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Solar irradiation prediction using empirical and artificial intelligence methods: A comparative review

Faisal Nawab [a,b], Ag Sufiyan Abd Hamid [c,*], Adnan Ibrahim [a,**], Kamaruzzaman Sopian [d], Ahmad Fazlizan [a], Mohd Faizal Fauzan [a]

[a] *Solar Energy Research Institute, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia*
[b] *Department of Renewable Energy, Khushal Khan Khattak University, Karak 27200, Pakistan*
[c] *Faculty of Science and Natural Resources, Universiti Malaysia Sabah, 88400 Kota Kinabalu, Sabah, Malaysia*
[d] *Department of Mechanical Engineering, Universiti Teknologi Petronas, 32610 Seri Iskandar, Perak, Malaysia*

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ABSTRACT

Solar irradiation data is essential for the feasibility of solar energy projects. Notably, the intermittent nature of solar irradiation influences solar energy use in all forms, whether energy or agriculture. Accurate solar irradiation prediction is the only solution to effectively use solar energy in different forms. The estimation of solar irradiation is the most critical factor for site selection and sizing of solar energy projects and for selecting a suitable crop selection for the area. But the physical measurement of solar irradiation, due to the cost and technology involved, is not possible for all locations across the globe. Numerous techniques have been implemented to predict solar irradiation for this purpose. The two types of approaches that are most frequently employed are empirical techniques and artificial intelligence (AI). Both approaches have demonstrated good accuracy in various places of the world. To find out the best method, a thorough review of research articles discussing solar irradiation prediction has been done to compare different methods for solar irradiation prediction. In this paper, articles predicting solar irradiation using AI and empirical published from 2017 to 2022 have been reviewed, and both methods have been compared. The review showed that AI methods are more accurate than empirical methods. In empirical models, modified sunshine-based models (MSSM) have the highest accuracy, followed by sunshine-based (SSM) and non-sunshine-based models (NSM). The NSM has a little lower accuracy than MSSM and SSM, but the NSM can give good results in sunshine data unavailability. Also, the literature review confirmed that simple empirical models could predict accurately, and increasing the empirical model's polynomial order cannot improve results. Artificial neural networks (ANN) and Hybrid models have the highest accuracy among AI methods, followed by support vector machine (SVM) and adaptive neuro-fuzzy inference system (ANFIS). The increase in efficiency by hybrid models is minimal, but the complexity of models requires very sophisticated programming knowledge. ANN's most important input factors are maximum and minimum temperatures, temperature differential, relative humidity, clearness index and precipitation.

* Corresponding author.
** Corresponding author.
E-mail addresses: pian@ums.edu.my (A.S. Abd Hamid), iadnan@ukm.edu.my (A. Ibrahim), k_sopian@yahoo.com (K. Sopian).

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1. Introduction

Energy is a fundamental requirement, not a luxury, and is crucial for sustainable development. Most energy produced today comes from fossil fuels, which are reliable yet unsustainable because their supplies deplete quickly and significantly negatively impact the environment. Greenhouse gas (GHG) emissions from fossil fuel combustion drive climate change and global warming. The Paris Agreement states that it is essential to decrease GHG emissions and keep the global temperature increase below 2 °C through the end of this century. Roughly 40% of GHG emissions are from the energy sector [1]. Energy source diversification is essential to transition to sustainable energy systems [2]. Including local renewable energy resources is necessary for diversifying energy sources and achieving carbon neutrality goals [3]. Based on the projected residual fossil fuel supply and worries about climate change, renewable energy will be an obligation, not a choice, for the next generation [4] and government in regions with higher potential renewable resources has started large-scale projects for a reduction in GHG emissions [5].

For this reason, numerous steps have been made to promote sustainable development since the United Nations (UN) Framework Convention on Climate Change was reinforced in 1994. One hundred ninety-six nations signed the Nationally Determined Contributions in Paris in 2015. All participants in the UN Climate Change Conference in 2019 agreed to take immediate action to combat climate change. The energy sector's recent shift toward Renewable energy sources (RES) has gained momentum [4].

Much academic research has been done to find environmentally friendly and energy-efficient alternatives to fossil fuel-based energy systems. Due to these initiatives, the energy cost of RES has decreased, making it more appealing to both developed and developing nations and most countries have started to modernize their energy systems [6,7].

According to International Renewable Energy Agency (IRENA) report IRENA 2021b [8], the proportion of renewable energy sources, including hydropower, in electricity generation has reached 26% and had a record growth of 1.1%in 2019. The amount of energy produced by RES in 2019 was 6963 TW h (TWh), of which hydro represented 61%, wind 20%, and solar 10%. Geothermal, marine, and bioenergy account for 9% of total energy production. Fig. 1 displays every RES contribution to power production.

Renewable energy sources' generation capacity will reach 2.8 TWh in 2020, expanding rapidly. The RES generation capacity is shown in Fig. 2. In the last ten years, the generation capacity has increased by 112%, with a growth rate of 10.23% in 2019. If the statistics for each RES are closely examined, it can be shown that in the last ten years, the total generation capacity of hydro has increased from 1056.7 GW to 1331.8 GW. The expansion of RES generation capacity is seen in Figs. 1 and 2. 2019 saw a 5.5% growth in renewable power generation, while solar power generation climbed by 23%. Additionally, the 46.7% growth in RES power output during 2015 has been related to solar energy [9].

Solar Energy, in particular, is widely accessible everywhere and may be used for various purposes, including crop drying, space and water heating and cooling, and power generation [10,11]. Due to the rapid advancement of solar energy systems, final energy costs are comparable to traditional energy systems, and solar energy has gained international attention.

However, several obstacles must be removed from how solar energy is fully utilized before the project can be implemented. One of these obstacles is how to manage and anticipate its intermittent nature. The energy produced by a solar system depends on how much of the sun's radiation reaches a particular location on earth [12]. The energy production from a solar system can be predicted if accurate solar radiation measurements are available for the chosen site. Without accurate solar radiation data, no solar system—photovoltaic (PV) or solar thermal—can be considered for implementation. It clarifies that correct solar radiation measurements are necessary for the best possible use of solar energy.

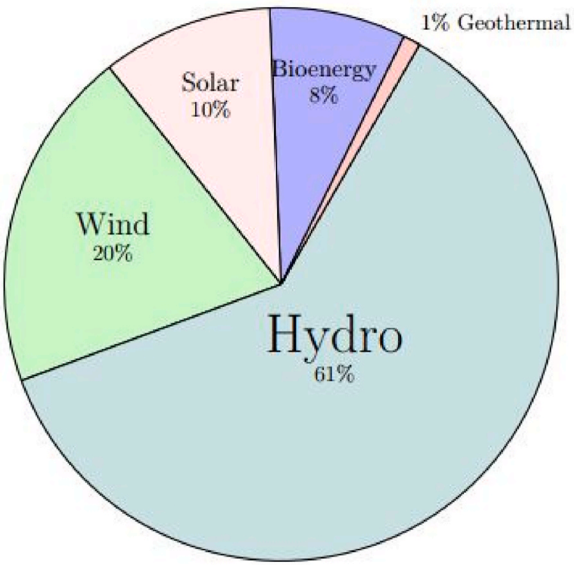

Fig. 1. Share of each RES in RE Electricity [8].

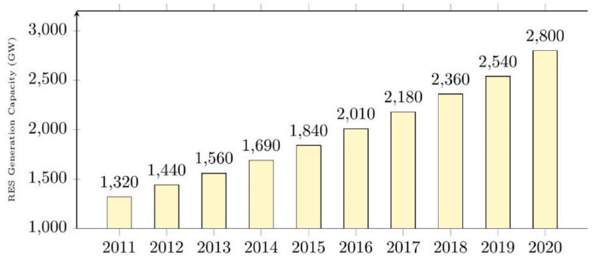

Fig. 2. Res power generation capacity.

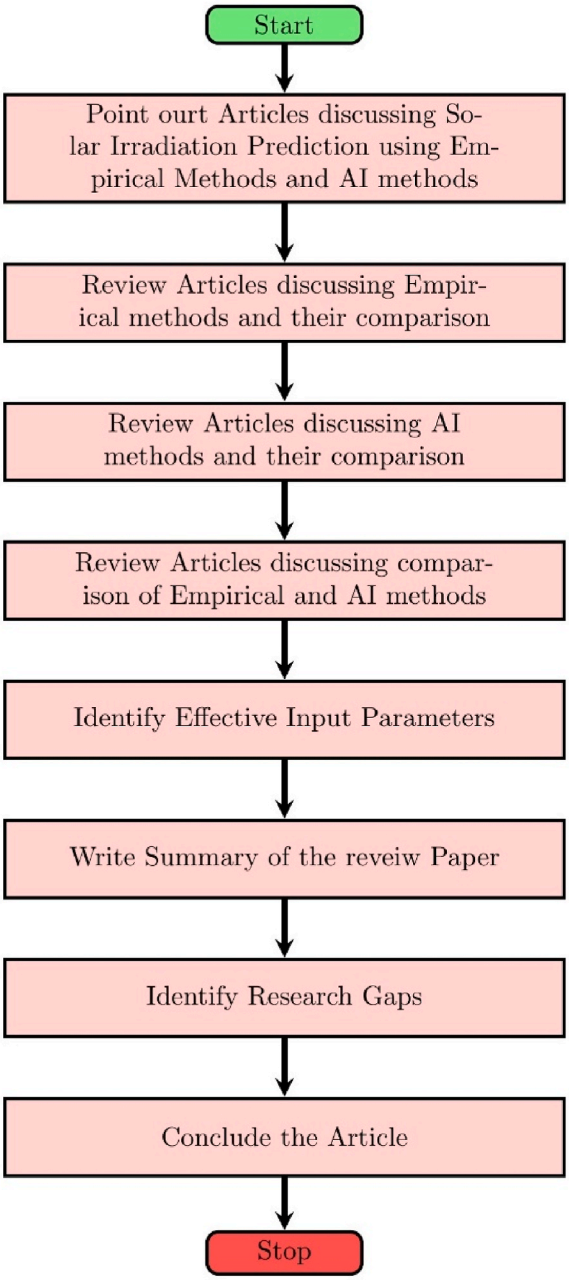

Fig. 3. Methodology.

Solar irradiation varies from location to location and is a function of different meteorological and geographical parameters and physical parameters of the atmosphere. In close areas, solar irradiation values may not be the same. And using the nearby station data for any feasibility study may lead to project failure. Physically measuring this data for all locations is practically hard, especially in developing countries, due to the costs and difficulties involved [13,14]. In the past, researchers developed various strategies to get around the challenges and costs of assessing global horizontal irradiation (GHI) on the ground. Empirical models and models based on artificial intelligence (AI) have received the most research attention. GHI forecasting using AI models has yielded encouraging results [13,15]. ANN has been widely implemented in several worldwide regions, including Turkey, Oman, China, India, Australia, and other places, with promising results [16].

The main objective of this paper is to compare the performance of different empirical and artificial neural network (ANN) methods and the comparison of empirical and ANN for solar irradiation prediction. In this paper, first of all, articles discussing empirical methods and the comparison of empirical methods are reviewed. Then, the articles related to ANN are reviewed, and the last section compares ANN and empirical methods. In addition to comparison, an effort to identify influential input parameters has been made. The detailed methodology of the review article is shown in Fig. 3.

2. Empirical methods

Empirical techniques have typically been used to predict solar radiation (SR). It uses mathematical formulas that take several meteorological factors into account. In 1924, Angstrom created the first SR prediction model [17]. The empirical model can be categorized into three groups based on meteorological inputs.

1. Sunshine Based Models (SSM)
2. Modified sunshine-based Models (MSSM)
3. Non-sunshine-based Models (NSM)

Following are some of the most recent models in each area mentioned above. Somayeh Naserpour et al. [18] calibrated and evaluated the performance of 21 SSM empirical models developed in the past. The results confirmed that cubic and linear logarithmic models developed by C. Ertekin et al. and F. Newland respectively performed best among all models with the coefficient of correlation (R) values of 0.93 [19,20];. Ayse Gul Kaplan et al. [21] have developed three SSMs (Linear, Quadratic, and Cubic) for monthly GHI prediction in the Antalya region of Turkey. They compared the model's performance yearly (2010–2016) with the 17 empirical models developed for the area using six statistical parameters. They found that the newly developed model's accuracy is higher than the existing models, and all models were not the same for all years, which means that with time the model's accuracy changes—the model accuracy changes with changing weather conditions. The average Mean absolute percentage error (MAPE) of the linear, quadratic, and cubic models was 6.28, 6.42, and 6.46, which confirms that the complexity of the model doesn't improve the accuracy [21]. Md Shahrukh Anis et al. [22] compared the performance of 104 SSM in the literature and developed seven new models for solar irradiation prediction at 23 sites in India. New models outperformed the models present in the literature based on the global performance indicator (GPI). The quartic form equation developed by researchers has the highest R and MBE values, 0.86 and −0.0001, respectively.

Yendoubé Lare et al. [23] developed an MSSM model for Togo, which combines linear and non-linear techniques with exponential and harmonic parts. They tested the model for five regional capitals across the country. The inputs incorporated in the model are latitude (L), relative humidity (RH), sunshine duration fraction ($S/S_{0)},$ and mean temperature (T_{mean}). They also checked their model against two best-performing models developed for the region. The first model is developed by Amou et al. [24], which is the only model for Togo present in literature, and the second model developed by Ajay et al. [25] is a model that applies to the largest country in Africa (Nigeria) and has been checked against a lot of other models. The MAPE of the model ranged from 7.73% in Lome to 10.50% in Dapaong. The Ajaye model ranged from 7.67% to 15.84 in the same cities. Finally, Yu Feng et al. [26] performed high-resolution solar radiation and energy assessment for 110 stations in China using 50 years of data. They used MSSM empirical model, which uses extra-terrestrial irradiation (H_0), RH, S/S_0, diurnal temperature range, precipitation (Prec), and mean air temperature as inputs. The Nash–Sutcliffe model efficiency coefficient (NS), relative root mean square error (RRMSE), mean average error (MAE), root mean square error (RMSE), and coefficient of determination (R^2) values of the model were 0.893, 16.8%, 1.69 MJ per meter square per day ($MJ/m^2/d$), 2.3 $MJm^{-2}d^{-1}$ and 0.89 respectively. After confirmation of model accuracy by statistical indicators, the model was used to predict the missing GHI in all 110 stations.

Nejib Ghazouani et al. [27] assessed the performance of four NSM (temperature-based) models using 35 years of data for Arar city in Saudi Arabia. Among these models, two models use mean monthly temperature (T_{mean}), the third one uses maximum Temperature (T_{max}) and minimum Temperature (T_{min}), and the fourth model uses the difference between T_{max} and $T_{min,}$ temperature difference (ΔT). All the models' R values are more significant than 0.99, while R^2 is higher than 0.96, which shows that all the models have accurately predicted the monthly GHI and confirms good fitting [27]. Y. El Mghouchi tested 42 NSM (temperature-based) models for six different climatic zones in Morocco. The best R^2 value obtained for clear sky conditions is 0.967, while for all sky conditions are 0.909. In the last step, the models are optimized using four machine learning algorithms. After optimization, the R^2 value reached closer to 1, which means that the optimization has improved the accuracy of models. The testing of many models confirmed that the complexity of the model doesn't improve the accuracy, and the same results can be obtained using simple models. They also concluded that some unfavourable weather conditions like dust storms and hot winds result in higher temperatures, and the dust storms also result in lower radiations value, which results in poor performance of models [28]. Junliang Fan et al. [29] compared fourteen existing temperature-based models developed in Refs. [30–43] with six newly proposed temperature-based models for solar irradiation prediction at 20 sites in China. Among existing models, eight models only use temperature, while six use other meteorological parameters in addition to temperature. In the proposed models, two models use only temperature, while the other uses pressure and RH in addition to temperature. The model developed by Ref. [32] performed best among existing models, while the complex proposed models incorporating temperature, RH, and precipitation performed best among all models. The results also confirmed that only temperature-based models could predict with high accuracy, but adding RH and precipitation improves the accuracy of temperature-based models.

Oliveira Lima et al. [44] assessed monthly solar irradiation for Rio de Janeiro, Brazil, using the Hargreaves-Samani and Bristow-Campbell models. The results confirm the superiority of the Bristow-Campbell model for regions with R^2 and RMSE values ranging from 0.60 to 0.85 and 1–2.99 $MJ/m^2/d$. De Souza [45]developed a new model using ambient temperature for solar irradiation prediction in Trinidad and Tobago. The results of the newly developed model were also compared with five existing models. The results confirmed the superiority of the newly developed model with the RMSE value of 0.51 $MJ/m^2/d$. Finally, Mohamed Blal et al. [46] reviewed six temperature-based models and evaluated all the model's performances under different weather conditions in Adrar, Algeria, over four years. Three of the six models use Tmean as input, while the other three use ΔT. The results showed that ΔT models outperform T_{mean} models. In addition, two different models performed best for different years. The authors concluded that temperature-based empirical model performance changes with changing weather conditions.

Keith De Souza [47] compared the performance of five existing models developed in Refs. [30,34,48–50], one modified form of [30], and a newly developed model for solar irradiation prediction in Trinidad and Tobago. The new model uses only monthly mean temperatures for solar irradiation. The results confirmed that the new model developed in this research outperformed all the models with R^2, RMSE, and NSE values of 0.94, 0.51 $MJ/m^2/d$, and 0.346, respectively. Followed by the modified form of [30]. The superior accuracy and elimination of H_0 make the newly developed model suitable for solar irradiation prediction in other regions. H. Yakoubi et al. [51] evaluated 24 clouds cover-based (CC) models' (NSM) performance for predicting monthly average GHI in 14 cities of Morocco. They used 18 years of data for the training and testing of models. Out of 24, seventeen models are newly developed by authors, and eight are taken from literature. The highest R^2 value was 0.77. They concluded that exponential and logarithmic models performed worse among all the models, while the increase in polynomial order positively impacted the model's performance. Similarly, the models that use RH, T, and wind speed (Ws) in addition to C/C0 have shown good performance compared to models that use C/C_0.

Muhammad Uzair Yousuf and Syed Muhammad Rashid Hussain [52] checked the accuracy of nine NSM (day of the year (DOY)) based models for 30 cities across Pakistan. The authors tested two sine wave-based models, one cosine wave-based model, one Gaussian Form model, one Lorentzin Correlation model, one 4th Order polynomial model, two hybrid sine-cosine models, and one Two-Gaussian Form model. The results showed that all the model's nRMSE and nMBE values are less than 10% for all cities except Muzaffarabad. The normalized mean bias error (nMBE) values of all models for all cities ranged from 0.22% to 15.52%, with an average value of 4.39%. The results showed that all day-of-the-year (DOY) based models could be used with acceptable accuracy at any location in Pakistan. Among all models, the Two-Gaussian Form model has the highest precision, while the sine wave model is predicted with the lowest accuracy. Shaban G. Gouda et al. [53] evaluated the performance of nine NSM (DOY-based) for five zones in China using 84 meteorological station data. They conclude that different models predicted best for different zones. Among all these models' hybrid sine cosine wave models performed best. They concluded that the models performed best for zones with high GHI potential, and the model's performance decreased with a decrease in GHI value across the zones. Shohreh Didari et al. [54] predicted solar irradiation in central and southern Iran under different sky conditions. For clear sky conditions, Alen [55] model was used, and for different cloud cover conditions, Angstrom [56] (SSM) and Kasten and Czeplak [57] (NSM) models were used. The Allen model RMSE value for clear sky conditions was 1.1 $MJ/m^2/d$. While in different cloudy conditions, the Angstrom model (SSM) outperformed the Kasten and Czeplak models with an RMSE value of 2.62 $MJ/m^2/d$.

S. Nabi Mughal., Y.R. Sood, and R. K. Jarial [58] proposed a novel model for predicting hourly solar radiation on the tilted surface of Kashmir. Using the non-linear autoregressive (NAR) model, they first predicted GSR and diffuse radiation. Then in the second step, they fed the results of the NAR model to the empirical model developed by Boxwell in 2010 [59], which will give the solar radiation on a specific tilt angle. They also checked the performance of 9 existing models. The proposed model MAPE is 5.61%, while the least error among the existing models is 31% which means that the proposed hybrid model result is far better than the current models. They also concluded that when a solar panel is tilted at a specific angle, the radiation reception increases by 9%.

Rahul G. Makade, Siddharth Chakrabarti, and Basharat Jamil [60] developed three empirical models for India using 20 weather station data and then compared the results of the developed model with three previously developed models present in the literature. The first model was Angstrom Prescot linear form (SSM), which uses S/S_0 as input. At the same time, the other two are cubic forms (MSSM) of the Angstrom Prescot model. The first cubic form relates the GHI with L, Alt, and S/S_0, and the second cubic model adds RH as additional input to inputs used by the first cubic form model. The statistical evaluation showed that newly developed models outperformed the existing model. The freshly developed second cubic model, which uses L, Alt, and S/S_0 as inputs, has led to the highest accuracy among all the models. The results confirmed that adding the input parameters such as RH, L, and Alt improves the accuracy of sunshine-based models. In the Fiji Islands, Olanrewaju M. Oyewola et al. [61] assessed 20 empirical models (six SSM, 14 MSSM) from previous studies for SR prediction. They initially checked the accuracy of satellite SR data by comparing it to SR data from the Naudi and Laucali meteorological stations. Satellite data PME is 12.5%, according to the authors. For all stations, the MSSM models that connect S, S_0, H_0, and air temperature to SR produced the best results. In addition, adding humidity to a collection of parameters enhance model performance. Recep Kulcu and Rabia Elsan [62] tested seven empirical models (5 SSM, 2 MSSM) for GHI prediction in the Hatay province of Turkey. They found that models incorporating S/S_0 and W_s results are more accurate than other models. At the same time, the model that contains only S/S_0 gave the worst results. The researchers recommend that for GHI prediction in a specific region, first several models should be tested, and after validation, the best model should be used. Tchilabalo E. Patchali et al. [58] assessed 20 empirical models (6 SSM, 14 MSSM) created by earlier researchers for four cities in Togo. ME values ranged between 0.550 MJ/m^2 to 28.9 MJ/m^2. The best five models are MSSM, whereas the top 5 models with the worst results are SSM and suggesting that SR prediction requires more than just S, S_o, and H_0. Air temperature and RH, in addition to these three, are crucial input parameters that have enhanced the accuracy of SR prediction.

Alhassan Ali Teyabeen et al. [63] compared seven empirical models developed in the past literature for twelve cities in Libya. Among seven models, two SSMs and five are NSM (three temperature, one RH and one RH with temperature). The results confirmed that the model incorporating Sunshine S/S_0 and $(S/S_0)^2$ was developed by AA El Sabaii et al. [64] for Jeddah in Saudi Arabia and performed best. The MAPE for the best model ranges from 1.12% to 3.52%. Results confirmed that for each location, empirical coefficients are different. For four Indian cities, Mahima Sivakumar et al. [65] compared the performance of nine SSM and eight NSM models based on temperature. SSM has outperformed NSM for two sites, whereas models NSM have produced better results for the other two sites. The study also found that simple models performed better than complex ones that contained quadratic or cubic equations. Jawed Mustafa et al. [66] developed 121 empirical models for Najran, Saudi Arabia. The R-value of 121 developed and six

Table 1
Empirical models.

References	Models	Country	Accuracy
Naserpour et al. [18]	SSM	Iran	–
Ayse Gul et al. [21]	SSM	Turkey	–
Anis et al. [22]	SSM	India	–
Lare et al. [23]	MSSM	Togo	–
Feng et al. [26]	MSSM	China	–
Ghazouani et al. [27]	NSM (T)	Saudi Arabia	–
Mghouchi [28]	NSM (T)	Morocco	–
Fan et al. [29]	NSM (T)	China	–
Lima et al. [44]	NSM	Brazil	–
De Souza [45]	NSM (T)	Trinidad and Tobago	–
Yakoubi et al. [51]	NSM (CC)	Morocco	–
Yousuf et al. [52]	NSM (DOY)	Pakistan	–
Gouda et al. [53]	NSM (DOY)	China	–
Didari et al. [54]	SSM NSM		SSM > NSM
Mughal et al. [58]	NSM	India	–
Makade [60]	SSM MSSM	India	MSSM > SSM
Oyewola [61]	SSM MSSM	Fiji Islands	MSSM > SSM
Kulcu [62]	SSM MSSM	Turkey	MSSM > SSM
Patchali [79]	SSM MSSM	Togo	MSSM > SSM
Teyabeen et al. [63]	SSM NSM	Libya	SSM > NSM
Sivakumar et al. [65]	SSM NSM	India	Two sites SSM > NSM Last two sites NSM > SSM
Mustafa [66]	SSM MSSM NSM (T, RH)	Saudi Arabia	MSSM > SSM > NSM
Uckan [67]	SSM NSM (L, Alt etc.)	Iraq	NSM > SSM
Balli [68]	SSM NSM (T)	Turkey	SSM > NSM
Bouchouicha et al. [69]	SSM NSM (T, DOY)	Algeria	SSM > NSM(T)>NSM(DOY)
Martins [70]	SSM NSM (T)	Brazil	SSM > MSSM
Al-Ghamdi [71]	SSM MSSM NSM	Saudi Arabia	NSM > MSSM > NSM
Masabi et al. [73]	SBDART SSM MSSM NSM (T, RH)		SBDART > SSM > MSSM > NSM
Chen [78]	SSM MSSM NSM (T)	China	NSM > MSSM > SSM (OSM using MODIS)

selected models are more than 0.95, indicating that the models are accurate. R values for three of the models were less than 0.95. They also found that MSSM is more accurate than SSM and NSM.

Irfan Kuckan and Kameran Mohammad Khudhur [67] evaluated 21 models developed in the past and also developed three new models for GHI prediction in Arbil, Duhok, and Sulemania regions in northern Iraq. 11 SSM models and 13 NSM models (including three new models) performance is evaluated in this study. The result of this article confirmed that NSM models' predictions are more accurate than SSM. The R^2 value for best SSM models ranged from 0.97 to 0.99, while the R^2 value for NSM was above 0.99. Ozgur Balli [68] developed six SSM models and 6 NSM (ambient temperature (T_a)-based) models using Eskisehir city-data. The statistical evaluation of models showed that all the models have predicted the GHI accurately and have the potential to be used by engineers. SSM outperformed the NSM. They also suggested that most developing countries' stations don't record sunshine duration data. So in the case of Sunshine duration-based data unavailability, the ambient temperature-based models can be used for GHI estimation as they have predicted GHI accurately. Kada Bouchouicha et al. [69] compared ten SSM and twenty NSM models (ten temperature and 10 DOY) for solar irradiation prediction in four Algerian cities. The results confirm that SSM models outperformed NSM models, with RMSE values ranging from 1.470 to 2.425 MJ/m2 day. Among NSM models, temperature-based models have higher accuracy than DOY-based models. Ana Fla'via Martins Monteiro and Fabrina Bolzan Martins [70] tested 13 empirical models (6 SSM, 7 NSM) developed in previous studies for Means Gerais in South-eastern Brazil. After testing 13 models, they validated the top 5 models with an independent validation data set. They found that each model's coefficients change with location and must be determined separately for each location. The models incorporating Tmax, Tmin, and P performed worst on the fitness test, while the models using S/S_0 as inputs performed best. The authors suggested that T_{max} and T_{min} models can be used for prediction when S/S_0 data is unavailable.

Saeed A. Al-Ghamdi [71] compared the performance of several SSM, MSSM, and NSM empirical models developed in the past literature and also proposed five new models for solar irradiation prediction in Al-Aqiq, Saudi Arabia. The results confirmed that models that NSM models that incorporate temperature, RH, and pressure produced better results than other models. The results also demonstrated that linear models are accurate, and the performance decreases when the model's polynomial order increases by three. The linear model [72], which incorporates temperature and RH, performed best with GPI and R^2 values of 0.037 and 0.87. Bijan Sedaqat Masabi, Zahra Aghashariatmadari, and Somayeh Hejabi [73] tested the performance of the parametric model (Santa Barbara DISORT atmospheric radiative transfer (SBDART)) performance with seven empirical models (2 SSM, 4 MSSM, 1 NSM) present in the literature for four cities in Iran. The R^2 value of all models ranged from 0.25 to 0.95, of which SBDART has the highest value (0.95) and the lowest value related to the Hargreaves model [30]. According to all statistical indicators, the SBDART model has the highest accuracy, followed by the Angstrom model. This research concludes that increasing the number of inputs in a model only increases the complexity and has no significant effect on the model's accuracy.

Cotrim Gomes et al. [74] predicted direct and diffuse components of global solar radiation for the coastal city of Salvador in Brazil. This research tested three diffuse component modeling models present in the literature. The models evaluated for the diffuse component are Ridley [75], Marques Filho [76] and Lemos et al. [77]. The Ridley and Lemos et al. models use five predictors to predict diffuse fractions and have shown greater prediction accuracy. In contrast, Filho models only use the clearness index (K_t) to predict the diffuse fraction. According to statistical evaluation using MBE, RMSE, and R^2, the Ridley model predictions are more accurate. After predicting diffuse fraction, they checked the consistency of GHI using the Angstrom-Prescot model. The R^2 value 0f 0.98 confirms the consistency of the data.

Ji-Long Chen et al. [78] coupled empirical models with Moderate Resolution Imaging Spectroradiometer (MODIS) products. They discovered that linear and non-linear models performed equally well, indicating that changing the model's structure to non-linear has little impact. Incorporating air temperature and atmospheric pressure in sunshine-based models results in higher accuracy, and adding RH and Prec does not affect the model's performance. While for temperature-based models, the models using only T_{max} or T_{min} are unsuitable for GHI prediction, while models using both have a little higher accuracy. Incorporating RH and T_{mean} in these models has shown higher accuracy, which means that RH and T_{mean} induction in models results in higher accuracy. And also, the addition of atmospheric pressure and ΔT has a positive effect on model accuracy. Among newly developed models, the model which uses all MODIS products as inputs has the highest accuracy. The coupling of the empirical model with freshly developed models has improved the accuracy of all the empirical models. Most of the research articles, also shown in Table 1, states that MSSM has the highest accuracy than NSM and SSM.

3. Artificial intelligence methods

Artificial Intelligence is gaining scope in every field of life. John McCarthy, who invented AI, stated that AI combines Science and engineering to develop intelligence devices for human welfare. Researchers have widely used AI in the past decade to solve complex problems in various fields. The AI has also shown compatibility in the renewable energy sector and has been widely used for predicting weather-dependent energy resources and power output from intermittent power plants such as wind and solar. AI models have surpassed the other models in solar radiation prediction [80]. AI consists of five groups which include ANN, GA, Fuzzy Logic, Hybrid systems (HS), and Expert systems (ES) [81]. This section reviews recent efforts in solar radiation prediction using AI methods.

For Semarang, Indonesia, Djoko Adi Widodo, Purwanto Purwanto, and Hermawan Hermawan [82] predicted monthly GHI. Satellite data were the source for this study's input. L, Lon, Alt, RH, Tmax, Prec, and Ws serve as the inputs. The outcomes demonstrated that ANN was capable of highly accurate solar prediction. The model's MAPE was 6.6%, which shows how accurate ANNs are in forecasting monthly GHI. Using ANN (FFNN), N. B. Sushmi and D. Subbulekshmi [83] forecasted hourly GHI for Chenia, India. Initially, the Pearson Coefficient Test was used to choose the influential characteristics. The test found that the most important characteristics were Zenith angle, RH, Ta, CC, and Precipitable water. An FFNN model is developed using these parameters to forecast hourly GHI. The model's MAPE and NRMSE values were 44.43% and 7.21%, respectively. Adi Kurniawan and Anisa Harumwidiah [84] evaluated the performance of the ANN model for Surabaya city in Indonesia. The input parameters used in this study are T_{max}, T_{min}, RH, T_{mean}, Prec, W_s, month (m), and sunshine duration (S). The data found that the amount of solar irradiation in Surabaya city is increasing yearly while input parameters such as T_{max}, T_{min}, and RH have been at the same level for the last five years. This trend of data confuses the ANN model. The ANN model MAPE for the first two years was 8.77% and 8.82%, but in the last two years, the model accuracy decreased due to an increase in GHI, and MAPE for 2018 and 2019 was 11.38% and 12.41%. The study recommends that the accuracy of the ANN model can be increased if separate models are used for rainy and dry seasons. Using chained ANN, Bashar Shboul et al. [85] predicted hourly GHI and wind speed for the Northern and Southern Arabian Peninsula (Jordan and Oman). First, an ANN model using m, d, and clock time was created to predict meteorological parameters such as Cloud Quality (CQ), Azimuth Angle, T_a, RH, Atmospheric Pressure (P_a), and Perceptible water. Then the predicted parameters, in addition to m, d, and clock time, are fed into another ANN model, which predicts GHI, Direct Normal Irradiation (DNI), Diffuse Horizontal Irradiation (DHI), and wind speed. The R^2 values for all parameters in Jordan and Oman are 0.96 and 0.97, respectively. The highest MAPE for GHI was 4%, while for wind, it was only 3%. The results confirmed the accuracy of ANN for wind and GHI prediction. Using L, Lon, Alt, m, d, RH, and T_{mean} for training ANN, Nait Mensour et al. [86] predicted solar irradiation for Abu Mousa, Morroco. The research confirmed that ANN could predict solar irradiation accurately, and ANN's R and RMSE values were 0.98 and 0.234 kWh/m^2/d.

Pratima Kumari and Durga Toshniwal [87] analyzed 31 different combinations of five input parameters (T_{max}, T_{min}, S, ΔT, H_0) using FFNN. In the first five combinations, each input parameter is tested alone, then in the 2nd and 3rd steps, ten combinations of 2 inputs and three inputs are developed. Five combinations contain four input parameters, and one subset comprises all five. The results confirmed that models with two and three inputs have higher accuracy than other combinations, and the model with the combination of T_{max}, $T_{min,}$ and ΔT from the third group has the lowest MAPE of 2.635%. Babatunde, Munda, and Hamam [88] analyzed the performance of ANN with weights calculated by differential evolution for monthly GHI prediction in Iseyin, Nigeria. Monthly averages of Tmax, Tmin, and S are input parameters. The results confirmed the potential of ANN for monthly GHI prediction. RMSE, NSE, and R^2 values of models are 1.01967 kWh/m2/d, 0.8137, and 0.8254. Olusola Bamisile et al. [89] developed four ANN (FFNN) models of different hidden layers (1–4) for Nigeria and tested all four models for six locations. Inputs for the training of ANN were years, m, d, hour, T_a, $W_{s,}$ and sun elevation. R^2 values for all location ranges from 0.90 to 0.97. ANN3, with three hidden layers, has the lowest average RMSE and MAE of 89.63 W/m2 and 39.62 W/m and the highest average R-value of 0.93, declaring this model the best model. The study also confirmed that for high solar irradiation potential areas, the error is small compared to the error for areas with lower potential. Adi Kurniawan and Eiji Shintaku [90] predicted monthly GHI, DNI, and DHI for five cities in Japan and also predicted only GHI for another six cities using ANN (FFNN). Eleven input parameters were used to train the ANN, including L, Lon, Alt, m, Tmax, Tmean, Tmin, S, Prec, Ws, and RH. The average MAPE for DNI, DHI, and GHI in the first five locations was 6.30%, 5.75%, and 3.70%, respectively. At the same time, the average MAPE for GHI in another six locations was 6.96%. Cahit Gurlek and Mustafa Sahin [91] predicted solar irradiation for Sivas, Turkey using ANN. Input parameters applied in the research were L, Lon, Alt, m, $T_{mean,}$ and S. Four station data were used for training and testing ANN. The R^2 of the model ranged from 0.994 to 0.984.

Heng et al. [92] tested four different combinations of three inputs (T_{mean}, RH, and W_s) with FFNN using LM, Bayesian regularization (BR), and scaled conjugate gradient (SCG) as training algorithms for Kuala Terengganu, Malaysia. The results confirmed that BR-trained FFNN using all three inputs is the best model with R, RMSE, MAE, and MAPE values of 0.81 MJ/m^2/d, 0.2581 MJ/m^2/d, 0.1789, and 10.64%, respectively. The results showed that RH and temperature are the effective input parameters for GHI prediction. In Tamil Nadu, India, A. Geetha et al. [93] used ANN with different training algorithms for hourly solar radiation prediction. The ANN used was FFNN, while the training algorithms used were Levenberg Marquardt (LM), Resilient Back Propagation (RP), and scaled conjugate gradient (SCG). The input data set consisted of seven input parameters which are L, Lon, day (d), month (m), ambient temperature (T_a), hour (h), and W_s. The LM algorithm proved superior to the other two algorithms regarding statistical metrics. The R-value for the best model was 0.9376 for training and 0.9340 for testing. Olanrewaju M. Oyewola et al. [94] predicted monthly GHI for 31 locations in Fiji Islands using FFNN. T_{mean}, RH, Prec, m, Alt, Lon, and L were the input parameters used for prediction of GHI prediction. LM and SCG were tested as training algorithms for ANN. Six different combinations of hidden layer layers and hidden layer neurons are tested using LM and SCG algorithms. Two hidden layer networks with ten neurons in each layer LM algorithm trained was the best model with 0.93 kWh/m^2/d MSE and 0.93 R for testing dataset. Zahraa E. Mohamed [95] predicted daily and monthly GHI for three cities in Egypt. ANN network has two backpropagation algorithms, i.e., basic backpropagation and backpropagation with momentum and learning rate coefficients. The ranking of models was done using RMSE. T_{max}, T_{min}, T_{mean}, RH, and atmospheric pressure were the inputs for the training of ANN. Based on RMSE values, the backpropagation algorithm with momentum and learning rate coefficients has better accuracy than the basic algorithm. The best model's average RMSE, MAPE, and R2 values are 2.05 MJ/m^2, 4.98%, and 0.999.

Nawab et al. [96] evaluated the performance of three types of ANN: Feed-forward Neural Network (FFNN), Cascaded feed-forward neural network (CFNN), and Elman Neural Network (EMNN) for solar irradiation prediction in Pakistan. All networks were tested for nine cities in different climatic zones of Pakistan. The results confirmed that all the networks had predicted very well. The FFNN has the highest accuracy among all the networks, with MAPE values ranging from 3.50% to 16.48%. Satellite data inputs were used to predict the ground-measured solar irradiation. The results also confirmed that RH, Satellite global horizontal irradiation (G_{sat}) are the most influential input parameters. The hourly GHI predictions of FFNN, K closest neighbour (k-NN), Auto Regressive Integrated Moving Average (ARIMA), and SVM for the Tetouan region of Morocco were compared by Brahim Belmahdi, Mohamed Louzazni, and Abdelmajid El Bouardi [97]. The input parameters, as determined by the Pearson Coefficient Test, are K_t, T, Ratio Temperature, T_{mean}, T_{max}, and H_0. The statistical measures proved that FFNN trained with the LM approach outperforms other models in terms of accuracy. The MAPE, NRMSE, RMSE, MBE, and t-stat values for the top-performing model were 1.80%, 0.57, 15.8, 23.88, and 6.68, respectively.

Using Ws, RH, cloud cover, temperature, wind direction, and other airborne contaminants, R Nisha Nandhini and A Geethakarthi [98] compared RSM with ANN. In terms of R and MSE, they discovered that ANN performed better than the RSM. R and MSE for ANN were 0.89 and 0.48 kWh/m2/d, respectively. According to the study, atmospheric contaminants have a greater impact on solar radiation than meteorological factors. For four Turkish provinces, Ümit Abulut, Ali Etem Gürel, and Yunus Biçen [99] predicted GHI. With input parameters Tmax, Tmin, CC, S_0, and H_0 recorded by Turkish meteorological stations, they employ ANN, k-NN, SVM, and Deep Learning (DL). All models had R^2, MABE, and RMSE values between 0.855 and 0.936, 2.273 and 2.820 MJ/m^2, and 1.87 and 2.32 MJ/m^2, respectively. According to the findings, ANN forecasts outperform all other models, followed by DL, SVM, and K-NN. Leila Naderloo [100] compared RSM, ANFIS, RSM, and ANN for solar irradiation prediction in Sarpol-e-Zahab Township, Kermanshah, Iran. The input parameters were S/S0, RH, monthly Tmean, and evaporation. The results confirmed that ANN and RSM outperformed the ANFIS model. The R and MSE values for ANN, RSM and ANFIS models are, 0.99 and 0.00029 0.99 kWh/m2/d and 0.00027 kWh/m2/d and 0.99 and 0.00005 kWh/m2/d. The results also confirmed that ANN and RSM are superior in speed and simplicity compared to ANFIS.

Sara Bamehr and Samaneh Sabetghadam [101] estimated GHI for Mashad, Iran, using FFNN and (Multi Linear Regression) MLR. The input data was collected from MODIS and the ozone monitoring instrument (OMI). The input parameters were aerosol optical depth, Angstrom exponent, cloud fraction, cloud optical depth, and precipitable water vapour amount from MODIS and Ultraviolet aerosol index from OMI. Seven subsets of input parameters were used to develop MLR and FFNN models. The seasonal evaluation of models showed that both models have high accuracy in the winter and autumn seasons and lower accuracy in summer and spring. The ANN models outperformed the MLR models with 20.2% and 21.4% MAPE values. The RMSE and MSE values for ANN and MLR models are (3.7 and 3.9) and (2.3 and 2.7), respectively. A. Burak Guher et al. [102]predicted hourly GHI for Mersin province in Turkey using ANN, SVR, and k-NN. First, they selected the most influential parameters using the WEKA program. After confirming significant input parameters (year (Y), m, d, h, T_a, P, RH, W_s, S), the ANN (FFNN), SVR, and k-NN models are developed using MATLAB. ANN predictions are superior to other models with a MAPE value of 6.12%, followed by k-NN and SVR with MAPE values of 7.22% and 12.72%. Tamara Rosemary Govindasamy and Naven Chetty [103] investigated the performance of ANN, SVR, General Regression Neural Network (GRNN), RF, and the effect of Particulate Matter (PM_{10}) for solar radiation prediction for nine sites in South Africa. In this study, 36 (6 include only H_0, S/S_0, eight models are temperature based, which use T_{max}, T^2_{max} T_{min}, T_{mean}, ΔT raised to different powers, six models use RH, four models are linear hybrid, and 12 models are non-linear hybrid) input combination without PM_{10} was developed first. The accuracy of all networks is checked with these input combinations. Then 16 input combinations from the above groups are selected, and PM_{10} is added to each combination. The addition of PM_{10} has improved the accuracy of all models, and also, in this model, ANN accuracy was superior to other networks. The ANN model outperformed all the models with R^2 and MBE values of 0.99 and 0.06199 $kWh/m^2/d$.

Md. Bengir Ahmed Shuvho et al. [104] predicted monthly solar irradiation and performed a performance evaluation of an 80 kWp PV plant in Bangladesh. For solar irradiation, ANN and Fuzzy logic were used. Input parameters used for ANN were T_a, RH, P_a, W_s, and earth temperature, while the inputs for fuzzy logic were T_a, W_s, and RH. The R^2 and A values for the ANN model were 0.99 and 97.44%, and for fuzzy logic, the values were 0.999 and 98.78%. Results confirmed that ANN model predictions are more accurate than Fuzzy logic. Taghadomi-Saberi et al. [105] evaluated the performance of ANN and ANFIS for solar irradiation prediction in Isfahan, Iran. Inputs used to train models were T_{max}, T_{min}, S, S_0, d, clear sky insolation, RH, Prec, and H_0. The RH and Prec are eliminated in the first stage as they don't follow the behaviour of solar irradiation and other input parameters. This research developed seven combinations of the remaining seven inputs to train the ANN and ANFIS. The ANN outperformed the ANFIS with an R-value of 0.92, while the best ANFIS model has an R-value of 0.89. Mohammad Mehdi Lotfinejad et al. [106] compared GRNN and ANFIS with ANN using a Bat Algorithm for soar irradiation prediction in four cities in Iran. Input parameters were S, T_{mean}, W_h, RH, and broadband solar irradiation. The R^2 values of ANN, GRNN, and ANFIS were 0.98, 0.96, and 0.65. The results confirmed that ANN outperformed GRNN and ANFIS in terms of accuracy. A. Khosravi et al. [107] developed one input-based and one-time series model for solar irradiation prediction in Abu Musa Island, Sharjah. SVR, RBN, ANN, Fuzzy inference system (FIS), and ANFIS were evaluated using input-based and time-series models. Input based model uses RH, P, W_s, T_{mean}, and local time as input parameters. For both models, SVR performed best with $R = 0.99$, followed by ANN with $R = 0.98$.

Ellysia Jumin et al. predicted solar irradiation for Malaysia using Boosted Decision Tree regression (BDTR) model for Malaysia. The researchers used two different data splits to train and test the model and then compared the results with neural network and linear regression models. All the models are optimized using conventional manual adjusting of the learning rate, while in the second method tune model hyperparameter is introduced for adjusting the learning rate. The results confirmed that 75% training and 25% testing data split gave more accurate results than 80%–20% data split, and also, the conventional optimization outperformed the models optimized with tune hyperparameter. The BDTR model results are more accurate, followed by linear regression [108].

Mohammad Ehteram et al. developed a model for solar irradiation prediction using a hybrid model consisting of a multi-objective shark algorithm and ANFIS for Iran. The model results are compared with multi-objective GA-ANFIS and multi-objective Particle swarm optimization-based ANFIS. The result confirmed that the multi-objective Shark algorithm-based ANFIS model has the best predictions among all models [109].

Hamidreza Ghazvinian et al. proposed the Improved Particle Swarm Based Optimization algorithm (IPSO) based SVR for solar irradiation prediction in two provinces of Turkey. The IPSO was integrated with SVM for optimal selection of SVM parameters. The proposed model results are then compared with the M5 tree model, Genetic programming, SVR integrated with optimization algorithms, and Multi Adaptive Regression models. The results confirmed that SVR-IPSO results are more accurate than other models [110].

The effectiveness of ANN and LSTM for predicting solar irradiation in Turkey was compared by Tugba Ozdemir et al. [111]. The inputs include the power output of three types of solar panels, Tmean, panel temperature (Tp), RH, S, and CC. The study's findings showed that, in terms of accuracy, LSTM surpassed ANN, with R2, MSE, RMSE, MAE, and MBE of 0.93, 0.008, 0.089, 0.17, and 0.09, respectively. Most of the reviewed articles, as clear from Table 2, confirm that ANN has the best accuracy among Artificial Intelligence models.

4. Comparative studies

For Lalibela in Ethiopia, Tegenu Argaw Woldegiyorgis et al. [112] compared the effectiveness of the ANN model and three empirical models. The Angstrom-Prescot and Louche sunshine duration-based models are examples of empirical models. The Glover McCulloch model, the third one, also takes latitude into account in addition to sunshine duration. The empirical model's value ranged from 0.126 to 0.17, whereas the ANN R2 value was 0.799. The empirical model's MBE values ranged from −0.468 to −0.05, while the MBE for the ANN was −0.0005. Similar to this, ANN had an RMSE value of 0.331 kWh/m2, whereas empirical models had RMSE values that ranged from 1.071 kWh/m^2 to 1.263 kWh/m^2. The ANN model forecasts are more accurate than the sunshine duration-based models, according to all three statistical measures.

Table 2
Artificial Intelligence methods.

References	Networks	No. of Inputs	Country	Accuracy
Widodo et al. [82]	FFNN	7	Indonesia	FFNN
Sushmi et al. [83]	FFNN	5	India	FFNN
Kurniawan et al. [84]	FFNN	8	Indonesia	FFNN
Shboul et al. [85]	FFNN	9	Jordan and Oman	FFNN
Mensour et al. [86]	FFNN	7	Morroco	FFNN
Kumari et al. [87]	FFNN	5	India	FFNN
Babtunde [88]	FFNN	3	Nigeria	FFNN
Bamisile et al. [89]	FFNN	7	Nigeria	FFNN
Adi Kurniawan [90]	FFNN	11	Japan	FFNN
Gurlek [91]	FFNN	6	Turley	FFNN
Heng et al. [92]	FFNN	3	Malaysia	FFNN
Geetha et al. [93]	FFNN	7	India	FFNN
Oyewola et al. [94]	FFNN	7	Fiji Island	FFNN
E. Mohamed [95]	FFNN	5	Egypt	FFNN
Nawab et al. [96]	FFNN CFNN EMNN	12	Pakistan	FFNN > CFNN > EMNN
Belmahdi et al. [97]	FFNN k-NN ARIMA SVM	6	Morocco	FFNN > ARIMA > k-NN > SVM
Nandhini et al. [98]	FFNN RSM	6	India	FFNN > RSM
Agbulut et al. [99]	FFNN SVM k-NN DL	5	Turkey	FFNN > DL > SVM > k-NN
Naderloo [100]	FFNN RSM ANFIS	4	Iran	FFNN > RSM > ANFIS
Bamehr et al. [101]	FFNN MLR	6	Iran	FFNN > MLR
Guher et al. [102]	FFNN SVR k-NN	9	Turkey	FFNN > k-NN > SVR
Govindasamy et al. [103]	FFNN GRNN SVM RF	8	South Africa	FFNN > SVR > RF > GRNN
Ahmed Shuvho [104]	FFNN, Fuzzy Logic	5, 3	Bangladesh	FFNN > Fuzzy Logic
Saberi et al. [105]	FFNN ANFIS	9	Iran	FFNN > ANFIS
Lotfinejad et al [106]	FFNN ANFIS GRNN	5	Iran	FFNN > ANFIS > GRNN
A. Khosravi et al. [107]	FFNN SVR FIS ANFIS RBN	5	UAE	SVR > FFNN > ANFIS > FIS > RBN
Ozdemir et al. [111]	FFNN LSTM	8	Turkey	LSTM > FFNN

Cícero Manoel dos Santos et al. [113] compared ten empirical models, six linear regression models (LRM), and five SVM and ANN models for solar irradiation prediction in Campo Grande, MS, Brazil. All the models are NSM (temperature based) and use T_{max}, T_{min}, ΔT, and T_{mean} as inputs. The results confirmed that the empirical model developed by Ref. [114] outperformed all the models with $R^2 = 0.693$. The empirical models performed better among all models, while the ANN models performed worst.

Yu Feng et al. [115] compared the performance of 4 temperature-based machine learning (ML) and four temperature-based empirical models using data from 4 stations in the temperate continental region of China. All four empirical models use ΔT as an input parameter. The machine learning models are ANN, a Hybrid mind Evolutionary algorithm that combines ANN, Random Forest (RF), and Wavelet neural network. The comparison showed that all the ML models outperformed the empirical models. Regarding R^2, the hybrid models performed best among all the models for four stations, followed by ANN with a minimal margin.

Qian et al. [116] developed ANN for GHI prediction in the Yellow River Basin, China, with input parameters T_{max}, T_{min}, T_{mean}, W_s, RH, S, and S_0. After the development of the model, the results are compared with the Angstrom Prescot model using RMSE, R^2, MSE, and MAE. The result confirmed that the ANN model accuracy is higher than Angstrom Prescot Model. The average R^2 value of the Angstrom Prescot was 0.88, while for ANN, it was 0.91. In terms of MSE, the ANN model MSE is 25.93% less than Angstrom Prescot Model. At the same time, The RMSE and MAE of the ANN model are 5.25% and 2.28% less than the Angstrom Prescot model.

Ali Etem Gürel, Ümit Ağbulut, and Yunus Biçen [17] evaluated the performance of 4 different methods named Machine learning (Feed Forward Neural Network), Time Response (Hot Winters), empirical (Three Angstrom Based models), and response surface methodology (RSM) for four provinces in Turkey. The empirical models used are linear, quadratic, and third-order polynomial-based models. The R^2 values of ANN, best empirical model, RSM, and time response model are 0.991, 0.984, 0.978, and 0.985. While the MBE values are 0.1323 MJ/m^2-day, 0.3191 MJ/m^2-day, 0.3689 MJ/m^2-day, 0.1884 MJ/m^2-day for ANN, time response, RSM and empirical models. And the MAPE values are 4.92%, 7.55%, 8.31%, and 7.83% for ANN, time response, RSM, and empirical models. The results concluded that the ANN model performed best verified by all the statistical indicators, followed by empirical models, which were the second-best predictors. Empirical modeling is the simplest method to predict GHI, but the empirical models cannot relate complex and non-linear relationships among variables.

Babak Jahani & Babak Mohammadi [117] compared one sunshine base and one temperature-based empirical performance with two simple ANN (1 temperature and one sunshine model) and 2 ANN coupled Genetic Algorithm (GA) (1 temperature and one sunshine model) models using data from the station of the Islamic Republic of Iran Meteorological organization. In terms of R^2, RMSE, and MBE, the sunshine-based empirical models (0.93, 37 J/cm^2, and 179 J/cm^2) outperformed the simple ANN model (0.90, 55.7 J/cm^2, 243.5 J/cm^2). When ANN has coupled with GA, the models' accuracy improved with R^2, RMSE, and MBE of 0.92 J/cm^2,38.4 J/cm^2 and 185.5 J/cm^2. In all three types, the accuracy of sunshine models is superior to temperature-based models.

Saeed Samadianfard et al. [118] compared six empirical models with data-driven models like Support Vector Machine (SVM), Model Trees (MT), Gene Expression Programming (GEP), and adaptive neuro-fuzzy inference system (ANFIS) in Tabriz, Iran. The inputs used for data-driven models are H_0, T_{max}, T_{min}, T_{min}, RH, DOY, S, S_0, and corrected clear sky solar irradiation. Nine different models of each data-driven method have been developed using nine combinations of input parameters. The testing of different combinations confirmed that S and RH are the most influential input parameters for data-driven techniques, followed by T_{min}, T_{max}, and H_0. The SVR models with inputs H_0, RH, T_{max}, T_{min}, and S/S_0 proved to be the most accurate model with R, RMSE, and MAE values of 0.98, 1.656 MJ/m^2, 0.99 MJ/m^2, respectively. Among all methods, SVR performed best.

Vassilis Z. Antonopoulos [119]compared the performance of the empirical model (Hargreaves model (Hargreaves, 1994)), ANN, and Multi Linear Regression (MLR) for AUTH and Amin stations in Greece. Two Hargreaves models were tested, one using default coefficient value and the second using adjusted local coefficient value. Three ANN models with inputs [Tmax, Tmin, Tmean, RH, and Ws], [H0, ΔT, $(\Delta T)^{0.5}$, RH], and [H0, $(\Delta T)^{0.5}$] were developed and tested for each station. Four MLR models are developed, using Tmax, Tmin, Tmean, RH, Ws, and H_0, while the other uses ΔT and $(\Delta T)0.5$. They found that MLR results were more accurate for AUTH station, while ANN performed more accurately for the Amin station.

Junliang Fan et al. [120] compared the performance of 12 sunshine-based empirical models with 12 machine-learning models for different climatic zones in China. The comparison confirmed that all machine learning models had outperformed the empirical models. The accuracy of all ML models was in an acceptable range. Among ML models, ANFIS models outperformed other models.

Vahid Nourani et al. [121] used three temperature-based empirical models developed by Refs. [30,33,122], one ANFIS, one ANN, one MLR, and two ensemble networks. The input parameters used for AI and MLR were T_{max}, T_{min}, T_{mean}, RH, and W_s. In single models, the ANFIS outperformed all the models with NRMSE values ranging from 0.099 to 0.104, followed by ANN with 0.097–0.116. Also, the ensemble networks improve the accuracy of single models by 16.8%.

M. Marzouq et al. [123] proposed an evolutionary ANN for solar irradiation prediction in Fez, Morocco. To validate the model; the researchers compared the proposed model results with the k-NN model and three temperature-based empirical models present in the literature [35,38,81]. The evolutionary ANN is a simple FFNN network, but a genetic algorithm is used for input selection. The results confirmed that the newly proposed model has the highest accuracy among all models with $R^2 = 0.97$, followed by k-NN with 0.96 R^2.

R. Meenal and A. Immanuel Selvakumar [124] compared sixteen empirical models (8 SSM, 4 MSSM, 4 NSM), 16 SVM, and 3 ANN models for solar irradiation prediction in 8 stations in India. Among empirical models, MSSM predicted best for all locations with R values ranging from 0.92 to 0.98. The SVM and ANN R-values are 0.9916 and 0.9968. The results confirmed that ANN outperformed SVM and empirical models in accuracy. The results also demonstrated that S and T_a are the most influential parameters for solar irradiation prediction. The RH alone is insignificant, but its addition to S and T_a improves the accuracy.

DV Siva Krishna Rao et al. [125]developed 32 ANN models from combinations of six inputs (T_{min}, T_{max}, S, S_0, H_0, and ΔT) for solar irradiation prediction in Tiruchirappalli, India. The results of ANN models are then compared with temperature- and sunshine-based empirical models developed by the authors in Refs. [65,126]. The results confirmed that models with two and three input parameters performed best among ANN models. The models with input parameters ΔT, S_0, and H_0 and ΔT, S_0 performed best with RRMSE values of 4.90% and 5.23%, respectively. The RRMSE values of the temperature-based and sunshine-based empirical models were 7.58% and 10.72%, respectively.

Ling Zou et al. [127] compared the performance of two improved forms of the empirical model developed by Bristow and Campbell (MSSM) [34] and Yang model [128] (modified Prescot (SSM) [129]) and one ANFIS model for three stations in China. For ANFIS, four combinations of S, RH, Prec, P, ΔT, $T_{max,\ and}$ $T_{min.}$ Results confirm the superiority of the ANFIS model to other models, followed by the Yang model. ANFIS model R^2 values ranged from 0.94 to 0.98, while the Yang model R^2 values ranged from 0.79 to 0.86.

Prado da Silva [130] compared the performance of SVM, ANN, and Angstrom Prescot (SSM) for solar irradiation prediction in Botucatu, Brazil. Four input combinations of input parameters, T_{max}, T_{min}, RH, S/S_0, H_0, and precipitation, are used to train SVM and ANN. The SVM model outperformed the ANN and SSM with RMbE and RRMSE values ranging from −2.7% to 1.06% and 9.4%–12.5%. On the other hand, ANN results are the worst of the three models, with RMBE and RRMSE values of −13%–8.1% and 15.6%–16.6%, respectively. Most of the articles reviewed in this section, as clear from Table 3, confirms that AI methods have better accuracy than empirical models.

Table 3
Comparative studies.

References	Models	Country	Accuracy
Woldegiyorgis et al. [112]	FFNN EM	Ethiopia	FFNN > EM
Zhang et al. [116]	FFNN EM	China	FFNN > EM
Feng et al. [115]	FFNN HE-FFNN RF WNN EM	China	HE-FFNN > FFNN > RF > ENN > EM
Gürel et al. [17]	FFNN Time response RSM EM	Turkey	FFNN > RSM > Time response > EM
Jahani et al. [117]	FFNN EM	Iran	FFNN > EM
Antonopoulos et al. [119]	FFNN MLR	Greece	FFNN (1 location) MLR (1 location)
Fan et al. [120]	FFNN ELM SVM ANFIS M5TREE XGBoost RF EM	China	ANFIS > ELM > LSVM > MARS> XGBoost > EM
Santos et al. [113]	FFNN EM SVM RSM	Brazil	SVM > EM > RSM > ANN
Qian et al. [116]	FFNN EM	China	FFNN > EM
Samadianfard et al. [118]	SVM MT GEP ANFIS EM	Iran	SV > MT > ANFIS > GEP > EM
Nourani et al. [121]	ANFIS FFNN MLR EM	Iraq	ANFIS > FFNN > MLR > EM
Marzouq et al. [123]	E-FFNN k-NN EM	Morroco	E-FFNN > k-NN > EM
Meenal et al. [124]	SVM FFNN EM	India	FFNN > SVM > EM
Rao et al. [125]	FFNN EM	India	FFNN > EM
Zou et al. [127]	ANFIS EM	China	ANFIS > EM
Silva et al. [130]	SVM FFNN EM	Brazil	SVM > EM > A'NN

Table 4
Pros and cons of methodologies.

Serial No:	Methodology	Pros	Cons
1.	Empirical Methods		
	a. SSM	Greater accuracy	Data is easily unavailable as most meteorological stations don't have Sunshine hours recording facility.
	b. MSSM	Best Accuracy among Empirical Models	Data is easily unavailable as most meteorological stations don't have Sunshine hours recording facility.
	c. NSM	The data is readily available as most stations record the required climatic parameters.	Have lower accuracy than MSSM and NSM
2.	AI Methods		
	a. Single AI models	Easy to develop models as they don't require sophisticated programming knowledge.	Has accuracy lower than Hybrid models
	b. Hybrid AI Models	Accuracy higher than Single AI models	Has the best accuracy among all methods.

5. Summary

1. Sunshine-based models have been employed frequently, producing favorable outcomes among empirical models. Modified sunshine-based models are among the most accurate sunshine-based models. However, since temperature and day-of-the-year data are readily available for most sites, the lack of sunshine data opens the door for temperature-based and day-of-the-year models.
2. SVR, SVM, ANFIS, ANN, k-NN, and RSM and Hybrid models have been utilized for GHI prediction globally among artificial intelligence models. The literature review indicates that AI has produced the most precise results, particularly FFNN and Hybrid models. But the hybrid models require very sophisticated programming knowledge and are very time-consuming, but their accuracy improvement as compared to other AI models is very minimal
3. The comparative studies confirm that AI models have produced good results than empirical models.
4. Air pressure and wind speed hardly ever affect a model's accuracy confirmed by most of the articles.
5. ANN's most important input factors are maximum, minimum, temperature differential, relative humidity, K_t, and precipitation. And in future research, these inputs should be combined with other input parameters.
6. The location dependability of models can be tackled by checking different input combination-based models for vast areas.
7. Advantages and Disadvantages of different methods are shown in Table 4.

6. Research gaps

1. All the models rely on inputs from meteorological stations, which restricts their applicability to regions with those stations and cannot predict data for areas without stations. Future models that correlate satellite data with ground-measured data should be developed in order to reduce the error present in satellite data since satellite data is readily available for the majority of sites.
2. Other factors could be taken into account, including ozone and pollutant chemicals, which are known to affect light transmission through the atmosphere, especially at particular wavelengths. Additionally, it is important to examine how these parameters affect the model's accuracy.
3. Some unfavourable weather conditions like dust storms and hot winds result in higher temperatures, and the dust storms also result in lower radiations value, which results in poor performance of models. So the effect of dust storms and hot winds on the model accuracy should be evaluated.
4. Greenhouse gases increasing volume in the atmosphere should be considered in solar irradiation prediction as greenhouse gases contribute to an increase in temperature while solar irradiation remains the same. This can affect the accuracy of the model incorporating temperature as input.
5. For ANN, the tick and trial selection of neurons is very time-consuming, and research should be done on identifying the rule for optimum neuron selection.
6. The location dependability of models is the main problem discussed in most articles. As the researchers stated, different models gave accurate results for different locations.

7. Conclusion

Notably, the intermittent nature of solar irradiation influences solar energy use in all forms, whether energy or agriculture. Accurate solar irradiation prediction is the only solution to effectively use solar energy in different forms. The estimation of solar irradiation is the most critical factor for site selection and sizing of solar energy projects and for selecting a suitable crop selection for the area. A thorough review of research articles discussing solar irradiation prediction has been done to compare different methods for solar irradiation prediction. First, articles relating to empirical models are reviewed, and a comparative analysis of different empirical models is done. The articles relating to artificial intelligence models have been reviewed in the second step, and various methods are compared. Articles comparing empirical and artificial intelligence methods have been reviewed in the last stage. The comparative study confirms that Artificial Intelligence methods have surpassed the empirical model in accuracy. The empirical models are divided into three categories, i.e., sunshine-based, modified, and non-sunshine-based. Modified sunshine-based models have the highest accuracy among these three categories, followed by sunshine-based models. The non-sunshine-based model's accuracy is lower than the sunshine-based model's. Still, the unavailability of sunshine data provides space for non-sunshine-based models, especially temperature-based and day-of-the-year-based models, as these input data are available for most locations. The ANN and Hybrid models had the highest accuracy among artificial intelligence models, followed by SVM and ANFIS. The hybrid model improvement in accuracy is very minimal, but their complexity makes it difficult to use for most of the researchers For ANN, the maximum temperature, minimum temperature, temperature differential, relative humidity, clearness index, and precipitation are the significant inputs that can be considered for predicting solar irradiation.

Author contribution statement

Faisal Nawab: Conceived and designed the experiments; Performed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Ag Sufiyan Abd Hamid, Ph. D: Conceived and designed the experiments; Wrote the paper.

Adnan Ibrahim: Analyzed and interpreted the data; Wrote the paper.

Kamaruzzaman Sopian: Conceived and designed the experiments; Analyzed and interpreted the data.

Ahmad Fazlizan; Mohd Faizal Fauzan: Performed the experiments; Contributed reagents, materials, analysis tools or data.

Data availability statement

Data will be made available on request.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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