
	GHS	0.15	0.57	0.14	0.59	0	0.13	0.59	0	0.12	0.63	0	0
	SCE	0.27	0.51	0.27	0.51	-0.0013	0.28	0.49	-0.0003	0.29	0.50	-0.0019	-0.0003
Kerman	HS	0.28	0.47	0.21	0.44	0.0109	0.18	0.59	0.0015	0.34	0.57	-0.0058	-0.0022
	IHS	0.24	0.54	0.32	0.46	-0.0025	0.38	0.41	-0.0012	0.19	0.58	-0.0011	0.0006
	GHS	0.26	0.50	0.28	0.50	-0.0013	0.30	0.48	-0.0006	0.36	0.50	-0.0061	-0.0009
	SCE	0.22	0.62	0.22	0.62	-0.0001	0.23	0.61	0	0.23	0.61	-0.0007	-0.0001
Mashhad	HS	0.24	0.59	0.19	0.56	0.01	0.12	0.65	0.0014	0.23	0.58	0.0077	-0.0008
	IHS	0.23	0.61	0.26	0.63	-0.0074	0.29	0.58	-0.0008	0.30	0.61	-0.0016	-0.0013
	GHS	0.21	0.63	0.25	0.63	-0.0055	0.23	0.59	0	0.26	0.61	-0.0002	-0.0008
	SCE	0.25	0.53	0.24	0.53	0.0003	0.29	0.51	-0.0006	0.30	0.51	-0.0012	-0.0007
Shiraz	HS	0.26	0.50	0.11	0.51	0.0029	0.18	0.57	0.0009	0.40	0.52	-0.0064	-0.0023
	IHS	0.27	0.51	0.3	0.51	-0.0029	0.35	0.49	-0.0017	0.18	0.52	0.0107	-0.0002
	GHS	0.20	0.58	0.24	0.55	-0.0002	0.23	0.58	-0.0004	0.37	0.46	-0.0063	-0.0007
	SCE	0.18	0.53	0.19	0.53	0.0003	0.22	0.64	-0.0006	0.24	0.65	-0.0035	-0.0007
Vord	HS	0.20	0.64	0.31	0.62	-0.0117	0.16	0.69	0.0003	0.10	0.63	0.015	0
1 820	IHS	0.19	0.66	0.16	0.66	0.0034	0.21	0.68	-0.0016	0.28	0.52	0.0084	-0.0015
	GHS	0.18	0.67	0.17	0.69	-0.0021	0.26	0.60	-0.0007	0.35	0.58	-0.0075	-0.0015

249 The locally calibrated of the models coefficients for the selected stations using optimization algorithms

The statistics of the calibrated A-P coefficients in six meteorological stations (Table 3) showed that the coefficient 'a' had low values in Esfahan in the HS algorithm and high values in Bandar Abbas in the IHS algorithm. The coefficients 'a' and 'b' were predicted by four models and by four optimization algorithms. Adding T_{max} , T_{min} and RH_{mean} terms to the A-P model have had little effect on improving the radiation estimation used by the models. Zero or nearzero values of T_{max} , T_{min} , and RH_{mean} coefficients indicate this.

256

257

Table 4

259 Statistical comparison of calibration (Ca) and validation (Va) estimated \mathbf{R}_{s} (using the locally calibrated of

the models coefficients)

-				А	-P Mode	1	Model1			Model2			Model3		
	Station	Algorithm													
-			~	RMSE		MBE	RMSE	R ²	MBE	RMSE	R ²	MBE	RMSE	R ²	MBE
		SCE	Ca	1.13	0.841	0	1.41	0.841	-0.80	1.13	0.841	0.00	1.17	0.840	0.30
			Va C	1.60	0.835	-0.41	2.08	0.840	-1.25	1.60	0.835	-0.41	1.55	0.836	-0.11
	D 1	HS	Ca Va	1.10	0.835	0.21	1.10	0.835	-0.03	1.22	0.816	-0.01	1.25	0.823	-0.10
	Bandar Abbas		va Ca	1.55	0.830	-0.19	1.02	0.827	-0.45	1.09	0.807	-0.42	1.05	0.818	-0.52
	ADDas	IHS	Ua Va	1.15	0.832	-0.15	1.17	0.030	-0.25	1.10	0.835	0.15	1.20	0.821	0.00
			va Co	1.09	0.032	-0.55	1.00	0.030	-0.04	1.50	0.830	-0.20	1.70	0.805	-0.34
		GHS	Ua Va	1.10	0.041	-0.19	1.17	0.041	-0.10	1.14	0.835	-0.09	1.55	0.814	0.02
-			Ca	0.83	0.000	0.09	0.83	0.041	0.01	0.83	0.035	0.09	0.83	0.969	0.10
		SCE	Va	1.3	0.941	0.40	1.29	0.940	0.32	1.31	0.940	0.4	1.29	0.946	0.32
			Ca	0.84	0.962	-0.07	0.90	0.966	-0.19	0.96	0.964	-0.02	1.13	0.943	0.12
		HS	Va	1.26	0.940	0.24	1.29	0.937	0.14	1.40	0.935	0.26	1.53	0.923	0.36
	Esfahan		Ca	0.85	0.966	-0.04	0.92	0.970	0.04	0.93	0.967	0.06	0.85	0.968	0.07
		IHS	Va	1.3	0.940	0.27	1.32	0.940	0.36	1.40	0.937	0.37	1.33	0.945	0.38
			Ca	0.84	0.968	-0.12	0.83	0.970	0.01	0.87	0.970	-0.28	0.94	0.968	0.26
		GHS	Va	1.27	0.941	0.19	1.28	0.940	0.32	1.24	0.940	0.03	1.39	0.946	0.58
-		SCE	Ca	1.15	0.923	-0.82	1.15	0.924	0.01	1.15	0.924	-0.13	1.14	0.925	-0.10
			Va	1.56	0.909	-0.27	1.54	0.910	-0.30	1.58	0.910	-0.43	1.55	0.911	-0.41
		HS	Ca	1.39	0.908	-1.34	1.36	0.895	-0.17	1.74	0.891	1.01	1.71	0.904	-0.34
			Va	1.23	0.895	-1.62	1.85	0.866	-0.44	1.79	0.870	0.69	1.72	0.890	-0.56
	Kerman	IHS	Ca	1.22	0.908	-1.10	1.24	0.923	0.18	1.30	0.912	0.18	1.29	0.917	-0.21
			Va	1.26	0.923	-1.35	1.71	0.910	-0.17	1.74	0.897	-0.13	1.55	0.901	-0.50
		GHS	Ca	1.29	0.923	-1.32	1.15	0.924	0.10	1.16	0.923	-0.08	1.21	0.919	0.25
			Va	1.56	0.909	-1.59	1.55	0.910	-0.22	1.57	0.908	-0.38	1.50	0.907	-0.06
		SCE	Ca	0.82	0.981	0.07	0.82	0.981	0.05	0.84	0.981	0.18	0.82	0.981	-0.10
		HS	Va	1.24	0.961	0.07	1.24	0.960	0.08	1.26	0.961	0.17	1.25	0.961	-0.11
			Ca	0.86	0.980	0.12	1.03	0.971	0.12	1.05	0.970	-0.10	1.02	0.972	-0.06
	Mashhad		Va	1.31	0.960	0.10	1.43	0.951	0.09	1.45	0.948	-0.10	1.34	0.952	-0.08
	Masnnad	IHS	Ca	0.84	0.981	0.18	0.90	0.977	-0.05	0.88	0.979	0.14	1.03	0.976	-0.12
			Va	1.26	0.960	0.17	1.30	0.957	-0.05	1.27	0.959	0.12	1.30	0.957	-0.12
		GHS	Ca	0.83	0.981	-0.04	0.86	0.979	0.03	0.87	0.981	-0.15	0.92	0.979	-0.22
-			Va	1.22	0.961	-0.04	1.27	0.959	0.03	1.32	0.960	-0.17	1.25	0.959	-0.22
		SCE	Ca	1.30	0.923	0.05	1.31	0.921	-0.18	1.28	0.923	0.05	1.27	0.923	-0.04
			Va	2.61	0.913	-2.09	2.21	0.913	-1.5	1.91	0.915	-1.03	1.95	0.916	-1.12
		HS	Ca	1.35	0.922	-0.32	2.15	0.918	-3.9	1.39	0.908	-0.03	1.48	0.911	0
	Shiraz		Va	2.99	0.912	-2.50	5.38	0.909	-5.09	2.15	0.899	-1.27	1.82	0.904	-0.86
	Sintuz	IHS	Ca	1.32	0.922	0.20	1.40	0.917	0.45	1.35	0.917	0.02	1.38	0.913	-0.11
			Va	2.54	0.912	-1.97	1.90	0.912	-0.75	1.83	0.909	-0.91	2.04	0.900	-1.16
		GHS	Ca	1.38	0.923	-0.33	1.30	0.921	0.15	1.37	0.922	0.06	1.4	0.917	-0.21
-			Va	2.85	0.913	-2.41	1.90	0.913	-0.98	1.79	0.915	-0.96	2.28	0.913	-1.39
		SCE	Ca	2.67	0.921	-2.36	2.21	0.921	-2.65	1.51	0.924	0.04	1.50	0.925	0.02
			Va	2.39	0.916	-2.68	2.11	0.916	-2.33	1.72	0.919	0.48	1.71	0.920	0.51
		HS	Ca	2.03	0.920	-1.39	1.73	0.913	-0.30	1.58	0.919	0.15	1.69	0.904	-0.04
	Yazd		Va	1.75	0.913	0.36	1.99	0.910	0.81	1.78	0.918	0.55	1.86	0.897	0.20
	*	IHS	Ca	1.94	0.921	-1.25	1.55	0.920	-0.05	1.70	0.920	-0.24	1.73	0.905	0.16
			Va	1.76	0.914	0.52	1.72	0.914	0.32	1.75	0.915	0.30	1.99	0.899	0.50
		GHS	Ca	2.00	0.921	-1.32	1.56	0.922	-0.26	1.56	0.924	0.25	1.59	0.920	0.19
$\gamma c^{\frac{1}{1}}$	DMOT	7 (MI 2.1 -1)	Va	1.73	0.915	0.45	1.66	0.917	0.19	1.84	0.919	0.67	1.88	0.915	0.73
201	KINSE	z (ivij m ⁻day *),	NIDE	uvij in -day)										

262 3.1.Evaluation of solar radiation (R_s) estimation models

In the studied stations, the values of R^2 , RMSE, and MBE for the calibrated models showed 263 in Table 4. When tested using the R^2 value, the calibrated models were found to execute best in 264 Mashhad, followed by Esfahan, Shiraz, Yazd, Kerman, and Bandar Abbas. Due to the 265 inaccuracy in recording and a large number of discarded data in Bandar Abbas station, this 266 station did not have very good results compared to other stations. The RMSE performance 267 indicated that the calibrated models had the smallest error in Mashhad, followed by Esfahan, 268 Bandar Abbas, Kerman, Shiraz, and Yazd. The mean RMSE values for the three improved 269 models were lower than 1.3, which also indicated acceptable exactitude. The mean R² value of 270 the improved models was largest in Mashhad (0.977), followed by the values for Esfahan, 271 272 Shiraz, Yazd, Kerman, and Bandar Abbas. The performance of the improved models in the same climates showed very small variation. The RMSE statistic showed that all models were 273 more accurate in Esfahan, with an average value of 0.89 MJ m⁻² day⁻¹, followed by Bandar 274 Abbas, Mashhad, Shiraz, Kerman, and Yazd. The fact that all improve models validated by the 275 two statistical indicators performed well and that there was no significant difference between 276 the models in each station show that these two indicators could not be used alone to specify the 277 best model in each station. Therefore, the MBE statistic was used to determine the difference 278 between the estimated and measured data. Based on Performance indicators RMSE, MBE, 279 calibration of the A-P model improved the accuracy of estimated R_s in most of the studied 280 stations. If the value of R^2 and RMSE are closer to one and zero respectively, the model is more 281 appropriate. 282

283 3.2.Comparison of results with other researchers

Calibrated the coefficients of the A-P model by various researchers showed in Table 5. In this research, the coefficients 'a' and 'b' were calculated for the selected stations with different optimization algorithms (Table 3). Coefficient 'a' varies from 0.13 to 0.39, Also coefficient 'b'

varies from 0.33 to 0.67 for six stations.

288 **Table 5**

289 Comparison of calibrated coefficients of the A-P model in the present study with the results of other

290 researchers

Station		Bandar Abbas		Esfahan		Shiraz		Kerman		Mashhad		Yazd	
		a	b	a	b	а	b	а	b	а	b	a	b
Khalili and Rezai-e	Sadr (1997)			0.30	0.42	0.29	0.42	0.28	0.45	0.30	0.37	0.21	0.64
Javadi and Moeini (2010)		0.34	0.306	0.361	0.35	0.317	0.405	0.322	0.421	0.335	0.332	0.345	0.398
Sabziparvar et al (2013)				0.271	0.48	0.247	0.512	0.267	0.518	0.274	0.418	0.304	0.492
Didari and Ahmadi	i (2019)					0.31	0.48						
	SCE	0.38	0.35	0.15	0.58	0.25	0.53	0.27	0.51	0.22	0.62	0.18	0.53
Dregent study	HS	0.38	0.36	0.13	0.60	0.26	0.50	0.28	0.47	0.24	0.59	0.20	0.64
Present study	IHS	0.39	0.33	0.16	0.56	0.27	0.51	0.24	0.54	0.23	0.61	0.19	0.66
	GHS	0.36	0.37	0.15	0.57	0.20	0.58	0.26	0.50	0.21	0.63	0.18	0.67

In comparison with previous researches, some differences were observed between the results 291 of this research and other works. For example, Javadi and Moeini (2010), Sabziparvar et al. 292 293 (2013), and Khalili and Rezai-e Sadr (1997) applied the A-P model for Shiraz and reported the following pairs of 'a' and 'b', 0.317, 0.405; 0.247, 0.512; 0.29, 0.42, respectively. Whiles in 294 295 the present research values of 'a' and 'b' coefficients were obtained as 0.25 and 0.53 with the 296 SCE optimization algorithm for the same station; that is in good agreement with the coefficients of Sabziparvar et al. In this research, the A-P coefficients 'a' and 'b' with the SCE optimization 297 algorithm were obtained 0.22 and 0.62 for Mashhad, but Khalili and Rezai-e Sadr (1997), Javadi 298 and Moeini (2010) and Sabziparvar et al. (2013) reported, 0.30, 0.37; 0.335, 0.332 and 299 0.274,0.418 for the same station, respectively. Javadi and Moeini (2010), Sabziparvar et al. 300 (2013), and Khalili and Rezai-e Sadr (1997) suggested the application of the A-P model for the 301 Esfahan station with the following pairs of coefficients 'a' and 'b': 0.361, 0.35; 0.271, 0.482; and 302 0.30, 0.42; but this research suggests values of 0.15 and 0.58 for 'a' and 'b' with the SCE 303 304 optimization algorithm, respectively (Table 3). The inconsistency of the results can be explained by a longer period of estimated R_s, which were applied in this research. Based on Liu 305 et al. (2009), sample size and the length of the observation period could illustrate such 306

307 differences in different researches. Also, the rules for quality control of the R_s dataset and the 308 higher restrictions for removing unreliable R_s data might somewhat cause such discrepancies 309 (Table 5).

The values of measured and estimated global solar radiation by the A-P model from 1992 to 2017 are compared as shown in Fig. 4. To appraise the prediction accuracy of R_s , computed from the regional best performing estimated data and the measured data, specific values of the A-P model statistics by different optimization algorithms (HS, IHS, GHS, and SCE) in the Kerman station were compared. Also, the R^2 values of both the measured data and the estimated data in this station were very close to the 1:1 line, which means that the R_s determined from the estimated data and measured data were in good accordance.

317 According to Table 4 and Fig. 4, the calibration and validation performance of the A-P model was better than three improved models in all stations. As shown in Table 4, the RMSE varies 318 between 0.82 and 2.67 MJ m⁻²day⁻¹ for the A-P model with the SCE algorithm in the calibration 319 phase. Besides, other indicators were lower in the case of the A-P models in the SCE algorithm. 320 Based on the results in Tables 4 and Table 5, the decrease rate of RMSE values in various 321 stations for four optimization algorithms was different. For example, in the SCE algorithm, the 322 value of RMSE decreased by about 4% and 7% for Mashhad and Kerman stations in the 323 calibration phase contrasted to the HS algorithm, respectively. In other words, the highest 324 decrease of RMSE is related to Kerman station. The lowest value of R² was observed in Bandar 325 Abbas station ($R^2 = 0.81$). Further, according to MBE values, a decrease occurred in the MBE 326 of all stations in the SCE algorithm contrasted to three algorithms (IHS, GHS, and Hs), in the 327 A-P and three improved models. 328



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The values of 'a' and 'b' in the harmonic memory sizes (HMS) (5, 10, 20, 30, and 40) in six meteorological stations are shown in Fig. 6. This Figure show that as the initial population increases, the values of the coefficients become convergent and a smaller range for the coefficients is obtained in different stations. For example, in Kerman station, with increasing HMS, the minimum and maximum coefficient 'a', changes from 0.18 to 0.35 and from 0.39 to 0.36, respectively. The maximum and minimum values of 'a' are close to each other, and this is true for coefficient 'b'.

363 4. Conclusion

The results of the based on daily R_s and meteorological data from six stations in Iran from 1992–2017, the performance of the calibrated A-P model, and three improved models for the A-P coefficients were evaluated, and the best performing those for each station were obtained. For practical usages, the use of a calibrated form of the A-P model seems necessary for Iran climatic situations.

The effect of T and RH was applied to the A-P model and the coefficients of these models were calibrated by optimization methods. The results showed that adding T_{max} , T_{min} , and RH_{mean} did not have much effect on the A-P model. Also, the SCE optimization algorithm method has shown better results than other optimization methods.

Considering the sunshine, which is an important factor for estimating R_s , and accepting that Iran is a country in which sunshine is significant, the Angstrom empirical model can well estimate total radiation. In this research, the coefficients 'a' and 'b' were calibrated. Coefficient 'a' varies from 0.1 to 0.47 and coefficient 'b' varies from 0.2 to 0.69 for studied stations.

In this research, three R_s estimation models were appraised and calibrated. The results indicate that, among the improved models, the A-P model ($R^2 = 0.981$ in Mashhad station) offers the best R_s estimations in the semi-arid and arid climate, as compared to the measured R_s .

380

381 5. Reference

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608The performance of the A-P model had more precision and less error than improved models in all the stations in609this research

610 The best performance of the A-P model was obtained with the Shuffled Complex Evolution (SCE) algorithm.

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Sunshine was the main factor determining the solar radiation