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Forecasting daily global solar radiation in hot semi-arid climate using a novel hybrid machine learning paradigm

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Abstract

Solar energy is one of the most important renewable energy sources. Assessing the solar potential of area needs analyzed information about the dataset of the measured global solar radiation (GSR). Recently, researches detected the high potential of state-of-the-art artificial intelligence (AI) methods in estimating the GSR successfully. In this study, a novel hybrid AI-based tool consisting of least square support vector machine (LSSVM) integrated with improved simulated annealing (ISA) is proposed to predict the GSR over the Ahvaz synoptic station located in the South-West of Iran. The potential of the proposed hybrid paradigm so-called LSSVM-ISA was evaluated by using multivariate adaptive regression spline (MARS), generalization regression neural network (GRNN), and multivariate linear regression with

interactions (MLRI). For precise assessment of efficiency of the AI models, various statistical metrics and validation methods were used to assess the precision of the developed models. A comparison of the obtained results indicated that the LSSVM-ISA method performed better than the MARS, GRNN, and MLRI models. The achieved RMSE values of the MARS, GRNN, and MLRI models were decreased by 9%, 16%, and 30% using the LSSVM-ISA model. Finally, the results demonstrated that the LSSVM-ISA model could be successfully employed for accurately predicting GSR.

Keywords: Global Solar Radiation, Sunshine hours, LSSVM-ISA, MARS, GRNN, MLRI.

1. Introduction

Solar energy is the electromagnetic energy emitted from the sun. Solar radiation is referred to as global solar radiation (GSR) that is the total of direct shortwave radiation received from the sun and diffuse sky radiation that has been scattered across the atmosphere (WMO 2014). The GSR data are essential for several theoretical and practical applications such as solar energy systems, architecture, agriculture, meteorological, and climatological models (Moradi 2009). Pyranometers use thermoelectric, photoelectric, pyroelectric, or bimetallic elements as sensors to measure the global solar irradiance (Radiant flux density/m²) at the meteorological stations (WMO 2014). However, the GSR measurements are limited and only available at a few meteorological stations, due to the high cost of solar measuring instruments, the accurate equipment calibration, installation, and maintenance requirements. Besides, the missing GSR data, incorrect data, measurements in a short and discontinuous period are other problems at many stations (Rahimikhoob 2010, Samadianfard et al. 2019).

Therefore, these problems have resulted in the recommendations for alternative techniques to determine the GSR accurately, including the utilize of empirical, deterministic,

and artificial intelligence (AI) methods (Kisi et al. 2019, Mohammadi et al. 2016). Recently, AI methods have been broadly applied to predicting the GSR. (Behrang et al. 2010) assessed the ability of ANN and radial basis function (RBF) methods for estimation of daily GSR in the station in Dezful at the southern West of Iran. They used various combinations of meteorological variables as the input dataset. Their results demonstrated that more precision could be obtained by using five variables of average air temperature, sunshine hours, relative humidity, wind speed, and day of the year as the input dataset. (Mostafavi et al. 2013) introduced a hybrid model by using the GP and simulated annealing (SA) model for predicting the GSR in Iran. They showed that maximum and minimum air temperatures are more effective input parameters to predict the GSR.

(Kisi 2014) introduced the fuzzy genetic (FG) model to predict the SR in Turkey. The proposed model generated good results during the testing stage and provided better performance compared with the MLP and ANFIS models. Hatice Citakoglu (2015) employed the adaptive neuro-fuzzy inference system (ANFIS), artificial neural network (ANN), multiple linear regression (MLR), and four empirical equations for prediction of the solar radiation (SR) in Turkey (Citakoglu 2015). The author showed that the ANN method has a better performance to predict the SR than the other empirical equations. Shamshirband et al. (2016) proposed to utilize the extreme learning machine (ELM), support vector machine (SVM), genetic programming (GP), and ANN methods to estimate monthly GSR in Iran (Shamshirband et al. 2016). The authors indicated that the ELM method could outperform the ANN, GP, and SVR models. (Belaid & Mellit 2016) used an SVM for the estimation of daily and monthly GSR in Ghardaïa (Algeria). They compared the proposed SVM model with multiple layer perceptron (MLP) and indicated that the proposed model had good accuracy. (Ibrahim & Khatib 2017) introduced a hybrid model for predicting the hourly GSR utilizing the random forest (RF) and firefly algorithm (FA).

In another research, Fan et al. (2018) compared extreme gradient boosting (XGB) and support vector regression (SVR) methods with the empirical models for estimating daily GSR. Based on the obtained results, the XGB and SVR were more precise than the empirical models (Fan et al. 2018). Li et al. (2019) developed the MARS model for estimating the hourly SR and compared it with ANN and logistic regression (LR) models (Li et al. 2019). The results demonstrated that the MARS method could provide more promising results compared with the ANN and LR methods. Kisi et al. (2019) developed a dynamic ANFIS model for modeling the SR and compared it with multivariate adaptive regression spline (MARS), M5 model tree, and least square support vector regression (LSSVM) (Kisi et al. 2019). The results showed that the proposed method could enhance the SR prediction ability over the MARS, M5 model tree, and LSSVR models. Gürel et al. (2020) compared the ability of the ANN method with empirical models, time series (holt-winters (HW)), and response surface methodology (RSM) for modeling the GSR in Turkey (Gürel et al. 2020). Regarding the results, the ANN presented the best results in comparison with the other peers. Fan et al. (2020) proposed three hybrid SVM with bat algorithm (SVM-BAT), particle swarm optimization (SVM-PSO), and whale optimization algorithm (SVM-WOA) for the prediction of daily diffuse solar radiation (Fan et al. 2020). These methods were compared with the SVM, MARS, and XGB methods. Their results indicated that the SVM-BAT could further enhance the prediction precision in diffused solar radiation when compared to the SVM, SVM-PSO, SVM-WOA, and EGB models. Alizamir et al. (2020) evaluated the potential of six machine learning methods, MLP, gradient boosting tree (GBT), MARS, classification and regression tree (CART), and ANFIS based on fuzzy c-means clustering (ANFIS-FCM) and subtractive clustering (ANFIS-SC) to forecast the SR from two stations in Turkey and USA (Alizamir et al. 2020). The results indicated that the GBT method provided better accuracy in modeling the SR than the MLP, MARS, ANFIS, and CART models.

Regarding the above literature on predicting the GSR using the AI methods, the motivation for exploring more accurate and reliable AI methods is still a challenging task. Among different AI methods, the LSSVM methods are one of the robust and reliable AI methods that has a promising predictive ability. Generally, AI models, especially the LSSVM model, are susceptible to their setting parameters that incorrect selection of these parameters yields to an optimal local solution. To address this, combining AI models with meta-heuristic algorithms can be a suitable approach to succeed. Hence, this paper introduces a new hybrid of the LSSVM with an improved version of the SA (ISA) method to optimize the control parameters of the LSSVM. For evaluation purposes, the LSSVM-ISA model was compared with several AI models on the GSR modeling, including generalization regression neural network (GRNN), multivariate linear regression with interactions (MLRI), MARS, and empirical equations.

The rest of this study is described as follows. Section 2 expresses the materials and methods, including empirical models, the dataset used in this paper, the procedure for data quality control, the introduction of the hybrid SA and the LSSVM model. It also provides a summary of other AI models employed in this study (i.e., MARS, GRNN, and MLRI). The results are discussed in Section 3. Validation of the proposed model with traditional approaches is presented in Section 4. Uncertainty analysis is implemented in Section 5. Finally, the study conclusions are expressed in Section 6.

2. Materials and methods

2.1. Empirical models to estimate global solar radiation

Numerous empirical models have been developed to estimate the GSR based on meteorological variables such as minimum daily temperature, maximum daily temperature, monthly temperature, sunshine hour, extraterrestrial radiation, relative humidity, albedo, precipitation, cloudiness, and evaporation. (Liu et al. 2009, Menges et al. 2006). The

important empirical models and their equations forms are illustrated in Table 1. Some of these models were modified to solve the problem of the availability of meteorological data by researchers.

2.2. Study area and data processing

The current study focuses on global solar radiation assessment at Ahvaz city. The meteorological data collected from Ahvaz synoptic station, belong to the IR of Iran Meteorological Organization (IRIMO), over historical data of 10 years (1 July 2009-1 July 2019). Ahwaz station is located in the Khuzestan province in the southwest of Iran with Latitude 31 20 N, Longitude 48 40 E, and elevation 22.5 m (Fig. 1). Ahwaz has a hot semi-arid climate with hot and long summers and moderate and short winters. The annual mean, maximum, and minimum air temperature of this region are 26.3, 33.4, 19.2 °C, respectively. The annual mean precipitation is 202 mm, and the annual mean relative humidity is 43.3 % (IRIMO). The collected meteorological data were including the average daily temperature (T_{ave} , °C), sunshine hours (S_h , hr), relative humidity (R_h , %), average wind velocity (W_s , m/s) at 10 m and day of the year in the range of [1 366]. These data were used as input values to estimate the predictive daily global solar radiation (GSR, Kw-h/m²/day) of the AI-based models. The predictor time series and observed values of GSR were shown in 10 years (3653 days) in Fig.2. Moreover, Table 2 summarized the descriptive statistics of the input time series for ten years.

Table 1. The most cited empirical models for predicting global solar radiation

Model	Equation	Empirical coefficient (Parameter)	Source
Angstrom and Prescott	$R_s = (a + b \left(\frac{n}{N}\right)) R_a$	a, b	(Prescott 1940)
Swartman and Ogunlade	$R_s = a + b \left(\frac{n}{N}\right) + c \cdot RH$	a, b, c	(Swartman &Ogunlade 1967)
Hargreaves	$R_s = a \sqrt{(T_{max} - T_{min})} \cdot R_a$	a	(Hargreaves 1981)
Bristow and Campbell	$R_s = a(1 - \exp(-b(T_{max} - T_{min})^c)) R_a$	a, b, c	(Bristow &Campbell 1984)
De Jong and Stewart	$R_s = a (T_{max} - T_{min})^b \cdot (1 + c P + d P^2) R_a$		(Jong &Stewart 1993)
Allen	$R_s = a (\sqrt{T_{max} - T_{min}}) R_a$		(Allen 1997)
Donatelli and Campbell	$R_s = a (1 - \exp\left(-b \cdot \frac{(T_{max} - T_{min})^c}{(T_{month})}\right)) R_a$	a, b, c	(Donatelli &Campbell 1998)
Hunt	$R_s = a \sqrt{(T_{max} - T_{min})} \cdot R_a + b$	a, b	(Hunt et al. 1998)
Hunt	$R_s = a \sqrt{(T_{max} - T_{min})} \cdot R_a + b T_{max} + c P + d P^2 + e$	a, b, c, d, e	(Hunt et al. 1998)
Goodin, Hutchin son, anderlip and Knapp	$R_s = a (1 - \exp\left(-b \cdot \frac{(T_{max} - T_{min})^c}{(R_a)}\right)) R_a$	a, b, c	(Goodin et al. 1999)
Elagib and Mansell	$R_s = a (\exp\left(b \cdot \left(\frac{n}{N}\right)\right)) R_a$	a, b, c	(Elagib &Mansell 2000)
Chen, Ersi, Yang, Lu and Zhao	$R_s = (a \ln (T_{max} - T_{min}) + b \cdot \left(\frac{n}{N}\right)^c + d) R_a$	a, b, d	(Chen et al. 2004)

where R_s , global solar radiation (MJ /m²/day); R_a , extraterrestrial radiation (MJ /m²/day); n , the actual duration of sunshine (hr); N , maximum possible duration of sunshine or daylight hours (hr); n/N , relative sunshine duration; T_{min} , minimum daily air temperature (°C); T_{max} , maximum daily air temperature (°C); T_{Month} , mean air temperature of the month (°C); RH , the relative humidity (%); P , daily precipitation (mm).

The histogram of the frequency related to all the time series variables and the probability density function of the normal distribution are illustrated in Fig.3. According to the Fig.3 and Table 1, the mean daily sunshine hours and average daily temperature dataset have the highest skewness and kurtosis, respectively. However, corresponding to (George 2011), the skewness and kurtosis values for the range of $[-1.96 +1.96]$ are acceptable to prove normal univariate distribution. Also, a visual correlation matrix between the predictor variables (Day, S_h , T_{ave} , W_s , and R_h) and the target variable (GSR) for Ahwaz synoptic station was indicated to survey the degree of influence of predictive parameters on GSR in Fig.4.

Fig.1. Study area: location of Ahvaz synoptic station.

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According to each provided scatterplot and Pearson correlation coefficient (Chen et al. 2014), it seems the average daily temperature (T_{ave}), relative humidity (R_h). Daily sunshine hours (S_h) due to having the highest Pearson correlation ($r_p=0.79$, -0.78 , and 0.77 , respectively) with the target are a more significant element in GSR forecasting whereas the day and mean wind velocity (W_s) by yielding the lowest magnitude of the correlation ($r_p=-$

0.06 and 0.24, respectively) play a weaker role in daily GSR forecasting process. However, a certain degree of the above analysis depends on the amount of nonlinearity dependence of the predictive variables with the objective parameter.

There is one ‘thumb of rule’ for data partitioning, and the researcher utilized different divisions between training and testing datasets, which has influenced the results of problems (Deo et al. 2016). In this research, the daily time-series from 01-July-2009 to 1- July -2019 were split into 80% (01-July-2009 to 1- July -2017) for the training dataset and 20% (02-July- 2017 to 1- July -2019) as the test set. Furthermore, all the datasets were normalized between zero and 1 range based on equation 1:

$$x_{nor} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where x is the original variable value, x_{nor} is the normalized value, and x_{max} and x_{min} are the maximum and minimum of the variable (x), respectively.

2.3. The methodology of Predictive models

2.3.1. Improved simulated annealing

(Kirkpatrick et al. 1983) introduced the simulated annealing (SA) as a single-based optimizer. The annealing process inspired this algorithm in metallurgy. SA has two main phases: heating and cooling. The proposed method employs a temperature factor (t) to transition from the heating to the cooling. Although the SA is a powerful optimizer, it may be stuck in the local solutions, because it is susceptible to the initial solutions (Ji et al. 2006). To alleviate this shortcoming, an improved version of the SA algorithm is used, which is called the ISA in this study. The proposed algorithm can be defined in the following stages:

Stage 1: Initialization: Produce an initial random solution (S_0). Specify the minimum and maximum temperature (t_{min} and t_{max}), and the total number of iterations ($MaxIt$). Set $t =$

199 t_{max} and $S_{best} = S_0$ (where x_{best} is the best-so-far solutions). The objective function of x_{best}
 200 is Z^* ($Z^* = Z(S_{best})$).

201 **Stage 2: Main loop:** In this step, the local search of the SA is defined. Also, two adaptive
 202 parameters ρ and T are formulated. The parameter ρ is a scale factor and sets how the
 203 position of solutions changes. The t parameter is updated in each iteration and is a
 204 termination condition for determining the end of a local search operation.

205 **While** $t > t_{min}$

206 **for** $it = 1$ to $MaxIt$

207 1. Produce the new solution $u_{it,i}$:

$$u_{it,i} = S_{it,i} + \mu \times (S_{max,i} - S_{min,i}) \times randn \quad (2)$$

Table 2. Descriptive statistics of meteorological variables and global solar radiation data for the
 Ahvaz stations located in Iran.

Variables	Day	S_h (h)	T_{ave} (°C)	W_s (m/s)	R_h (%)	GSR(Kw-h/m ² /day)
Minimum	1	0	3.64	0.85	4.96	0.21
Maximum	366	13	44.55	11.82	88.97	8.49
Range	365	13	40.91	10.97	84.01	8.28
Mean	183.1	8.602	26.79	3.594	30.03	5.397
Std. Deviation	105.4	3.442	10.25	1.351	19.41	1.918
Skewness	2.109E-05	-1.194	-0.1415	0.890	0.743	-0.404
Kurtosis	-1.2	0.434	-1.337	1.124	-0.5069	-0.889
Correlation with GSR	-0.064	0.772	0.786	0.236	-0.784	1.000

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Fig.2. The measured predictive and output variable over 10 years (1 July 2009-1 July 2019) at Ahvaz synoptic station.

Fig.3. The histogram of the frequency and probability density function of the predictive and objective variable

Fig.4. The correlation matrix of the implemented variables

where i is a randomly chosen integer value from $[1, D]$. S_{min} and S_{max} are the lower and upper bounds of the problem. $randn$ is a random normal distribution number and the (average = 0) and (standard deviation = 1). μ is an adaptive factor which decreased by the equation $\mu = \mu_0 \times \exp(-a)$. Based on (Ji et al. 2006), $a = 1.01$ and the initial value of μ_0 is 1.

(b) Check constraints on the solution $u_{it,i}$:

$$u_{it,i} = \begin{cases} S_{min} + (u_{it,i} - S_{max}) & \text{if } u_{it,i} > S_{max} \\ S_{max} + (S_{min} - u_{it,i}) & \text{if } u_{it,i} < S_{min} \\ u_{it,i} & \text{if } S_{min} \leq u_{it,i} \leq S_{max} \end{cases} \quad (3)$$

2. Determine the $\Delta Z^* = Z(u_{it,i}) - Z^*$ and $\Delta Z = Z(u_{it,i}) - Z(S_{it,i})$.

3. If $\Delta Z^* \leq 0$ set $S_{best} = u_{it,i}$, $Z^* = Z(S_{best})$.

4. If $\Delta Z \leq 0$ set $S_{it+1} = u_{it,i}$.

5. If $\Delta Z > 0$ update the S_i with the solution u with probability $\exp(-\frac{\Delta Z}{T})$.

end for

Decrease the T utilizing the following equation,

$$t = \beta \times t_{max} \quad (4)$$

end

Stage 3: Presentation of the best solution S_{best} .

It is noteworthy that in Eq. (4), β is a constant number in the range of (0.5, 1). The flowchart of the ISA algorithm is displayed in Fig. 5.

Fig. 5. Flowchart of the ISA algorithm

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232 2.3.2 Least square support vector machine (LSSVM)

233 The LSSVM is a different version of the support vector machine (SVM), which was
 234 presented by (Suykens & Vandewalle 1999). The LSSVM employs a set of linear equations to
 235 increase its convergence speed, while the SVM uses a quadratic programming technique for
 236 training (Han et al. 2019). The simple structure and high speed of LSSVM convergence make
 237 it widely used in regression and classification fields (Han et al. 2019, Zhu et al. 2019). In this
 238 model, the training dataset is described by (x_m, y_m) , $m = 1, 2, \dots, M$, where x_n and y_m are

$$\text{Minimize}_{\omega, \eta} Z(\omega, \eta) = \frac{1}{2} \omega^T \omega + \frac{1}{2} \gamma \sum_{n=1}^M \eta_n^2 \quad (5)$$

239 the input and output dataset. The main formulation of the LSSVM are expressed as:

240 *Subject to:*

$$y_m = \omega^T \phi(x_m) + c + \eta_m, \quad m = 1, 2, \dots, M \quad (6)$$

241 where ω^T is the vector of the transposed output layer, γ is a penalty parameter, η is a
 242 regression error, $\phi(x_m)$ is a nonlinear function, c is a bias parameter to be estimated. Using
 243 the Lagrange method, the Eqs. (5) and (6) can be defined as,

$$L(\omega, c, \eta, \alpha) = Z(\omega, \eta) - \sum_{m=1}^M \alpha_m (\omega^T \phi(x_m) + c + \eta_m - y_m) \quad (7)$$

244 where α_m is Lagrange multiplier. Based on the Karush-Kuhn-Tucker (KKT) conditions, the
 245 following solutions are achieved:

$$\frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{m=1}^M \alpha_m \phi(x_m) \quad (8)$$

$$\frac{\partial L}{\partial c} = 0 \rightarrow \sum_{m=1}^M \alpha_m = 0 \quad (9)$$

$$\frac{\partial L}{\partial \eta_m} = 0 \rightarrow \alpha_m = \gamma \eta_m \quad (10)$$

$$\frac{\partial L}{\partial \alpha_m} = 0 \rightarrow \omega^T \phi(x_m) + c + \eta_m - y_m = 0 \quad (11)$$

246 By eliminating ω and η_m the following linear equations can be obtained,

$$247 \begin{bmatrix} 0 & e_m^T \\ e_m & Kernel + \gamma^{-1}e \end{bmatrix} \begin{bmatrix} c \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \quad (12)$$

248 where $e_m = [1, \dots, 1]^T$, $\alpha = [\alpha_1, \dots, \alpha_m]^T$, $y = [y_1, \dots, y_m]^T$, and e is the unit matrix. *Kernel*
 249 is the kernel functions, which is expressed as,

$$250 K(x_m, x_i) = \phi(x_m)\phi(x_i) \quad (13)$$

251 Radial basis functions (RBF) are used as the kernel function in this research, which is defined
 252 as:

$$K(x_m, x_i) = \exp\left(\frac{-||x_m, x_i||}{\delta^2}\right) \quad (14)$$

where δ is a constant parameter, which is determined by the ISA algorithm.

In this paper, the ISA algorithm was employed for the optimization of the LSSVM parameters (i.e., δ and γ). The proposed method is called LSSVM-ISA. Fig. 6 demonstrates the flowchart of the LSSVM-ISA algorithm.

Fig. 6. Flowchart of the LSSVM-ISA method

2.3.3. Multivariate adaptive regression spline (MARS)

Multivariate adaptive regression spline (MARS) scheme, as a nonlinear and nonparametric statistical regression model, is one of the most popular machine learning models, which was first introduced by Friedman (1991) (Friedman 1991). The MARS model

automatically is capable of mapping the intrinsic nonlinearities and interactions between predictors in data without an assumption about the relationships between dependent and predictor variables to predict continuous objective variables accurately (Leathwick et al. 2005). The main concept of MARS is splitting the predictor training data into several piecewise linear disjoint regions (or splines) by specific connection points (called 'knots'). Generally, the MARS model can adequately result in the flexible continuous modeling by fitting piecewise linear regression belong to each segment (spline) and predicting the linear and nonlinear objective (Friedman 1991, Friedman &Roosen 1995). Splines, which are known as the basis functions (BFs) by the smoothing process connection point, are capable of capturing the nonlinearities, curvatures, and threshold features based on the piecewise linear functions. MARS model involves two-step forward and backward pruning iterative procedures. During the stepwise forward process, the BFs were selected, and the location of potential knots was explored by an adaptive regression algorithm, which mostly leads to a very complex and over-fitted model (Zhang &Goh 2016, Zheng et al. 2020). Mathematically, the MARS model can explain the relationship between predictors and output variable as follows:

$$Y = f(x) = \beta_0 + \sum_{i=1}^{N^*} \beta_i \prod_{j=1}^K B_{F_{ji}}(x_{v(ji)}) \quad (15)$$

where Y is objective variable; β_0 is the intercept term; β_n is the coefficient vector of i^{th} spline basis functions; $B_{F_{ji}}$ is basis function; $x_{v(ji)}$ is the independent predictor of i^{th} and j^{th} products; K is the order of interaction limit, and N^* is the number of independent predictors. The piecewise linear basis functions implemented in the MARS model are generally expressed as (Mohanta &Patra 2019):

$$B_{F_{ji}}^+ = (x - s_{ji})_+ = \begin{cases} x - s_{ji} & x > s_{ji} \\ 0 & \text{therwise} \end{cases} \quad (16)$$

$$B_{Fji}^- = (s_{ji} - x)_+ = \begin{cases} s_{ji} - x & x < s_{ji} \\ 0 & \text{otherwise} \end{cases} \quad (17)$$

where B_{Fji}^+ and B_{Fji}^- are the positive and negative parts of spline functions, respectively, and s_{ji} denotes the knot of the spline (threshold value).

Likewise, in the backward stepwise process, the redundant BFs provided among the previous process were eliminated by implementing the generalized cross-validation (GCV) technique until the ‘lack of fit’ criterion is a minimum and forecasting accuracy enhancement (Wang et al. 2020). The GCV value is given as follows (Mohanta & Patra 2019, Zheng et al. 2020):

$$GCVE = \frac{\sum_{j=1}^N (Y_i - \hat{Y}_i)^2}{N(1 - \frac{F + 0.5d^*(F-1)}{N})^2} \quad (18)$$

where Y_i is the observed value of output variable of i^{th} ; $\hat{Y}_i$ is i^{th} predicted value by MARS; N = number of datasets; F is the number of basis functions and d^* is a penalty value for each basis function comprised into the developed model.

2.3.4. Generalization regression neural network (GRNN)

Generalized regression neural network (GRNN), as a probabilistic-based neural network, was firstly proposed by Specht (1991) (Specht 1991). GRNN model based on the nonparametric kernel regression network has been widely implemented in the field of classification and regression. It is adequately capable of handling the nonlinear fitting problems with large-scale training samples. Unlike the backpropagation and radial basis function ANN, GRNN has fewer adjustment parameters, and its learning algorithm rarely falls into the local minimum (Yu 2020). GRNN has four-layer comprising the input layer, radial layer, regression layer, and an output layer. The architecture of a GRNN model consists of precisely four layers, with a pattern (radial neurons) layer and a summation

(regression) layer placed between the input and output layers (Ramsami &Oree 2015), as it has been illustrated in Fig. 7. The pattern layer contains the clustering of the input data in the training stage, and consequently, the neurons number in that is exactly equal to the number of data samples. Furthermore, the summation layer always has a new neuron in comparison with the output layer, which is devoted to calculating the probability density function whereas rests of neurons are used for output calculation. Eventually, GRNN du to directly selecting an approximate function between predictors and output variables spends less time than other ANNs (Ramsami &Oree 2015).

2.3.5. Multivariate linear regression with interactions (MLRI)

The multivariate linear regression with interactions (MLRIs) is an efficient data-driven model that can obtain a regression by considering the interaction between the predictors (x_i) on the independent variable (outcome) (Coulton &Chow 1993, Jaccard et al. 2003). An interaction effect happens when a predictor has a different impact on the dependent output variable, depending on the values of another predictor. MLRI can capture the regression relationship considering some interactions between a dependent variable (Y) and independent variables (x_i) by the following logic (Coulton &Chow 1993, Jaccard et al. 2003):

$$Y = \theta_{i0} + \sum_{i=1}^K \theta_i x_i + \sum_{i=1}^K \sum_{j=1, j \neq i}^K \theta_{ij} x_i x_j + \varepsilon \quad (19)$$

where θ_{ij} is the interaction coefficient; ε is a random error; and i, j are the index of two considering predictors.

In the framework of the MLRI model, the significance of the interaction effect specifies using analysis of variance (ANOVA). In this process, the p-value or probability value indicates the importance of each integration term in regression by $\alpha = 0.05$, as a criterion, which lower values of p -values or its corresponding F -values show it is the more

statistically significant. Whenever the p -values of each interaction term become less than α , that interaction term will be preserved in outcome correlation (Y) and vice versa.

Figure 7 illustrated the flowchart of the proposed procedure and a brief algorithm of each data-driven approaches used in the daily GSR forecasting process is shown in Fig.7

2.4. Performance evaluation

To measure the degree of accuracy of the provided models, various visual efficient tools and statistical performance metrics were employed. The graphical tools include scattering plots, error analysis plots, and Taylor diagrams. Taylor diagram is employed for comparing the similarity patterns in polar space between predicted and observed values of GSR as the robust graphical tool. Basically, the Taylor diagram simultaneously demonstrates the correlation coefficient (R), standard deviation (S_d), and centered root mean square error (cRMSE) (Taylor 2001). The performance criteria consist of the correlation coefficient (R), mean root square error (RMSE), mean absolute percentage error (MAPE), and Nash–Sutcliffe coefficient (NS) (Nash & Sutcliffe 1970) which are expressed as following relationships:

$$R = \frac{\sum_{i=1}^N (GSR_{p,i} - \overline{GSR_p}) \cdot (GSR_{o,i} - \overline{GSR_o})}{\sqrt{\sum_{i=1}^N (GSR_{p,i} - \overline{GSR_p})^2 \sum_{i=1}^N (GSR_{o,i} - \overline{GSR_o})^2}} \quad (20)$$

$$RMSE = \left(\frac{1}{N} \sum_{i=1}^N (GSR_{o,i} - GSR_{p,i})^2 \right)^{0.5} \quad (21)$$

$$MAPE = \left(\frac{100}{N} \right) \sum_{i=1}^N \left| \frac{GSR_{o,i} - GSR_{p,i}}{GSR_{o,i}} \right| \quad (22)$$

$$NS = 1 - \frac{\sum_{i=1}^N (GSR_{o,i} - GSR_{p,i})^2}{\sum_{i=1}^N (GSR_{o,i} - \overline{GSR_o})^2} \quad (23)$$

$$cRMSE = \left(\frac{1}{N} \sum_{i=1}^N \left[(GSR_{o,i} - \overline{GSR_o}) - (GSR_{p,i} - \overline{GSR_p}) \right]^2 \right)^{0.5} \quad (24)$$

$$S_{do} = \frac{1}{N} \sum_{i=1}^N (GSR_{o,i} - \overline{GSR_o})^2, \quad S_{dp} = \frac{1}{N} \sum_{i=1}^N (GSR_{p,i} - \overline{GSR_p})^2 \quad (25)$$

where $GSR_{o,i}$ is the i^{th} observed daily global solar radiation, $GSR_{p,i}$ is the i^{th} predicted daily global solar radiation, $\overline{GSR_o}$ is mean value of the i^{th} observed daily global solar radiation, $\overline{GSR_p}$ is mean value of the i^{th} predicted daily global solar radiation, and N is the number of datasets.

3. Result and discussion

For the development of predictive models, the employed influential input parameters at Ahvaz station include the day of the year [1 365] (366 for leap year), daily sunshine hours (S_h), mean daily air temperature (T_{ave}), mean daily wind velocity (W_s), daily relative humidity (R_h), and the daily global solar radiation (GSR) was considered as subjective models. In this study, a novel robust data-driven model, namely the LSSVM, together with improved simulated annealing (ISA) approach (LSSVM-ISA), is provided to predict the global solar radiation (GSR) accurately. Three other AI-based models validate the proposed method, namely MARS, GRNN, and MLRI.

To measure the best combination of predictor variables, a combination consists of all influential variables plus five combinations obtained by successively excluding the influence of each predictor were examined for each predictive model by four metrics consist of the R, RMSE, MAPE, and NS. The best possible accuracy of the forecasted datasets could be achieved when $R=1$, $RMSE=0$, $MAPE<10\%$, and $NS=1$. According to the results of the first six combinations, the day and daily sunshine hours were utilized continuously for constructing other combinations due to having a significant impact on the results. According to the above explanations, a total of 10 combinations were examined for each data-driven model.

Fig. 7. The flowchart of data-driven models to forecast the daily GSR

Exploration of the results of the ten combinations is tabulated in Table 4. As tabulated in Table 4, we can recognize that the LSSVM-ISA model with the combination of five factors consists of day, S_h , T_{ave} , and R_h has revealed the best performance in forecasting the daily GSR with the highest R (0.973 and 0.980) and NS (0.947 and 0.957), and lowest $RMSE$ (0.442 and 0.391 Kw-h/m²/day) and $MAPE$ (8.171% and 8.233%) for training and testing modes.

Table 3. Performance of the forecasting skills of the LSSVM-ISA model with various input variables over the training and testing phase.

Model	inputs	Train				Test			
		R	RMSE	MAPE%	NS	R	RMSE	MAPE%	NS
1	All	0.973	0.446	8.246	0.946	0.978	0.399	8.429	0.955
2	All-day	0.940	0.659	12.639	0.883	0.935	0.687	14.055	0.866
3	All- S_h	0.930	0.710	14.481	0.864	0.935	0.672	14.687	0.872
4	All-T	0.973	0.445	8.194	0.947	0.978	0.414	8.466	0.951
5	All- W_s	0.973	0.442	8.171	0.947	0.980	0.391	8.233	0.957
6	All- R_h	0.971	0.464	8.621	0.942	0.976	0.421	9.103	0.950
7	All-T- W_s	0.975	0.431	7.942	0.950	0.977	0.420	8.682	0.950
8	All-T- R_h	0.971	0.458	8.493	0.944	0.974	0.445	9.435	0.944
9	All- W_s - R_h	0.972	0.449	8.311	0.946	0.976	0.425	9.085	0.949
10	All- W_s - R_h -T	0.972	0.453	8.647	0.945	0.976	0.431	9.381	0.947
Optimum	All- W_s	0.973	0.442	8.171	0.947	0.980	0.391	8.233	0.957

Besides, the implemented kernel functions in LSSVM-ISA consisting of two tuning parameters (λ, σ) are optimized for each combination by improved simulated annealing (ISA), which are tabulated in Table 4. In the current work, an open MATLAB toolbox ARESLab was utilized to develop the MARS model. In order to verify the robustness and efficiency of the MARS performance model, 10-fold cross-validation was considered. In order to provide the MARS model, the maximum number of basis functions in the forward building stage was selected between 15 to 30 numbers by a trial and error procedure, which

after backward step and removing over-fitting model, some of the basis functions were eliminated. Table 5 shows the adjustment parameters of the MARS model.

Table 4. The tuning parameters of LSSVM for each combination (Note: σ = kernel width; γ = loss-function parameter)

Model	inputs	LSSVM-ISA	
		σ	γ
1	All	25.459	577.538
2	All-day	1.523	2.700
3	All-S _h	2.993	4.819
4	All-T	8.697	272.880
5	All-W _s	4.579	16.475
6	All-R _h	8.243	68.488
7	All-T-W _s	0.995	4.497
8	All-T-R _h	1.574	9.171
9	All-W _s -R _h	1.173	6.998
10	All-W _s -R _h -T	0.227	1.025

Table 5. Setting parameter of the MARS model for forecasting GSR

Parameter	value
Maximum basis Functions	15-30
Maximum Self Interactions	0
Maximum degree of interactions	2-3
Threshold	0
Prune	Yes

Likewise, Table 6 sums the results achieved from MARS model which showed that the combination of 7 comprising day, S_h and R_h outperformed the other combinations in terms of R (0.968 and 0.974), $RMSE$ (0.485 and 0.426 Kw-h/m²/day), $MAPE$ (9.596% and 9.003%) and NS (0.937 and 0.948) for training and testing modes, respectively.

Table 6. Performance of the forecasting skills of the MARS model with various input variables over the training and testing phase.

Model	inputs	Train				Test			
		R	RMSE	MAPE%	NS	R	RMSE	MAPE%	NS
1	All	0.968	0.487	9.480	0.936	0.973	0.433	9.409	0.947
2	All-day	0.928	0.717	14.118	0.862	0.930	0.692	14.109	0.864
3	All-S _h	0.920	0.754	15.908	0.847	0.930	0.691	15.011	0.865
4	All-T _{ave}	0.968	0.485	9.596	0.937	0.974	0.426	9.003	0.948
5	All-W _s	0.968	0.487	9.490	0.936	0.973	0.433	9.409	0.947
6	All-R _h	0.967	0.489	9.563	0.936	0.972	0.444	9.916	0.944
7	All- T _{ave} -W _s	0.968	0.485	9.596	0.937	0.974	0.426	9.003	0.948
8	All- T _{ave} -R _h	0.968	0.485	9.505	0.937	0.972	0.444	9.923	0.944
9	All-W _s -R _h	0.967	0.489	9.563	0.936	0.972	0.444	9.916	0.944
10	All-W _s -R _h - T _{ave}	0.968	0.485	9.505	0.937	0.972	0.444	9.923	0.944
Optimum	All- T _{ave} -W _s	0.968	0.485	9.596	0.937	0.974	0.426	9.003	0.948

The corresponding basis functions $B_{F,i}$ and the coefficients β_i of the MARS model for the optimum combination (No.7) are listed in Table 7.

In the GRNN model, the most significant criterion is the spread values that were obtained by a trial and error process for each combination. The spread values for each combination are summarized in Table 8.

The statistical metrics obtained from the GRNN model to predict the daily GSR are tabulated in Table 9. In the GRNN model, the combination (No.10) including day and S_h provided more precise results in terms of R (0.964 and 0.971) and RMSE (0.526 and 0.469 Kw-h/m²/day), MAPE (11.042% and 11.384%) and NS (0.926 and 0.938) in training and testing phases, respectively than the other combinations in assessing the daily GSR.

Table 7. Basis functions and coefficients obtained to forecast the daily GSR in the optimum combination (Day, S_h , R_h) using the MARS model

Basic function	Equation	Coefficient β_i
intercept	-	8.3675
$B_1(x)$	$B_{F1} = \max(0, \text{Day} - 181)$	-0.028177
$B_2(x)$	$B_{F2} = \max(0, 181 - \text{Day})$	-0.023802
$B_3(x)$	$B_{F3} = \max(0, S_h - 10.8)$	-0.36892
$B_4(x)$	$B_{F4} = \max(0, 10.8 - S_h)$	-0.78284
$B_5(x)$	$B_{F5} = B_{F2} \times \max(0, R_h - 31.23)$	-3.8718E-05
$B_6(x)$	$B_{F6} = B_{F2} \times \max(0, 31.23 - R_h)$	0.00022022
$B_7(x)$	$B_{F7} = B_{F4} \times \max(0, R_h - 25.41)$	-0.0014453
$B_8(x)$	$B_{F8} = B_{F4} \times \max(0, 25.41 - R_h)$	0.0086739
$B_9(x)$	$B_{F9} = B_{F4} \times \max(0, 317 - \text{Day})$	0.0026546
$B_{10}(x)$	$B_{F10} = B_{F3} \max(0, \text{Day} - 196)$	0.014655
$B_{11}(x)$	$B_{F11} = B_{F3} \times \max(0, 196 - \text{Day})$	0.0079019
$B_{12}(x)$	$B_{F12} = B_{F4} \times \max(0, \text{Day} - 133)$	0.0030269
$B_{13}(x)$	$B_{F13} = B_{F4} \times \max(0, 133 - \text{Day})$	-0.0017473

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Table 8.The Spread values of GRNN for each combination

Inputs Combination	All	All-day	All-S _h	All-T	All-W _s
Spread value	0.1	0.05	0.05	0.05	0.05
Inputs Combination	All-R _h	All-T-W _s	All-T-R _h	All-W _s -R _h	All-W _s -R _h -T
Spread value	0.05	0.05	0.05	0.05	0.05

Table 9. Performance of the forecasting skills of the GRNN model with various input variables over the training and testing phase.

Model	inputs	Train				Test			
		R	RMSE	MAPE%	NS	R	RMSE	MAPE%	NS
1	All	0.974	0.436	8.652	0.949	0.967	0.495	10.792	0.931
2	All-day	0.967	0.494	8.543	0.934	0.927	0.724	14.443	0.851
3	All-S _h	0.948	0.615	11.790	0.898	0.917	0.752	16.142	0.840
4	All-T	0.990	0.275	4.992	0.980	0.967	0.484	9.781	0.933
5	All-W _s	0.985	0.329	6.001	0.971	0.970	0.471	9.740	0.937
6	All-R _h	0.986	0.322	6.116	0.972	0.970	0.474	10.239	0.936
7	All-T-W _s	0.965	0.511	10.518	0.930	0.966	0.488	10.714	0.933
8	All-T-R _h	0.966	0.515	10.832	0.929	0.970	0.477	11.384	0.935
9	All-W _s -R _h	0.965	0.510	10.338	0.930	0.970	0.481	11.289	0.934
10	All-W _s -R _h -T	0.964	0.526	11.042	0.926	0.971	0.469	11.384	0.938
Optimum	All-W _s -R _h -T	0.964	0.526	11.042	0.926	0.971	0.469	11.384	0.938

In the last alternative, the MLRI model is surveyed in both training and testing procedures based on the correlation (R), RMSE, MAPE, and Nash-Sutcliffe efficiency (NS) for ten input combinations. As mentioned before, in the MLRI method, based on the number of predictor parameters and how they interact, the relevant analysis of variance (ANOVA) is performed for each combination. Assessments of 10 combination schemes are given in Table 10. The statistical analysis demonstrates that in the MLRI model, the combination (No.6) consists of all predictors excluding the relative humidity (R_h) achieved the best prediction by the highest R (0.945 and 0.958) and NS (0.892 and 0.902) in training and testing stages, respectively. The ANOVA associated with the optimum combination (No.6) is given in Table

11, which reveals that the term ($Day \times W_s$) regarding p-value and F-value is less effective than other terms and can be eliminated from the forecasting process of daily GSR. Similarly, while the concept of this model is based on the linear dependence between predictors and target, so the average daily temperature (T_{ave}) and sunshine hours (S_h) with highest Pearson correlation coefficients ($r_p=0.79$ and 0.77 , respectively) have the most influence on obtained correlation as below equation:

$$GSR = -2.1812 + 0.0053131Day + 0.36946S_h + 0.25816T_{ave} + 0.090826W_s - 0.0002626Day \times S_h - 0.00039114Day \times T_{ave} - 0.0049445S_h \times T_{ave} - 0.00017948Day \times W_s + 0.022838S_h \times W_s - 0.0072242T_{ave} \times W_s \quad (26)$$

Table 10. Performance of the forecasting skills of MLRI model with various input variables over the training and testing phase.

Model	inputs	Train				Test			
		R	RMSE	MAPE%	NS	R	RMSE	MAPE%	NS
1	All	0.949	0.612	11.231	0.899	0.956	0.584	11.567	0.903
2	All-day	0.911	0.796	15.209	0.829	0.919	0.772	15.525	0.831
3	All- S_h	0.883	0.918	19.692	0.773	0.883	0.902	19.784	0.769
4	All-T	0.901	0.841	15.087	0.810	0.899	0.849	15.360	0.796
5	All- W_s	0.947	0.625	11.435	0.895	0.955	0.599	12.080	0.898
6	All- R_h	0.945	0.634	11.585	0.892	0.958	0.587	12.706	0.902
7	All-T- W_s	0.896	0.861	15.323	0.801	0.895	0.867	15.417	0.787
8	All-T- R_h	0.800	1.163	21.328	0.636	0.847	1.016	21.315	0.707
9	All- W_s - R_h	0.943	0.642	11.735	0.889	0.957	0.596	12.794	0.899
10	All- W_s - R_h -T	0.771	1.234	22.510	0.590	0.834	1.043	21.313	0.691
Optimum	All- R_h	0.945	0.634	11.585	0.892	0.958	0.587	12.706	0.902

Table 12 summarized the best performance of each data-driven model among all input combinations, which demonstrated that the LSSVM-ISA outperformed the MARS, GRNN, and MLRI in forecasting daily GSR in both testing and training stage. Also, MARS and GRNN are identified as the most second and third predictive model for simulating daily GSR, respectively.

Table 10. ANOVA results for identifying the influence of predictor's interaction in MLRI model for the combination No.6.

Terms	Sum of squares	<i>F</i> -value	<i>p</i> -value
<i>Day</i>	535.37	2572.2	0
<i>S_h</i>	2222.6	10672	0
<i>T_{ave}</i>	2616.2	12561	0
<i>W_s</i>	6.635	31.858	1.818E-08
<i>Day</i> × <i>S_h</i>	21.044	101.04	2.16E-23
<i>Day</i> × <i>T_{ave}</i>	234.15	1124.2	0
<i>T_{ave}</i> × <i>S_h</i>	50.380	241.92	0
<i>Day</i> × <i>W_s</i>	1.244	5.972	0.0146
<i>W_s</i> × <i>S_h</i>	23.347	112.10	0
<i>W_s</i> × <i>T_{ave}</i>	13.397	64.321	1.510E-15

Table 12. Comparison between the outcomes from 4 data-driven models to forecast daily GSR.

Model	Optimum combination	Train				Test			
		R	RMSE	MAPE%	NS	R	RMSE	MAPE%	NS
LSSVM-ISA	All- <i>W_s</i>	0.973	0.442	8.171	0.947	0.980	0.391	8.233	0.957
MARS	All- <i>T-W_s</i>	0.968	0.485	9.596	0.069	0.974	0.426	9.003	0.056
GRNN	All- <i>W_s-R_h-T</i>	0.964	0.526	11.042	0.926	0.971	0.469	11.384	0.938
MLRI	All- <i>R_h</i>	0.945	0.634	11.585	0.892	0.958	0.587	12.706	0.902

The results in Tables 4, 6, 9, and 10 indicate that the optimal input combination in each data-driven model is different due to the discrepancy in the performance mechanism of each of them. Figure 8 illustrated the bar plot of R, RMSE, MAPE, and NS values for all input combinations and provided models. Based on the shown metric values in Fig.8, the LSSVM-ISA has the best predictive performance in all combinations, whereas the MARS and GRNN models are ranked as the best second and third predictive models, respectively. However, MARS and GRNN in the combination No.2 have similar performance in

453 forecasting the daily GSR. It can be mentioned that MLRI cannot perform better than the last
 454 model in terms of the accuracy of all the proposed data-driven models.

Fig.6. The correlation (R), RMSE, MAPE, and NS values for all AI models in 10 combinations versus predictors number

The performances of the LSSVM-ISA, MARS, GRNN, and MLRI models were compared by the daily observed and simulated GSR plots over the training and testing periods (Figs. 7–10). As can be seen in these figures, the GSR values predicted by the LSSVM-ISA model are in better agreement with the observed data than those of MARS, GRNN, and MLRI models in both testing and training stages. Moreover, the scatter plots of the GSR data points simulated by the LSSVM-ISA model is closer to the 1:1 line than those from the other developed data-driven models, which imply the superiority of LSSVM-ISA model in forecasting daily GSR. Moreover, a closer look at the distribution of points at scatter plots reveals that for the range of $GSR > 4$, all provided AI-based models have promising performance in simulation of daily GSR, especially in testing mode.

Fig.7. The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of LSSVM-ISA model for both training and testing datasets

Fig.8. The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of MARS model for both training and testing datasets

Fig.9. The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of GRNN model for both training and testing datasets

Fig.10. The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of MLRI model for both training and testing datasets

For visual comparison between the results of the LSSVM-ISA and those of other data-driven approaches, the Fig.11 shows forecasted and observed GSR values over the two selected intervals of (1 June 2013-31 December 2013) and (1 July 2017-1 July 2019) at the training and testing periods, respectively. It is so clear that the LSSVM-ISA performs significantly better than other predictive models due to having the best fit and lowest overestimation and underestimation. However, the MARS and GRNN models, as the next alternatives, can simulate the daily GSR at an acceptable level of precision. The violin plot in Fig.12 shows the distribution of standardized observed and forecasting daily global solar radiation (GSR) using the LSSVM-ISA, MARS, GRNN and MLRI model for both testing and training modes in the best input combinations. Distribution of predicted GSR values in violin plot for training (Fig.12-A) and testing (Fig.12-B) stages reveal that all predictive models have relatively similar forecasting performance in the median 50 percentile (thick solid line). In contrast, the LSSVM-ISA model is energetically superior to other data-driven

480 models in upper and lower quartiles (dashed lined) of violin plots in comparison with
 481 observational daily GSR. Also, the MARS model with having the second-best consistency of
 482 distribution with observational values has acceptable performance in forecasting daily GSR.

Fig.11. Comparison of the predictive and measured daily solar radiation with all developed AI models throughout (1 June 2013-31 December 2013) and (1 July 2017-1 July 2019) at the training and testing datasets

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Fig.12. The violin plots of the predicted and measured daily GSR values for the best combination of each data-driven model.

In the next validation graphical tools, the Taylor diagrams for evaluating the robustness of the developed predictive models in training and testing period of the simulation were plotted in Fig.13. According to findings in Fig.13, the locus of data obtained from the LSSVM-ISA model is in the closet distance to the target point compared to those of the other data-driven methods in both training and testing phases. This fact is due to having the highest correlation coefficients ($R=0.974$ and 0.980), and the minimal difference of standard deviations ($S_d=1.887$ and 1.873). The MARS and MLRI models have closer standard

492 deviation to the target than the GRNN model. It is noteworthy that the standard deviation (
 493 S_d) of the observed GSR values for the training and testing datasets is 1.880 and 1.738,
 494 respectively.

Fig.13. The Taylor diagram of the training and testing modes for LSSVM-ISA, MARS, GRNN, and MLRI for forecasting the GSR.

In this part of the study, a comprehensive error analysis was conducted to evaluate the accuracy and reliability of current AI models. The relative deviation value by formula ($D_r = (GSR_i - GSR_0) / GSR_0$) was displayed versus observed GSR for training and testing period of simulation for each model in Fig. 14. Figure 14 demonstrates that the range of the relative deviation for the LSSVM-ISA model by $-3.35 \leq D_r \leq 0.526$ is less than the MARS by $-5.80 \leq D_r \leq 0.582$, GRNN by $-6.20 \leq D_r \leq 0.550$ and for MLRI by $-4.47 \leq D_r \leq 1.260$. Close examination of the error distribution plots vividly shows that for $GSR > 4$ all understudy predictive models have reliable performance and acceptable accuracy in forecasting daily GSR and the relative deviation restricted in the range of $-1 \leq D_r \leq 0.520$.

Fig. 14. The relative deviation plots of the developed data-driven models for predicting GSR: (a) LSSVM-ISA, (b) MARS, (c) GRNN, and (d) MLRI.

505 Finally, a substantial error criterion is carried out to the better vision of the quantitative
506 performance of all proposed models, which expresses the amount of cumulative absolute
507 percent of error frequency (Fig.15). LSSVM-ISA model can predict 75% of the daily GSR
508 data with absolute relative error less than 6.1% whereas, 75% of the MARS, GRNN, and
509 MLRI models as the second, third and fourth most accurate approaches, provided prediction
510 errors less than or equal to 8.2%, 9.74%, and 11.56%, respectively. Also, all the provided
511 models can assess 90% of the data with an absolute relative error of less than 25%, which
512 implies the reliability of all data-driven approaches for the prediction of daily GSR. It is
513 vividly clear that the results of LSSVM-ISA are in the most satisfactory agreement with
514 observed data sets in comparison with all the provided models.

Fig.15. Percentage of cumulative frequency of proposed AI models
versus the absolute percentage of relative error in forecasting GSR.

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516 **4. Validation of the model with traditional approaches**

517 In order to investigate the accuracy of the empirical equations in comparison with the AI-
518 based methods used in the research, nine empirical equations were examined and evaluated,
519 which were introduced in Table 1. The inputs of the selected equations are the same as the
520 AI-based models utilized in this research. The coefficients of the empirical equations are

521 calculated using the ordinary least square (OLS) method separately, and their values are
522 given for each equation in Table 13. According to Table 13, the Bristow and Campbell
523 (Bristow & Campbell 1984) equation with a mean absolute percentage error (MAPE) of
524 14.811% provides more accurate results than other equations. The MAPE of Goodin et al.
525 (Goodin et al. 1999) and Hunt equations (Hunt et al. 1998) are 14.843% and 14.857 %,
526 respectively.

Table 13. Coefficient and accuracy of empirical equations to predict GSR

Model	a	b	c	d	e	R	RMSE	MAPE%	NS
Swartman and Ogunlade (Swartman & Ogunlade 1967)	6.08	1.8	-0.065	-	-	0.814	1.115	21.775	0.662
Hargreaves (Hargreaves 1981)	0.158	-	-	-	-	0.919	0.754	17.011	0.845
Bristow and Campbell (Bristow & Campbell 1984)	0.708	0.015	1.818	-	-	0.925	0.728	14.811	0.856
De Jong and Stewart (Jong & Stewart 1993)	0.162	0.490	-0.010	-0.010	-	0.925	0.727	15.473	0.856
Allen (Allen 1997)	0.158	-	-	-	-	0.919	0.754	17.012	0.845
Donatelli and Campbell (Donatelli & Campbell 1998)	0.665	0.006	3.526	-	-	0.911	0.791	15.501	0.830
Hunt (Hunt et al. 1998)	0.159	-0.053	-	-	-	0.919	0.754	16.984	0.845
Hunt (Hunt et al. 1998)	0.144	0.012	-0.135	0.002	0.079	0.927	0.719	14.875	0.859
Goodin, Hutchinson, anderlip and Knapp (Goodin et al. 1999)	0.681	0.011	2.846	-	-	0.921	0.751	14.843	0.847

527

528 Table 14 shows a comparison between the best results of each model. According to Table 14,
529 AI-based models have performed better than the empirical and MLRI models. LSSVM-ISA
530 model with MAPE = 8.233 % has the least error among models.

531

Table 14. Comparison between the best empirical correlation and AI models

Model	R	RMSE	MAPE%	NS
Best LSSVM-ISA	0.980	0.391	8.233	0.957
Best MARS	0.974	0.426	9.003	0.948
Best GRNN	0.970	0.471	9.740	0.937
Best MLRI	0.956	0.584	11.567	0.903
Best Empirical	0.925	0.728	14.811	0.856

532

533 Table 15 shows MAPE percent error for different empirical equations used at this research
534 and error improvement by the best LSSVM-ISA model. The results of Table 15 show that the
535 best LSSVM-ISA model has been able to reduce the MAPE error rate compared to empirical
536 models significantly. A comparison of the best empirical model (Bristow and Campbell
537 (Bristow & Campbell 1984)) and the best LSSVM-ISA model shows a 6.578% reduction in
538 MAPE percent.

Table 15. Error improvement by best LSSVM-ISA model compared to empirical equations

Model	MAPE%	Error improvement by LSSVM-ISA %
Swartman and Ogunlade (Swartman & Ogunlade 1967)	21.775	13.542
Hargreaves (Hargreaves 1981)	17.011	8.778
Bristow and Campbell (Bristow & Campbell 1984)	14.811	6.578
De Jong and Stewart (Jong & Stewart 1993)	15.473	7.240
Allen (Allen 1997)	17.012	8.779
Donatelli and Campbell (Donatelli & Campbell 1998)	15.501	6.968
Hunt (Hunt et al. 1998)	16.984	8.751
Hunt (Hunt et al. 1998)	14.875	6.642
Goodin, Hutchinson, erlip and Knapp (Goodin et al. 1999)	14.843	6.610

5. Uncertainty

In this section, the uncertainty analysis of the utilize models in predicting global solar radiation is examined and evaluated. The error value of each sample is calculated from the relation $e_j = GSR_p - GSR_o$. The mean value of the error of the relation is calculated using $\bar{e} = \sum_{j=1}^n e_j$ and finally, the standard deviation of the estimation error is calculated from the relation $S_{de} = \sqrt{(e_j - \bar{e})^2 / n - 1}$. If the value of $\bar{e}$ is negative, it indicates that the model underestimates the predicted values, and its positive value indicates the overestimation of the model. High values of s_e indicate the high scattering of the model error and increasing it will increase the uncertainty of the model prediction.

Confidence intervals for the estimation values of the models can be determined using the values $\bar{e}$ and S_e . Considering the $\pm 1.96S_e$, values of 95% confidence intervals are obtained. Table 16 shows the mean values of estimation error, standard error deviation, and 95% error confidence intervals. In all five models used in the present study, except for the empirical equation, the mean value of the prediction error is positive, which indicates that the model is overestimating predicting values. Among the applied models, the best empirical equation has the lowest mean value of the prediction error with a value of -0.011. Among AI-based models, LSSVM-ISA and MARS have the lowest average error ($\bar{e} = 0.074$). The LMRI method has the highest average error value ($\bar{e} = 0.207$). The lowest value of the uncertainty band ± 0.792 is for the LSSVM-ISA model, which indicates that this model has a lower uncertainty. The highest uncertainty band ± 1.427 is for the Bristow and Campbell (Bristow & Campbell 1984) equation, which indicates more uncertainty about the results of the empirical model than other models.

Table 16. Uncertainty estimates for GSR for best of each model

Model	Mean prediction error $\bar{e}$	S_e	Width of uncertainty band
Best LSSVM-ISA	0.074	0.404	± 0.792
Best MARS	0.074	0.426	± 0.835
Best GRNN	0.132	0.469	± 0.919
Best MLRI	0.207	0.587	± 1.150
Best Empirical	-0.011	0.728	± 1.427

6. Conclusions

Given the importance of accurately estimating solar radiation in the design of solar energy systems, a novel hybrid data-driven approach comprised of LSSVM coupled with improved simulated annealing (ISA) approach (LSSVM-ISA) is developed to accurately predict the daily global solar radiation (GSR) over the period of 10 years (from 01-July-2009 to 1- July -2019) at Ahvaz station, in Iran. In this research, the predictive input variable was the day of the year (1 to 366), average daily temperature (T_{ave} , °C), sunshine hours (S_h , hr), relative humidity (R_h , %), average wind velocity (W_s , m/s) at 10 m and GSR (Kw-h/m²/day) was considered as a target for ten input combinations. According to the obtained results, LSSVM-ISA model in the combination (No.5; comprised of day, S_h , T_{ave} , and R_h) due to having highest R (0.980) and NS (0.957) and lowest $RMSE$ (0.391 Kw-h/m²/day) and $MAPE$ (8.233%) for testing modes outperformed the MARS, GRNN and MLRI model in forecasting daily GSR. The MARS model, in combination (No.7; comprising day, S_h and R_h) in terms of ($R=0.974$, $RMSE=0.426$ Kw-h/m²/day, $MAPE=9.003\%$, and $NS=0.948$) was identified as the second accurate predictive approach for daily GSR forecasting. Also, the GRNN model as third best rank carried out the best performance in combination (No.10; including day and S_h) provided in terms of $R=0.971$, $RMSE=0.469$ Kw-h/m²/day, $MAPE=11.384\%$, and $NS=0.938$) and eventually MLRI model in the combination (No.6) consist of all predictors excluding the relative humidity (R_h) in terms of ($R=0.958$, $RMSE=0.587$ Kw-h/m²/day, $MAPE=12.706\%$,

and $NS=0.902$). According to (Lewis 1982), for judgment of the accuracy of the GSR forecasting procedure, the LSSVM-ISA and MARS models by having $MAPE < 10\%$ are identified as high accurate forecasting tools and GRNN and MLRI model by $10 \leq MAPE \leq 20$ are classified as good predictor data-driven model to assess the daily GSR. Besides, a comparison between all models in 10 combinations demonstrated that the day of the year and sunshine duration (S_h) due to existing in any the best combination performance are identified as the most effective predictive variables in the daily GSR forecasting process.

Besides, comparing the obtained results of the empirical equations with the AI models indicated that the AI models, especially the LSSVM-ISA method ($R = 0.98$, $RMSE = 0.391$ $Kw-h/m^2/day$, $MAP\% = 8.23$, and $NS = 0.957$), can predict the GSR more accurate than the empirical methods. Finally, the uncertainty analysis showed that the proposed LSSVM-ISA has the lowest uncertainty (± 0.792) compared with the other AI methods. This demonstrates that the proposed method is more reliable and precise to predict the GSR.

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Mehdi Jamei: Conceptualization, modeling, data Formal analysis, writing up the main manuscript, Software, revision editing. **Iman Ahmadianfar:** Methodology, Introduction, **Mozhdeh Jamei:** writing up the main manuscript, data visualization; **Masoud Karbasi:** writing up the main manuscript, revision editing. **Ali Asghar Heidari:** Supervision, writing up the main manuscript, revision editing. **Huling Chen:** Supervision, revision editing.

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Figures

Figure 1

Study area: location of Ahvaz synoptic station. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

The measured predictive and output variable over 10 years (1 July 2009-1 July 2019) at Ahvaz synoptic station.

Figure 3

The histogram of the frequency and probability density function of the predictive and objective variable

Figure 4

The correlation matrix of the implemented variables

Figure 5

Flowchart of the ISA algorithm

Figure 6

Flowchart of the LSSVM-ISA method

Figure 7

The flowchart of data-driven models to forecast the daily GSR

Figure 8

The correlation (R), RMSE, MAPE, and NS values for all AI models in 10 combinations versus predictors number

Figure 9

The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of LSSVM-ISA model for both training and testing datasets

Figure 10

The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of MARS model for both training and testing datasets

Figure 11

The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of GRNN model for both training and testing datasets

Figure 12

The scatter plots of GSR (Right); Comparison of the measured and predicted GSR (Left) using of MLRI model for both training and testing datasets

Figure 13

Comparison of the predictive and measured daily solar radiation with all developed AI models throughout (1 June 2013-31 December 2013) and (1 July 2017-1 July 2019) at the training and testing datasets

Figure 14

The violin plots of the predicted and measured daily GSR values for the best combination of each data-driven model.

Figure 15

The Taylor diagram of the training and testing modes for LSSVM-ISA, MARS, GRNN, and MLRI for forecasting the GSR.

Figure 16

The relative deviation plots of the developed data-driven models for predicting GSR: (a) LSSVM-ISA, (b) MARS, (c) GRNN, and (d) MLRI.

Figure 17

Percentage of cumulative frequency of proposed AI models versus the absolute percentage of relative error in forecasting GSR.