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Solar Irradiance Prediction Model: A Review

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***Abstract*— This review explores the advancements in Solar Irradiance Prediction Models (SIPMs) driven by Artificial Intelligence (AI) techniques. The demand for accurate solar irradiance forecasts has intensified with the growing reliance on solar energy. AI, particularly machine learning algorithms, has demonstrated its efficacy in enhancing the precision of solar irradiance predictions. This paper systematically reviews and analyzes various AI-based approaches employed in SIPMs, emphasizing their strengths, limitations, and potential for future improvements. The synthesis of existing literature provides insights into the evolving landscape of AI-driven solar irradiance forecasting, paving the way for informed decision-making in renewable energy applications. The simulated will be done using the python spyder IDE 3.7 version. The simulated result will be shown in terms of performance parameters improvement like root means square error, mean absolute error etc.**

***Keywords*— AI, MPPT, Photovoltaic, Battery, Python, Spyder, Energy, Machine, Deep Learning.**

I. Introduction

Solar energy, as a clean and sustainable resource, has garnered increasing attention for addressing the global energy demand. Efficient utilization of solar power necessitates accurate forecasting of solar irradiance, a key parameter influencing energy production in solar photovoltaic systems. Traditional meteorological methods, while valuable, often struggle to capture the complex and dynamic nature of atmospheric conditions affecting solar radiation. In recent years, the integration of Artificial Intelligence (AI) techniques has emerged as a promising avenue to overcome these limitations.

This review aims to provide a comprehensive overview of AI-based techniques applied to Solar Irradiance Prediction Models (SIPMs). AI, particularly machine learning algorithms such as artificial neural networks, support vector machines, and ensemble methods, has shown remarkable potential in improving the accuracy of solar irradiance forecasts. The adaptability of these techniques to non-linear and dynamic relationships within atmospheric variables enhances their capability to capture intricate patterns in solar radiation variations.

The review systematically categorizes and critically examines the existing literature on AI-driven SIPMs, highlighting the strengths and weaknesses of different approaches. Key challenges, including data availability, model interpretability, and scalability, are discussed. Additionally, the paper explores the integration of emerging technologies, such as Internet of Things (IoT) sensors and satellite imagery, to enhance the input data quality for AI-based SIPMs.

Figure 1: Solar Panel

Figure 1 presents the diagram of the solar panels. It does not take into account diffuse sun radiation (radiation that is scattered or reflected by atmospheric components). By synthesizing the current state of research, this review aims to guide researchers, practitioners, and policymakers in understanding the evolving landscape of AI-driven solar irradiance forecasting. The insights derived from this exploration can inform the development of robust and reliable models, ultimately contributing to the optimization of solar energy systems and promoting sustainable energy practices.

Beam radiation is another name for direct normal irradiance (DNI), which is measured on the surface of the Earth at a specific spot using a surface element that is perpendicular to the direction of the sun.

The extraterrestrial irradiance that is above the atmosphere is subtracted from the total amount of light that is scattered and absorbed by the atmosphere to arrive at the direct irradiance. Losses are determined by the time of day (the length of time it takes for light to travel through the atmosphere is dependent on the angle at which the sun is above the horizon), the amount of cloud cover, the moisture content, and any other components. Although this impact is often less substantial when compared to the effect of losses on DNI, the irradiance above the atmosphere also changes with time of year (since the distance to the Sun varies). This is because the distance to the Sun fluctuates.

II. LITERATURE SURVEY

S. M. J. Jalali et al.,[1] This work presents a novel method for improving the forecasting performance of global horizontal irradiance that is based on deep learning and takes into account many steps ahead (GHI). To get the best characteristics possible for precise prediction of the GHI, a deep convolutional long short-term memory is used in this process. The effectiveness of such deep neural networks is directly proportional to the designs of such networks. To solve this issue, a swarm evolutionary optimization approach known as the sine-cosine algorithm is used to and improved upon in order to automatically optimise the network design. This helps to ensure that the network is functioning at its optimal level. In order to broaden the demographic range of the population and forestall untimely convergence of the optimization process, a model of modification with three distinct stages has been developed. The effectiveness of the suggested strategy is evaluated with the use of three datasets obtained from three solar stations located in the eastern region of the United States. The results of the experiments show that the suggested technique is superior to other forecasting models in comparison to the results of the experiments.

E. Cook et al. [2] provide a model for the solar detection issue in a machine learning setting that is based on labelled data, which is another name for supervised learning. However, the majority of utilities face the difficulty of having restricted labels or labels that focus on just one category of consumers. As a result, we develop novel approaches for semi-supervised learning and one-class classification that are based on autoencoders. These methods significantly enhance the nonlinear data representation of human behaviour and solar activity. Not only have the suggested approaches been tested and verified on synthetic data based on a publicly accessible data set, but also on real-world data from utility partners. This ensures that the offered methods are accurate and reliable. The numerical findings demonstrate accurate and reliable identification, setting the groundwork for the management of dispersed energy resources in distribution networks.

P. Singh et al.,[3] solar photovoltaic (PV) energy forecasting is achieved by using two dependent data variables such as (a) solar irradiance and (b) temperature, as well as previous solar PV energy production using machine learning and deep learning (DL) methods. DL is a kind of advanced learning that is modelled after the way humans learn. Examples of this kind of network include the Long Short Term Memory (LSTM) network and the Gated Recurrent Unit (GRU) network. The problem of selecting features and defining appropriate error metrics is the focus of this paper's investigation. The DL model was constructed and put through its paces using actual solar PV energy generated on the MNNIT Allahabad campus in India. The effectiveness of constructed models in terms of their ability to predict is assessed in terms of three essential variables, which are as follows: (a) mean absolute error (MAE), (b) mean squared error (MSE), and (c) root mean square error (RMSE).

In the work by A. K. Parida and colleagues[4,] solar irradiance and temperature are taken into consideration as the input for the forecast of solar power. For the purpose of solar power prediction, a hybrid Stacked Long Short-Term Memory Extreme Learning Machine complete with dropout and optimised kernel has been developed. The grey wolf optimization method is used in order to get optimal performance of the kernel parameter. It is observed that the proposed stacked LSTM based optimised kernel ELM

(SLSTM-OKELM) shows better result with a MAPE value of 1.54%,1.56% and 1.34% for three different seasons as compared to other learning techniques which show a minimum MAPE value of 4.59%, 3.95, and 3.59% for the same seasons. These statistical performance measures are taken into consideration in order to compare the output results.

U. T. Kartini et al.,[5] For the purpose of research to accurately quantify solar irradiance from solar cell systems, a new hybrid deep convolutional neural network (CNN) method for efficient probabilistic forecasting solar irradiance approach has been proposed. This method uses convolutional neural networks (CNNs) instead of traditional neural networks. In contrast to combination models, a Deep Convolutional Learning Neural Network optimization model with a multilayer-based prediction model for solar irradiance in a photovoltaic (PV) generation system is built on the foundation of a learning machine and possesses high reliability as well as high computational efficiency.

C. N. Obiora et al. [6]. Despite the fact that Artificial Intelligence (AI) models have been of great assistance, researchers are still hard at work designing algorithms that can make the fewest number of incorrect predictions possible. Using a network with Long Short-Term Memory (LSTM), the authors of this research demonstrate an increase in their ability to accurately estimate sun irradiation. The historical weather observations from Cape Town were utilised to compile the data for the input dataset, and they were taken from five distinct horizons. The acquired results indicate that LSTM performed better than the Support Vector Regression (SVR) model, with a nRMSE value of 2.4 percent at 5-minute intervals of prediction. This was determined by looking at the results. It has been hypothesised that the production of dependable energy for customers may be improved by applying these results in practise to the management of solar power plants situated in the area under investigation.

G. S. Thirunavukkarasu et al.,[7] describes a case study in which machine learning based multi-layered long-short term memory neural networks (LSTMNN) with Adam optimizer are used to anticipate DNI. This research was presented in the form of a case study. This study mainly focuses on determining the most accurate technique of predicting subtropical conditions and evaluating its performance in comparison to the most common forecasting methods, which include ARIMA, ARMA, SVR, Persistence, and AR. The nested LSTM model that was suggested was evaluated by comparing its RMSE(27.35), MAE(6.879), and MBE(0.42) values with those of the other approaches that were discussed before. The findings point to an ideal performance for LSTM, characterised by a reduction in operating time as well as improvements in precision and accuracy.

In the hybrid model that M. Pi, N. Jin, and colleagues[8] suggested, the original solar radiation data is decomposed using wavelet transform in order to decrease the amount of noise. The temporal convolution neural network is responsible for the extraction of features. When a long-short-term memory neural network (LSTM) and an attention mechanism are combined, the attention is directed to the significant aspects of prediction, which ultimately leads to improved prediction outcomes. The data that was used in this article includes the solar irradiance data that was obtained during the last year's time frame. Experiments were carried out at varying intervals of time during each of the four seasons. The findings of comparing many machine learning and deep learning models indicate that the model that was developed in this study has a greater prediction accuracy than the other models.

T. A. Fathima and colleagues [9] Forecasting the solar irradiance time series several steps ahead in time is a difficult challenge. Within the scope of this research, we offer a model for multi-step forward forecasting that is based on machine learning. The trignometric transformation of time step information is what we use in our machine learning models to describe the diurnal fluctuation of solar irradiation. The incorporation of temporal data into the forecasting model, as our observations have shown, results in a significant improvement in the predictive model's level of precision.

C. N. Obiora et al.,[10] to estimate solar irradiance on an hourly basis. The input dataset consisted of five years' worth of historical meteorological information collected in Johannesburg, and it was used there. The model was trained using 80% of the complete dataset for up to 1,000 epochs until there was no significant increase in its accuracy. This continued until there was no significant improvement. The testing data were included into the analysis in order to evaluate how accurate the prediction model was. The Root Mean Square Error (RMSE) statistic was used so that its correctness could be evaluated. The outcome of this experiment was compared to the results achieved by employing Support Vector Machine (SVM) and Extreme Gradient Boosting (XGB) models, each of which was trained independently using the same quantity of data. Indicators of performance revealed that the ConvLSTM model performed better than the XGB and SVM models, with a nRMSE value that was 1.62% lower than theirs. It has been hypothesised that putting ConvLSTM into practise for the purpose of solar power prediction in Johannesburg might lead to improved management of the effects of cascading solar radiation on the links between power grids.

III. CHALLENGES

Solar irradiance prediction models offer valuable insights into solar energy generation and weather forecasting, they also face several challenges that researchers and practitioners need to address:

1. **Complexity of Atmospheric Processes**: The atmosphere is a complex and dynamic system with numerous variables affecting solar irradiance. Modeling these processes accurately requires sophisticated algorithms and a deep understanding of atmospheric physics.
2. **Spatial and Temporal Resolution**: Achieving high spatial and temporal resolution is essential for accurately capturing localized variations in solar irradiance. However, increasing resolution can lead to computational challenges and require large datasets for training and validation.
3. **Data Availability and Quality**: Solar irradiance prediction models rely on various data sources, including satellite imagery, weather station measurements, and atmospheric models. Ensuring the availability and quality of these data, especially in regions with limited monitoring infrastructure, can be a significant challenge.
4. **Uncertainty Estimation**: Predicting solar irradiance involves inherent uncertainties due to factors like cloud cover, atmospheric aerosols, and measurement errors. Developing robust methods for quantifying and propagating uncertainty through prediction models is essential for decision-making and risk management in solar energy applications.
5. **Model Calibration and Validation**: Solar irradiance prediction models require calibration and validation against ground-truth measurements to ensure accuracy and reliability. Obtaining comprehensive and representative datasets for calibration and validation across different locations and climatic conditions can be challenging.
6. **Integration with Energy Systems**: Integrating solar irradiance predictions into energy system planning and operation requires considering factors like grid infrastructure, energy storage, and demand variability. Developing models that account for these complexities and support decision-making at both operational and strategic levels is crucial.
7. **Climate Change Impact**: Climate change can alter atmospheric dynamics and cloud cover patterns, affecting the accuracy of solar irradiance predictions. Incorporating climate change projections into prediction models and understanding their impact on long-term solar energy potential is essential for sustainable energy planning.

IV. CONCLUSION

In recent years, solar energy has established itself as one of the most extensively used forms of renewable energy sources, which has allowed it to carve out a space for itself in the highly competitive market for electricity. The development of new technologies in recent decades has made it feasible for humans to tap into this renewable and cost-free source of energy in either its electrical or thermal forms. Because it is widely acknowledged to be the renewable energy type that is both the cleanest and the most plentiful, power grids have been forced to accommodate a significant increase in the proportion of this form of energy included within their systems. In this research, a review of the artificial intelligence-based approach for improving the performance of a solar irradiance forecast model is presented. In addition, the recommended method is discussed together with the computation of the performance metrics. In the near future, we will develop a forecast model for the solar irradiance based on simulation data.

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