Solar Energy Forecasting: Perspectives of the State-Of-The-Art

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Abstract. Solar energy is a promising renewable energy source, but its intermittent and variable nature poses significant challenges for accurate forecasting. Over the recent years, there has been a remarkable surge in research dedicated to improving the precision of solar energy forecasting models. This review article delves into the state-of-the-art in solar energy forecasting. Beginning with an exploration of the hurdles faced in forecasting solar radiation, we proceed to provide an extensive survey of various forecasting models that have been developed to tackle this complex problem. Factors influencing the accuracy of solar energy forecasts are discussed, and an insight into the future trends in solar energy forecasting is provided. Key areas of focus include machine learning techniques, artificial neural networks (ANNs), and support vector regression.

Keywords: Machine learning, ANN, support vector regression, solar power forecasting.

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1 Introduction

Fossil fuels have been used for centuries because they are easy to exploit, can beused in their raw form, and can be easily refined to increase their energy density. However, fossil fuels are a finite resource, and their use contributes to climate change. In recent years, there has been a growing awareness of the need to transition to renewable energy sources. Solar energy is a promising renewable energy source because it is abundant, clean, and sustainable. The global installed solar power capacity has increased by several times in the past ten years. India and China are the leading market for solar power, followed by the United States and Europe. India has several of the largest solar plants in the world[1].

The use of solar energy is not without challenges. One challenge is the variability of solar radiation. Solar irradiance can vary significantly depending on the time of day, the season, and the weather conditions. Another challenge is the need to store solar energy. Solar energycannotbestored in large quantities, soit must be used immediately or stored in batteries or other energy storage devices. Despite these challenges, solar energy is a promising renewable energy source with the potential to meet a significant portion of the world's energy needs.

Challenges of Solar Energy Forecasting

The main challenges of solarenergyforecasting are:

The short-termvariability of solar radiation: Solar radiation can varyrapidly due to changes in cloud cover, atmosphericaerosols, and otherfactors. This makesitdifficult to forecastsolar radiation accurately for short time horizons (e.g., 1 hour).The long-termvariability of solar radiation: The amount of solar radiation received at a particular location can varysignificantlyfromyear to year. This makesitdifficult to forecastsolar radiation accurately for long time horizons (e.g., 1 year).

The non-linearrelationshipbetweensolar radiation and othermeteorological variables-the amount of solar radiation received at a particular location is not linearlyrelated to othermeteorological variables, such as cloud cover and temperature. This makesitdifficult to developaccurateforecastingmodelsthat use these variables.

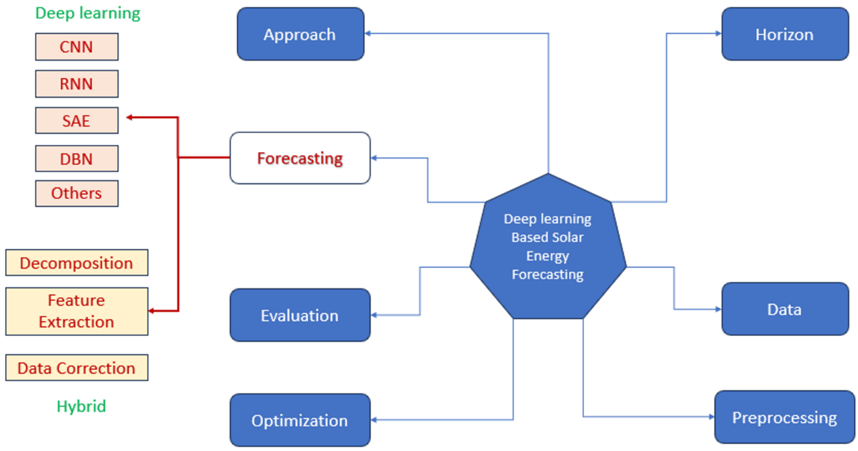

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Fig.1.Taxonomy of deeplearning-basedsolarenergyforecasting

2 Forecasting

The figure 1 shows the Taxanomy of deep learning based solar energy forecasting.

Deep learning models

Deep learning models are a category of machine learning models that draw inspiration from the organization and operation of the human brain. These models are typically composed of multiple layers of artificial neurons, and they can learn complex relationships between input and output data.The most used deep learning models for solar energy forecasting are:

- Convolutional neural networks (CNNs): CNNs are particularly adept at handling data that exhibits a spatial or temporal arrangement, such as images or time series data.
- Recurrent neural networks (RNNs): RNNs are well-suited for processing data that has a sequential structure, such as time series data.
- Self-organizing maps (SOMs): SOMs are a type of neural network that can be used to cluster data and extract features.
- Deep belief networks (DBNs): DBNs are a category of neural networks that have the capability to acquire hierarchical representations of data.

Hybrid models

Hybrid models combine the strengths of different deep learning models or other machine learning techniques. For example, a hybrid model might combine a CNN with an RNN to learn both spatial and temporal features from the data.

Optimization techniques

Optimization techniques can be used to improve the performance of deep learning models. The methods outlined can be applied to adjust the hyperparameters of the model, including the quantity of layers and the quantity of neurons within each layer. Optimization techniques can also be used to prevent overfitting, which is a problem that can occur when a model learns the training data too well and is unable to generalize to new data.

Evaluation methods

The performance of a forecasting model can be evaluated using a variety of methods. These methods include:

- Evaluation metrics: Evaluation metrics are used to quantify the accuracy of the model's predictions.

- Benchmarking models: Benchmarking models are used to compare the performance of the model to other models.
- Computation time comparison: The computation time of the model can be compared to other models to assess its efficiency.
- Statistical testing: Statistical tests can be used to determine whether the model's predictions are statistically significant.
- Weather types comparison: The performance of the model can be compared for different weather types to assess its robustness.
- Input timesteps and data resolution comparison: The performance of the model can be compared for different input timesteps and data resolutions to assess its sensitivity to these factors.
- Data fusion: The performance of the model can be compared when it is trained on different datasets to assess its ability to generalize.
- Decomposition methods comparison: The performance of the model can be compared when it is trained on data that has been decomposed using different methods to assess its sensitivity to these methods.

Recent Developments

Recently several developments have been reported by researchers across the globe in the area of solar power forecasting and its effective utilization with the help of deep technologies. Here. Jurj et al built a solar-powered real-time deep learning (DL)-based system that can run inference using four different DL model architectures: VGG-19, InceptionV3, ResNet-50, and MobileNetV2[2].The system uses a dual-axis solar tracker to optimize the sun ray exposure for the solar panel, which generates electricity to power the system. The system also uses an accumulator to store energy for times when the solar panel is not generating enough electricity[2].The solar tracker is used to optimize the sun ray exposure for the solar panel. The solar panel converts sunlight into electricity, which is stored in the accumulator. The accumulator provides power to the low-power embedded platform, which runs the DL model. The webcam is used to capture images, which are then sent to the DL model for inference.The authors conducted experiments to test the system's performance. They found that the system can run 100% using renewable and green energy from the sun. They also found that the system consumes significantly less energy than a system that uses a laptop with an Nvidia GTX 1060 (6 GB) GPU.The authors concluded that the solar-powered real-time DL-based system is a promising approach for reducing the environmental impact of DL. They plan to conduct further experiments on other low-power platforms and train other DL model architectures using 100% solar energy.

The Convolutional Graph Autoencoder (CGAE) is a novel deep generative model that outperforms state-of-the-art methods in terms of sharpness, reliability, and Continuous Ranked Probability Score (CRPS) for spatio-temporal solar irradiance forecasting. CGAE can handle different weather conditions well and is relatively fast to train and predict [3][7].Here are some additional details about these findings:

- The reliability of the GHI data is determined by how accurately the predicted probabilities align with the actual frequencies observed. CGAE demonstrates superior reliability compared to alternative methods, resulting in more precise predictions.

- Sharpness is a measure of how concentrated the prediction distribution is. CGAE has moderate sharpness, which means that it provides informative predictions without being overly confident [3].
- CRPS is a metric that combines reliability and sharpness to measure the overall accuracy of a prediction. CGAE has better CRPS than the other methods, which means that its predictions are more accurate overall [3].
- The ability to handle different weather conditions is important for a solar irradiance forecasting model, as the weather can vary significantly from day to day and even within a single day. CGAE can handle different weather conditions well, which makes it a versatile model that can be used in a variety of settings [3].
- The speed of training and prediction is also an important factor for a solar irradiance forecasting model, as these models are often used in real-time applications. CGAE is relatively fast to train and predict, which makes it a practical choice for real-world applications [3].

Overall, the study presented demonstrates that CGAE is a promising new approach for spatio-temporal solar irradiance forecasting. It has better reliability, sharpness, and CRPS than the other methods, and it can handle different weather conditions well. CGAE is also relatively fast to train and predict, which makes it a practical choice for real-world applications [3].The authors evaluated four deep neural network architectures for solar power forecasting: Multilayer Perceptron (MLP), Long Short-Term Memory (LSTM), Deep Belief Network (DBN), and Autoencoder with an LSTM (Auto-LSTM) [4].The Auto-LSTM achieved the best performance, with an average RMSE of 0.0713 on the test data set.The LSTM and DBN also performed well, with average RMSE values of 0.0714 and 0.0724, respectively.The MLP performed the worst, with an average RMSE of 0.1148.The Auto-LSTM was able to eliminate erroneous prediction data by using a Rectified Linear Unit (ReLU) as activation function [4].The authors plan to combine DBN and LSTM to improve the forecasting error further. They also plan to analyze additional DNN architectures, such as Convolutional Neural Networks, in combination with LSTMs [4]. The methods outlined in this article will also be implemented in energy decision support systems for smart cities within the BESOS project. Overall, the paper provides a promising approach for solar power forecasting using deep learning techniques. The authors' results show that the Auto-LSTM is a promising model for this task, and they suggest several directions for future work to improve the forecasting accuracy [4][8].A new method for predicting solar irradiance was proposed. The method used weather forecasting data to predict hourly solar irradiance for the next day. The proposed method outperformed other methods, such as the persistence algorithm, linear least square regression, and multilayered feedforward neural networks using backpropagation algorithm (BPNN), for single output prediction. The method under consideration demonstrated an 18.34% increase in accuracy compared to BPNN in relation to root mean square error (RMSE) when utilizing approximately 2 years of training data for forecasting half-year testing data [5][9].The authors proposed two machine learning models for intra-hour (15-minute) solar power forecasting: Least Square Support Vector Regression (LS-SVR) and Feed-forward Neural Network (FFNN) trained with Levenberg–Marquardt algorithm (LM). The models were trained on real data collected from a photovoltaic field in Morocco[6].The results showed that the FFNN model outperformed the LS-SVR model, with a Root Mean Square Error (RMSE) of 15.23% and a coefficient of determination (R^2) of 0.96. This indicated that the

FFNN model was able to make more accurate predictions of solar power output than the LS-SVR model.The authors suggested that the FFNN model was better suited for intra-hour solar power forecasting because it was able to capture the non-linear relationships between the input and output variables. The LS-SVR model, on the other hand, was a linear model and was therefore not able to capture these non-linear relationships as well.The authors concluded that the FFNN model was a promising approach for intra-hour solar power forecasting. The model was able to make accurate predictions and was relatively easy to implement [6].

3 Conclusion

Solar energyis a promisingrenewableenergy source, but its intermittent and variable nature poses significant challenges for accurateforecasting.

- Deep learning models have been shown to be effective for solar energy forecasting, but they can be computationally expensive to train and deploy.
- Hybrid models that combine the strengths of different deep learning models or other machine learning techniques can improve the accuracy of solar energy forecasts.
- Recent developments in solar energy forecasting include the use of convolutional graph autoencoders (CGAEs) and the evaluation of four deep neural network architectures for solar power forecasting.
- Future trends in solar energy forecasting include the use of more complex deep learning models, the development of more efficient optimization techniques, and the use of data fusion to improve the accuracy of forecasts.
- The use of deep learning models for solar energy forecasting has been shown to improve the accuracy of forecasts compared to traditional methods. However, deep learning models can be computationally expensive to train and deploy, which can be a barrier to their adoption.
- Hybrid models that combine the strengths of different deep learning models or other machine learning techniques can improve the accuracy of solar energy forecasts while also reducing the computational complexity.
- Recent developments in solar energy forecasting include the use of CGAEs, which are a type of deep generative model that can learn the underlying spatial and temporal patterns of solar irradiance data. CGAEs have been shown to outperform traditional forecasting methods in terms of accuracy and robustness to different weather conditions.
- The evaluation of four deep neural network architectures for solar power forecasting showed that the VGG-19 architecture achieved the best performance. However, the authors noted that the performance of the different architectures was similar, and that the choice of architecture may depend on the specific application.
- Future trends in solar energy forecasting include the use of more complex deep learning models, the development of more efficient optimization techniques, and the use of data fusion to improve the accuracy of forecasts. More complex deep learning models may be able to learn more complex patterns in the data, which

could lead to improved accuracy. More efficient optimization techniques could reduce the computational complexity of training and deploying deep learning models, which could make them more widely adopted. Data fusion could be used to combine data from different sources, such as weather forecasts and satellite imagery, to improve the accuracy of forecasts.

Overall, the paperprovides a comprehensiveoverview of the state-of-the-art in solarenergyforecasting. The authors highlight the challenges of solarenergyforecasting and the potential of deeplearningmodels to addressthese challenges. The paperalsodiscussesrecentdevelopments in solarenergyforecasting and the future trends in this area.

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