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Review Article

Solar Irradiance Prediction for Optimal Photo-voltaic Power Generation: A Comprehensive Review of Artificial Intelligence Replicas

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A B S T R A C T

Many variables, such as the growing world population and shifting consumer tastes, might be linked to rising energy demands and power consumption. The rapid depletion of fossil fuels, the worrisome rise in air pollution, the impact of global warming on more frequent natural disasters are additional major reasons to adopt clean and renewable energy sources for generating power and improving energy efficiency.A key source of renewable energy is the generation of solar power. The potential power output of a photovoltaic system is greatly influenced by solar irradiation. Predicting energy production from solar power plants, climate modelling, weather forecasting are just a few of the crucial applications for studying and measuring solar irradiance.

The many tools and techniques for estimating solar irradiance using data-driven methodologies based on machine learning and deep learning algorithms are summarised in this study. The forecasting horizons that can be employed by the algorithm depend on the input data used to "train" it. Although it has been demonstrated that these algorithms can estimate solar radiation, differences in their performance make comparing and selecting the best method an interesting job. The two most often utilised machine learning techniques in this study are artificial neural networks (ANN) and support vector machines (SVM), along with a comparison of these two techniques with Deep Learning models.

Keywords: Solar Power, Solar Irradiance, SVM,ANN, Machine Learning , Deep Learning Models

Introduction

Many variables, such as the growing world population and shifting consumer tastes, might be linked to rising energy demands and power consumption. The rapid depletion of fossil fuels, the worrisome rise in air pollution, global warming's role in increasing the frequency of natural disasters are all significant factors in the usage of clean and renewable energy sources for producing power and improving energy efficiency.[1]

Renewable Energy

Renewable energy comes from non-depletable or limited natural resources found on Earth, such the wind and sunlight.In wind farms, turbines are utilised to capture wind energy and transform it into electricity. There are many different configurations for photovoltaic and wind energy systems, each having its own advantages and disadvantages. Numerous industries might be powered by a wind-driven mass production system, while energy companies already in operation could benefit from standard turbines. Since wind energy does not pollute the environment as much as other renewable energy sources, it is a valuable energy source.[2]

The radiant energy from the sun is captured and transformed into heat and light to create solar energy. Rechargeable (PV) systems use solar cells to turn daylight into electricity.

Energy Generation by Renewable Sources

The "fundamental transformation" of the global energy markets towards renewable was signalled in 2008 by the construction of more renewable energy capacity than conventional electricity capacity in both the European Union and the United States. In 2010, a third of newly built power generating capacity was powered by renewable energy.[2]

By the end of 2011, the capacity of renewable energy has surpassed 1,360 GW, an 8% increase. Over half of the 208 GW of new capacity installed globally in 2011 came from renewable energy sources. Wind energy and solar photovoltaic (PV) accounted for about 40% and 30%, respectively, of the energy.[3] Traditional biomass makes up 9% of all energy consumed, whereas hydroelectricity makes up 3.8 percent, non-biomass heat makes up 4.2 percent, and electricity from sources like wind, solar, geothermal, and biomass makes up 2%.[4] In 2020 compared to 2019, there were more than 45 percent more renewable energy capacity additions, including 23% more new solar photovoltaic installations (yellow) and 90% more new wind power (green).[1]

Solar Energy

Solar energy is ideal as a power source for any home or commercial enterprise because it is pollution-free and has no resource restrictions. It is challenging to predict how much energy will be produced because the outputs of renewable energy sources, in particular, vary substantially depending on the circumstances and characteristics of the locations in which they are used. Compared to wind energy, solar energy follows a more predictable pattern and derives a sizable portion of its energy from the Sun. Solar radiation is transformed into electrical energy using photovoltaic technology, which is then transferred for uses other than heating. Thermal solar energy transforms solar radiation into thermal energy, which is used in manufacturing, desalination, housing, or water treatment processes. Photovoltaic solar energy transforms solar radiation into electrical energy, which is used in manufacturing, desalination, housing, or water treatment processes. Despite being used everywhere, solar energy produces a variety of outcomes.[5]

Solar Irradiance

It describes the amount of electromagnetic radiation that is absorbed by a specific area from the Sun per unit area as determined by equipment. Watts per square metre (W/m2) is the SI unit of measurement for solar irradiation.The radiant radiation that is emitted into the natural atmosphere over time is frequently explained by integrating the radiant energy released into the external region (joule per square metre, or J/m2) through time. After environmental absorption, irradiance can be seen in space and on the Earth's surface. These variables affect illumination on the ground atmosphere in conjunction with the tilt of the recording land, the angle of the light just over the skyline, weather systems.[3] Measurements and studies into solar infrared could be useful. There appear to be three types of solar radiation listed below.

- Diagonal Global Luminous intensity
- Dispersed Lateral Illumination
- Average Solar Illumination
- Diagonal Worldwide Illumination

The sum of diffuse vertical radiation and direct normal radiation that falls directly on the surface of the planet from any direction is known as universal horizontal light. Global Diagonal Illumination = Refracted Diagonal Illumination + Cross Correlation Average Solar Insolation Total Globally Lateral Insolation (GHI), which appears to be the entire irradiance on the horizontal of the atmosphere. It is the entire combined dispersed longitudinal energy of all direct light (adjusted for such sun's azimuth angle elevation z).[4]

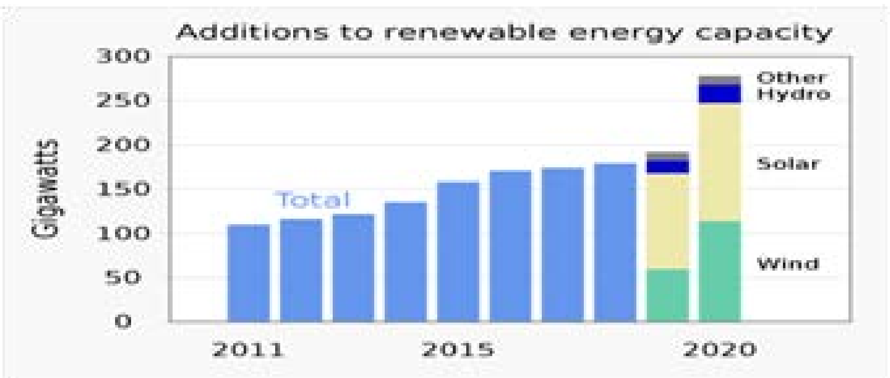

Figure 1.Renewable Energy Capacity

Diffused Horizontal Irradiance (DHI)

Distributed Diagonal Illumination is the radioactivity at the Planet's surface caused by light dispersed by the environment. It is calculated on a level surface using energy among all locations in the sky except electromagnetic heat (radiation coming from the sun disk). Within elimination of oxygen, there would've been essentially no DHI.[4]

Direct Normal Irradiance(DNI)

DNI or beam energy is calculated at a specific location in the Earth's atmosphere with a strong horizontal axis facing the Sun. Sun energy that is diffused is excluded. The alien lighting above the troposphere is the same as pure radiation, minus meteorological losses that are scattered and absorbed. Damages are determined by the time of day, the amount of cloud cover, the humidity, other variables.[4]

Total Solar Isolation (TSI) is a measurement of the impact of renewable solar energy on the form of particles across all frequencies, every time unit. It is measured in the direction the sun's energy is moving. A popular approach of measuring mean PV at one astronomical distance is by the photovoltaic common factor.

Depending on the location, the time of day, how the panel is positioned in relation to the Sun and the sky, the solar irradiance may be high or low.[4] Solar energy is hence erratic and unpredictable by nature. Forecasting and modelling of solar energy are crucial despite the practical constraints.

For instance, solar irradiance refers to the energy output per square metre. Forecasting solar radiation helps the power system keep its energy output steady. Isolation forecasts could be important for choosing power distribution plans or act as a helpful guide for optimising battery charge regulator algorithms. Increasing the precision of solar irradiance prediction systems will be crucial for the development of this source of energy in the near future.

Machine Learning and Deep Learning Algorithms

In a variety of sectors, machine learning approaches have been employed to address difficult technological problems. The Artificial Intelligence (AI) technology known as Machine Learning (ML) enables software developers to improve their systems' ability to predict events without explicitly programming them to do so. Algorithms use historical data as an input to predict future accurate output. Generic Algorithms (GAs),[13] neural (NNs[6]SVM,[4] extrapolation have all been suggested and applied in this area to predict and anticipate solar irradiation.

The unstructured dataset was divided into groups using the K-means clustering method.

Each category includes a representation of weather data from several sources.

In the second stage, forecasting is done using machine learning techniques including decision trees, artificial neural networks, support vector machines.

Yang and others presented a dynamic deep learning technique for PV power output forecasting with a time step of 1 hour based on weather types in light of the current rapid development of AI-driven IoT technologies. The three steps in the proposed method are categorization, training, prediction. For categorization, a self-organizing map (SOM) [26] is employed. LVQ)[27] and Vector Quantization Learning.

The Unstructured Dataset was Divided Into Groups using the K-Means Clustering Method

The fuzzy training approach is used in the training and prediction process to select the best candidate and to generate the most ideal deep learning model for the prediction. Weather data from many sources is represented in each.[28] proposed a multimodal PV power interval prediction method that considers both the absolute power deviation and the seasonal aspect of PV power.A support vector machine model (GASVM) based on a geneti method was proposed by VanDeventer et al.[29] The GASVM model first uses an SVM classifier to categorise historical weather data before employing an ensemble approach to enhance the genetic algorithm.

Deep Learning

The purpose of this study is to determine whether it is feasible to use solar activity forecasting to produce precise future projections for the production of solar power for mobile phones.[3] Increase the amount of power produced using renewable or recycled energy. We outline our analysis of solar prediction methods in this publication.

Prediction of monthly global sun irradiance is made in.[25] This was achieved to reduce the total number of nodes in the hidden layer using bio-inspired optimisation techniques such as the cuckoo search algorithm and differential evolution algorithms, which are both successful and novel approaches, by converting a neural network to a multiple linear regression (MLR) issue with the inclusion of a hard edge consequence. In,[26] an artificial neural network (ANN) model was used to forecast the characteristics of solar radiation. It was determined that increasing the number of input parameters led to an efficient estimation of future solar radiation data after investigating the effects of increasing the number of input factors on solar radiation.

Table 1.Machine Learning Models For Solar Irradiance Forecasting

Author et al.	Model/ Technique used	Accuracy
R. Mejdoul et.al[1]	A framework for projecting daily average solar sun's energy (DGSR). using ANN was constructed in this paper	This Model educated that use the 4/41 Based scheduling approach has a reliability of 0.98, an absolute average accuracy of 1%, just a sum of squared error of 1.2 Marajuana.
T. Vaisakh1 et.al[2]	Multilayer Perceptron (MLP), Convolution Neural Network (CNN), Recurrent Neural Network (RNN) are three machine learning algorithms (RNN). The number of hidden neurons in all of these networks is optimised through a hybrid technique called Grey Updated DHOA, which integrates the Deer Hunting Optimization Algorithm (DHOA) and Grey Wolf Optimization (GWO) (GU-DHOA).	GU-DHOARNN outperforms MLP, CNN, RNN, GU-DHOA-MLP, GU-DHOA-RNN in terms of RMSE by 20.8, 18.8, 81.8, 1.1, 33 percent, respectively.
Usman Munawar et.al[3]	The best combination for short-term solar power forecasting is discovered utilising machine learning methods including such random forest, artificial neural network, extreme gradient boosting (XGBoost), along with feature selection techniques such as feature importance and principle component analysis (PCA).	The ensemble of the XGBoost model and the PCA technique performed much better, with the lowest root mean mean squared error (2.49082 w/m2) and the highest r 2 score (0.9994).
Mohammad Sina Jahangir et.al[4]	This research examines the ability of various IVS methods, like the Gamma test (GT), Procrustes analysis (PA), Edge worth approximation based conditional mutual information (EA), to improve Rs prediction accuracy by coupling them with popular non-linear data-driven models, like the multilayer perceptron (MLP), support vector machine, extreme learning machine, multi-gene genetic programming (MGGP).The Rs prediction models were constructed utilizing meteorological data from eight sites in northern Iran.	When the EA technique was utilized for Input variable selection, the results indicated that MGGP generated the least accurate predictions, with the nRMSE rising by up to 40% when compared to MLP.
Sabrina Belaid et.al[5]	It comprises of integrating the Support Vector Machine (SVM) supervised machine learning method with the time series principle.A HGSR dataset was used, which has been collected in Ghardaa, Algeria's south. Artificial Neural Network (ANN), Firefly Fourier Algorithm (FFA), Random Forest (RF), Auto Regressive Moving Average (ARMA), Support Vector Machine (SVM) are the methods that have been compared using the time series principle (develoed in this work).We used an ensemble of feed-forward neural networks to develop a novel, data-driven solar-irradiance model to see if models and observations could be brought closer along.A non-linear relationship between solar-activity proxy and irradiance with a high degree of freedom, that emerges from the integration of a solar-activity proxy, is among the core components of our model architecture.	Traditional approaches are outperformed by the SVM model created by the proposed methodology R2. R=0.99 percent, NRMSE=13.08 percent, NMBE=0.79, MAPE=19.72 percent are the predictions of the chosen SVM model (yearly model by the second technique R2).

Steffen Mauceri ·et. al[6]	We constructed a novel, data-driven solar-irradiance model using an ensemble of feed-forward neural networks to see whether models and observations might be brought closer along. The inclusion of a greater number of solar-activity proxies than prior proxy models results in a non-linear relationship between solar-activity proxy and irradiance with a high degree of freedom.	The Neural Network for Solar Irradiance Modeling (NN-SIM) approach has been used to reconstruct total solar irradiance and SSI from 205 nm to 2300 nm and from 1979 to the present day..
Md. Burhan Uddin Shahin et.al[7]	We used an Artificial Neural Network (ANN) in our study, which is essentially a Machine Learning (ML) approach.We used daily data from the renewable energy community of NASA's database for the past 15 years (2000-2015) because this is a time series-based forecast.For this study, we chose a coastal area like Saintmartin in Teknaf, which plays an important role in Bangladesh.	We changed the title of tapped delay lines from 2 to 4 at the end of training this model with 21 hidden layer neurons to observe how something impacted the output MSE. We observe that as the number of delays increases, the value for output MSE climbs approximately linearly.
A. Costa Rocha1 et.al[8]	Using a 14-year data set containing daily values of meteorological variables, three convolutional neural networks (ANNs) are created for daily, weekly averaged, monthly averaged global sun radiation forecast for Fortaleza, in Brazil's Northeast area. Inside the area, the climate is semiarid and coastal. The day of the year, maximum and minimum temperatures, irradiance, precipitation, cloudiness, extraterrestrial radiation, relative humidity, evaporation, wind speed were all employed as predictors.	E.Six ANN architectures were tested with different parameters in the daily case study. The quantity of neurons and inputs, as well as RMSE values varying between 0.044121 and. There were 0.167655 discovered.
Hamza Ali-Ou-Salah, et.al[9]	This research provides a new hybrid approach for forecasting 1 h-ahead global solar radiation based on seasonal clustering algorithm and artificial neural network (ANN). The fuzzy c-means method (FCM) was used to divide three years of monthly average experimental data into separate seasons based on solar and meteorological characteristics in Évora.	A value of 0.14 was calculated to use the model presented in [36].
Hatice Citakoglu[10]	The multi-gene genetic programming (MGGP) method is offered as a novel compact method for this purpose, it has been shown to produce better accurate sun radiation estimates in Turkey.	For solar radiation prediction, the MGGP multi-data models and calibrated empirical equations are proven to be more successful than single-data models.
Dongha Shin1[11]	An adaptive neuro-fuzzy inference system and artificial neural network (ANN) approaches, such as dynamic neural network (DNN), recurrent neural network (RNN), long short-term memory, are used in the prediction algorithm (LSTM).	The ANN technique outperforms the neuro-fuzzy approach. The experimental results showed that Model 4's forecasting outcome was the most accurate, with an RMSE of 1.85 times better than Model 1's.

Olusola Bamisile[12]	The application of artificial neural network (ANN) models for forecasting solar irradiance and solar PV characteristics in Nigeria is presented in this paper.	Solar irradiance and solar PV characteristics can be predicted using the models created. For solar irradiance prediction, R values range from 0.9046–0.9777, while for solar PV multi-parameters prediction, R values range from 0.7768–08739.
Weipeng Xinga.et al[13]	We propose using a deep belief network (DBN) to estimate GHI under all-sky conditions generated from Himawari-8 satellite photos with high accuracy and efficiency, as well as a high spatial and time resolution for a vast geographical area, using Himawari-8 satellite images. T	The hourly comparison with ground-based data yielded a very strong Pearson correlation coefficient (r) of over 0.95, with a Root-Mean-Square-Error (RMSE) of 30 to 80 w m2.
Kumari P et al[14]	In this paper, a new ensemble model for hourly global horizontal irradiance forecast is developed, which consists of two advanced base models, namely extreme gradient boosting forest and deep neural networks (XGBF-DNN).	The RMSE variances for the XGBF-DNN,XGBoost, DNN were 1.081, 12.547, 14.953 correspondingly. The proposed 452 ensemble model has the lowest variance of the XGBF-DNN model, indicating that it not only achieves excellent prediction accuracy but also has great resilience.
Xiaoqiao Huang[15]	The novel WPDeCNNeLSTM-MLP model is based on a multi-branch hybrid structure with multi-variable inputs that integrates wavelet packet decomposition (WPD), convolutional neural networks (CNN), long short-term memory (LSTM) networks, multi-layer perceptron networks (MLP),	In comparison to the generic persistence model, the suggested WPDeCNNeLSTM-MLP model exceeds others in prediction performance, with a minimum RMSE of 32.1 W/m2, a minimum nRMSE of 15.4795 percent, a maximum s of 0.4438, a maximum FS of 0.6624.
Diego J.et.al[16]	This technology is simple to develop and incorporate into existing business computer systems. We compare our strategy to a number of well-known alternatives, including deep recurrent neural networks and autoregressive integrated moving average models.	Our technology generates forecasts that are 20% more accurate than those generated by recurrent neural networks.

A number of variables, including the day of the year, time, pressure, sky cover, wind speed, were utilised to forecast the hourly solar irradiance using the Nonlinear Autoregressive Network with Exogenous variables (NARX) technique.[27] The NARX neural network outperforms the linear regression model. The two ANN models with four different techniques were found to be the best for estimating mean monthly global radiation in order to build or study solar PV systems based on least Mean Absolute Error (MAE), root mean square error (RMSE), maximum linear correlation coefficient (R).[28] The three separate components of solar irradiation (horizontal global, beam, diffuse) have been forecast using artificial neural networks and random forests, it has been found that the forecasting in spring and summer is more accurate. Research Journal of Chemistry and Environment Special Issue on Renewable Energy and Sustainable Environment 177, Vol. 24 (Special Issue I), 2020 The meteorological data for the autumn is less dependable than that of the winter and the summer due to these variations.[29].A support vector machine (SVM) for predicting daily and monthly global sun radiation was described for a horizontal surface.[30]. Only a few fundamental parameters are needed for SVM-centered models to achieve great accuracy. Hybrid solar forecasting methods: It was shown how to forecast solar radiation using fuzzy and neural networks. After classifying the cloud and temperature data as distinct fuzzy sets and fuzzy rules and merging them with a neural network, the prediction was demonstrated to be accurate.[31] Artificial neural networks (ANN), autoregressive moving average (ARMA), support vector machines (SVM) were employed in[32] but were shown to be erroneous due to their inability to capture long-term scalable data. Deep recurrent neural networks (DRNNs) were used to calculate solar radiation.

By enabling high-level feature extractions without defining what form the variation should be accepted in, DRNNs make the model more complex. For hourly sun radiation, a hybrid strategy combining a clustering algorithm and multilayer perception is given.[33]The proposed hybrid technique exceeds all existing well-known forecasting models in terms of performance. A standard of supervised machine learning techniques (neural networks, Gaussian processes, support vector machines) were introduced to predict the Global Horizontal Solar Irradiance (GHI). Machine learning algorithms fared pretty well for forecasting horizons longer than one hour.[34]

Conclusion

Solar energy will continue to play a crucial role in the future, reducing dependence on conventional fuels and addressing environmental concerns. Photovoltaics (PV) panels convert sunlight into electricity, providing a backup service in power outages. However, their dependability and production costs have not yet reached full replacement. To maximize PV plants, accurate weather forecasts are essential. This study analyzes AI techniques for forecasting weather parameters, focusing on hybrid systems. Future work will propose and validate deep learning algorithms for creating a novel hybrid forecasting model for solar irradiance.

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