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The Artificial Neural Network (ANN) Approach for Enhancing the Efficiency of Renewable Energy Sources– A Review

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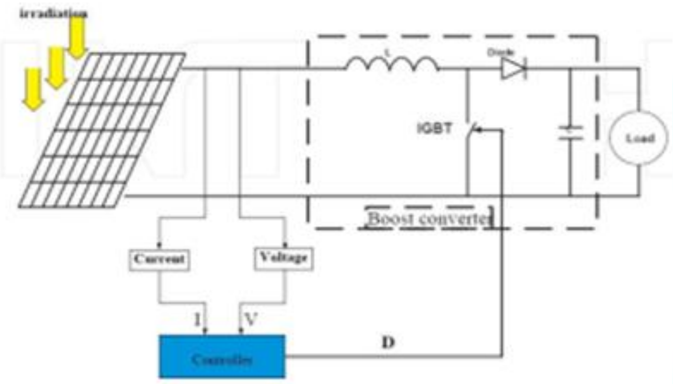
ABSTRACT

Estimating solar radiation is critical in a variety of energy systems. The goal of this work is twofold: first, it is an updated analysis of solar radiation prediction models employing ANNs based on 32 retained publications, by assessing the forecast horizon, the ANN architecture, and the associated performance metrics. Second, the inadequacies of the study are followed with suggested suggestions and points of view for further research.

KEYWORDS—solar radiation prediction; solar energy modeling;artificial intelligence; artificial neural networks (ANN)

I.Introduction

Solar radiation information is of brilliant significance in solar energy research and engineering. In fact, an appropriate understanding of the supply and variability of solar radiation intensity could be very important, especially for solar devices along with flat plate collectors [1], sizing photovoltaic structures, evaluation of the thermal load onhomes, environmental impact analysis and agriculture [2-7]. However, there is a challenge of the wide variety of meteorological stations that degree solar radiation with dependable and calibrated pyrometers, due to the cost and preserve the issue of sunradiation measuring devices [8, 9]. Moreover, maximum stations only have confined measured parameters inclusive of relative humidity, temperature, wind speed, and sunshine duration. Hence, considering these parameters are extra easy to be had around the world, they're used to estimate sun radiation, as an opportunity manner, to generate those wanted data using suitable fashions. Since the primary models [10, 11], syntheticintelligence (AI) techniques have become useful as exchange strategies. Specifically,ANNs carry out a computational simulation with a high capability to modelize the complicated, nonlinear, and time-varying input-output systems [12]. ANNshad been broadly hired to estimate international sun radiation the use of various geographical and meteorological parameters. In this study, a review is made on Artificial Neural Network techniques with the motive of highlighting realistic methodsavailable in the literature for solar radiation prediction. Our contribution is to encompass latest researches on this area up till 2016 with an exhaustive list of important works. The aim is toassist future researchers to effortlessly identify posted papers by specifying the prediction horizon, ANN structure and the corresponding obtained overall performance signs. Another contribution is to factor out the research obstacles and endorse recommendations and outlooks for future studies initiatives. This paper gives statistical signs and a evaluate of solar radiation fashions (Section II and III) followed by a discussion and guidelines and a conclusion in Section



UnifiedDiagramofPVSystem

PVTechnologyReview:Nowadays renewable power strategies for strength manufacturing are mature and dependable. The photovoltaic (PV) power is the most promising source of energy because it's miles pollutants-loose and abundantly to be had anywhere inside the international. PV electricity is especially beneficial in far-flung websites like deserts or rural zones where the problems to transport gas and the dearth of strength grid lines make the usage of traditional resources impossible.

STATISTICAL INDICATORS USED IN LITERATURE

To examine the ANN prediction performance, many well-known prediction accuracy indices are adopted inside the literature. Our precise inspection of the publications under examine allowed the extraction of the list wearing desk I.

TABLE I. Indicators Used In The Underlying Studied Works

Performance indicators	Formula
R (correlation coefficient)	$\frac{\sum_i^n\left(o_i-\left(\frac{1}{n}\sum_i^n(o_i)\right)\right)\left(t_i-\left(\frac{1}{n}\sum_i^n(t_i)\right)\right)}{\sqrt{\sum_i^n\left(o_i-\frac{1}{n}\sum_i^n(o_i)\right)^2\sum_i^n\left(t_i-\frac{1}{n}\sum_i^n(t_i)\right)^2}}$
R^2 (coefficient of determination)	$1-\left(\frac{\sum_i^n(t_i-o_i)^2}{\sum_i^n(o_i)^2}\right)$
RMSE (root mean square error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i-t_i)^2}$
MAPE (mean absolute percentage error)	$\frac{1}{n}\sum_i^n\left\lvert\frac{o_i-t_i}{t_i}\right\rvert\times 100$
MBE (mean bias error)	$\sqrt{\frac{1}{n}\sum_i^n(o_i-t_i)}$
RMBE (relative mean bias error)	$\frac{\sum_i^n(o_i-t_i)}{\frac{1}{n}\sum_i^n(o_i)}\times 100$
MAE (mean absolute error)	$\frac{\sum_i^n\lvert o_i-t_i\rvert}{n}$
MRV (mean relative variance)	$\frac{\sum_i^n(t_i-o_i)^2}{\left(t_i-\left(\frac{1}{n}\sum_i^n(t_i)\right)\right)^2}$
DA (degree of agreement)	$1-\frac{\sum_i^n(o_i-t_i)^2}{\sum_i^n\left(\left\lvert o_i-\frac{1}{n}\sum_i^n(t_i)\right\rvert-\left\lvert t_i-\frac{1}{n}\sum_i^n(t_i)\right\rvert\right)^2}$

REVIEW OF SOLAR RADIATION PREDICTION USINGANNS

A. Inclusion criteria

In order to make certain a high pleasant of the publications protected in our assessment, an automated seek changed into completed at the databases of the most prestigious publishers with extra criteria. This was followed with the aid of including works stated in formerly selected guides so that it will have a listing that is as exhaustive as possible. During our search process,conference articles, running papers, commentaries, and ebook evaluation articles were excluded [13].

B. Distribution of literature researches

In the following section, we present the distribution of thereviewed publications according to journal publisher (fig.1.a)and prediction horizon (fig.1.b).

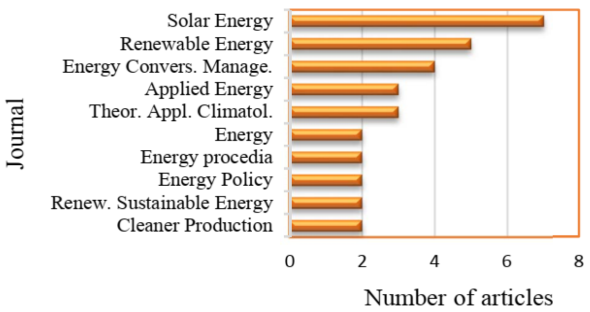
C. Monthly/Daily/hourly solar radiation prediction

In existing studies works, we discover different prediction horizons: monthly, each day, and hourly. In fact, month-to-month prediction permits a realization of a pre-sizing of sun devices, at the same time as the day by day and hourly sun radiation values are essential for a dependable and specific sizing. Indeed, our first standards of study are to categorize papers with the aid of the prediction horizon. The acquired results of month-to-month and each day/hourly sun radiation prediction category are illustrated in Table III and IV respectively. In these tables, we've categorized the courses chronologically by way of specifying the anticipated factor, the ANN architecture, the location, and the corresponding overall performance assessment signs. Tables display that more works were achieved at the prediction of world solar radiation in comparison with diffuse and beam (direct) additives. Furthermore, we observe that the selected research burns up to forty neurons in a single hidden layer and few of them undertake two hidden layers with up to sixty-nine neurons. The ANN models used one of a kind input parameter depending on available meteorological and geographical statistics. Concerning overall performance assessment signs, the maximum usedin examined articles are R2, MAPE, RMSE, and MBE. Thefound MAPE values falls in the range [0.3 - 10.1] which is highprediction accuracy according to [14]. All the models showgood performances with a coefficient of determination (R2)between 0.82 and 0.99.

DISCUSSION AND RECOMMENDATION FOR FUTURERESEARCH WORKS

In the following section we will point out some observationsand problems we have noted during our study of the alreadymentioned papers with our corresponding recommendations.

• To take a look at and validate sun power prediction models, long term climate data are required. However, such data aren't effortlessly available due to the excessive price of measuring devices and the issue inaccessibility of the measuring websites which puts intense dilemma in conceiving reliable and correct fashions.Through our inspection of the studied literature, we've got noticed the dearth of a fashionable database having a large range of entering kinds with the recording intervals of facts. Also, the education and test subsets in the sort of database need to be statistically representative in order to have correct fashions (One rule of thumb is that the education set size must be 10 times the community weights to accurately classify information with ninety% accuracy [47]). In all the ANN fashions, the range of hidden layers and corresponding neurons is decided experimentally (which may additionally require massive computational evaluation) and there may be no mentioned systematic method to optimize thisnumber. This task remains an open and challengingproblematic and must be addressed in future works.Genetic algorithms, Particle Swarm optimization,simulated annealing techniques can be considered as optimization techniques for this aim.



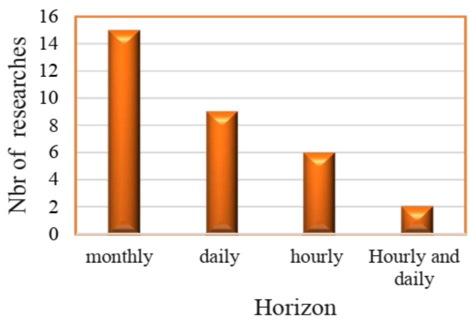


Fig. 1. Distribution of the reviewed publications according to journal (a), according to prediction horizon (b)

TABLE III. MONTHLY SOLAR RADIATION PREDICTION PUBLICATION OF OUR STUDY

Component	Reference	Authors	Journal	Year	The ANN architecture	Performance indicators	Location
Global	[15]	M.Laidi,et al.	Theor.Appl.Climatol.	2016	One Hidden Layer (8-35-1)	RMSE (Wh/m^2)= 5.750 R^2=0.999	Algeria
Global	[16]	E.F.Alsina et al.	Energy Conver. Manage.	2016	One Hidden Layer (7-4-1)	MAPE(%) = about 1.67 NRMSE(%)= 1.01	Italy
Global	[17]	O.Celik et al.	Cleaner Production.	2016	One Hidden Layer (6-3-1)	MAPE(%) = >99 R^2(%)= around	Turkey

						5.0	
Global	[18]	J.Waewsak et al.	Energy Procedia	2014	One Hidden Layer (6-9-1)	RMSE= 0.0031 to 0.0035 MBE= 0.0003 to 0.0011	Bangkok ,Thailand
Global	[19]	A.K. Yadav et al.	Renew. Sustainable Energy Rev.	2014	One Hidden Layer (5-10-1)	MAPE(%) = 6.89	India
Diffuse	[20]	Y.Jiang	Energy Policy	2008	One Hidden Layer (2-5-1)	R^2=0.90 MPE(%)=1.55 MBE(MJ/m^2)=0.040 RMSE(MJ/m^2)=0.746	China
Global	[21]	J.Mubiru et al.	Solar Energy	2008	One Hidden Layer (6-15-1)	R=0.974 MBE(MJ/m^2)=0.059 RMSE(MJ/m^2)=0.385 MAPE=0.3	Uganda
Beam	[22]	S.Alam et al.	Renewable Energy	2006	One Hidden Layer (7-3-1)	RMSE(%)= from 1.65 to 2.79	India
Global	[23]	F.S. Tymvios et al.	Solar Energy	2005	Two Hidden Layer (3-46-23-1)	MBE(%)= 0.12 RMSE(%)= 5.67	Cyprus ,Athen
Global	[24]	A.Sozen et al.	Energy Coners. Manage.	2004	Two Hidden Layer (6-2-5-1)	MAPE(%)= 6.735 R^2= 0.993 RMS(%)= 4.465	Turkey
Global	[25]	A.Sozen et al.	Applied Energy	2004	(6-N/A-1)	MAPE(%)= ≤6.73 R^2(%)= 99.89	Turkey
Global	[26]	A.S.S.Dorvlo et al.	Applied Energy	2002	(5-N/A-1)	RMSE(%)= 0.83	Oman
Global	[27]	M.Mohandes et al.	Solar Energy	1999	One Hidden Layer (5-10-1)	MAPE= 10.1	Saudi Arabia
Global	[28]	S.M.Al-Alawi et al.	Renewable Energy	1998	One Hidden Layer (8-15-1)	MAPE(%)= 5.43 R^2(%)= 95	Sultanate of Oman
Global	[29]	M.Mohandes et al.	Renewable Energy	1998	One Hidden Layer (4-10-1)	MAPE(%)= from 6.5 to 19.1	Saudi Arabia

From posted literature, the best desire forgeographical and meteorological enter parameters arevital to expect sun radiation with reliability andhigher accuracy. Unless few studies running in thistricky [19, 43], there is but no automatedtechnique sporting out the choice of maximum relevant input variables for ANN models.

• In the work of [19], the impact of the sunshine period at the prediction accuracy has been highlighted. This observation have to be generalized to peer the impact of every variable on the overall ANN model performances.

• Regarding desk III and IV showing the fewness ofpapers on diffuse and beam solar radiation predictionthe use of ANN and because of the significance of thosecomponents for the strength packages, greater studiesare required in destiny works.

• In order to pick out the first-class ANN prediction models, a comparison of various ANN fashions such as MLP, RBF, Generalized Regression Neural Network, and so forth. In the prediction of solar radiation has been finished [35, 36]. Unfortunately, confined attention has been given to the assessment between ANN and different prediction models [23, 48, 49].

• As indicated in [14], special ANN fashions want to be evolved the usage of latitude, longitude, altitude,extraterrestrial radiation as entering parameters andchecked for accuracy. This could be useful for the onesplaces wherein no meteorological stations have beenhooked up even if it is found that range and longitude have minimal impact on solar radiation prediction as established in [19].

CONCLUSION

This study offered a thorough examination of solar energy estimate using artificial neural networks. Renewable solar energy requires a thorough understanding of the availability and fluctuation of solar radiation. Solar radiation forecasting is more trustworthy with ANN models than with other existing models because to its high ability for modeling dynamic, non-linear, and time-varying input-output processes. As a result, this page lists one-of-a-kind experiments mostly focused on ANN models used to forecast solar radiation. A updated evaluation is included in our study to assist prospective enquiries in this area. It employs carefully established bibliography, projection horizon, ANN layout, and overall success measures. Furthermore, the goal of studying these guides has been to highlight difficulties, such as the absence of a universal database (with a wide range of input forms and record time periods) and the lack of a scientific approach for developing the ANN design. Furthermore, unless a few research are conducted on this subject, there is no method for selecting the most essential input variables for ANN designs. We have found a small number of publications that utilize synthetic neural networks to estimate the sun's radiation components (spread and beam).

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