International Journal of Applied Engineering Research ISSN 0973-4562 Volume 18, Number 1 (2023) pp. 7-11

Forecasting of Solar Panel Output Using Numerical Weather Prediction & Image Proceiing Techniques

Rahul Saraswat[1] Deepak Jhanwar[2] Rahul Agarwal[3]

[1]*Research Scholar, Rajasthan Technical University Kota (India)*

[2]*Govt .Engg. College Ajmer (Rajasthan, India)* [3] *Anand Engg. College Agra (UP, India)*

Abstract

Several statistical, physical, and ensemble techniques are used in this investigation. As an example of the physical approach, we look at satellite-based models, cloud imagery, and NWP models. Such models are used when other data sources are unavailable and have a few hours to several days forecasting horizon. The lack of spatial and temporal resolution is the only problem with the physical method. We explore time series and learning models in the statistical model. When sufficient historical data is available, learning models like the Markov chain, artificial neural network, and support vector machine provide reasonable solar irradiance predictions. Nowadays, it is common to practice using a hybrid strategy combining elements of many models. The accuracy of forecasts may be improved by using these methods. Several error measures are used to assess a prediction model's accuracy. In cases of significant mistakes in the solar forecast, it is possible to understand the model better and re-evaluate it.

Introduction

Global energy consumption of the planet would still need much power even with constant upgrades to the current energy infrastructure. Sufficient clean energy supplies are linked to global security, economic progress, and quality of life. Finding enough energy to fulfill the world's growing needs is one of the world's biggest problems. Progress in solar prediction would be a significant step toward meeting these issues. The features of solar power plants that convert solar energy to electric power, the scattering process, knowledge of the sky course, and the environment. all play a role in solar forecast [1]. Operations and long-term planning need accurate solar forecast data. Grid operators may use forecasting information to plan for the future of energy generation and consumption and initiate discussions between suppliers and consumers through bilateral contracts. Accurate techniques of forecasting improve the reliability of the grid's energy supply while decreasing the expenses of auxiliary devices [2]. Different prediction methods are shown, each tailored to specific input data sources and forecasting timeframes. The time series model may be constructed using data collected locally for brief periods. Using a high-resolution ground-based sky imager, we can predict the next hour.

Predictions of cloud velocities using photos captured throughout the day have shown to be accurate. These predictions are based on NWP models. Integrating photovoltaic systems with the grid requires foresight of at least two days. Solar forecasting considers the use of both concentrating and non-concentrating solar power technologies. Concentrated PV systems are strongly associated with DNI. Monitoring DNI is crucial for controlling and maintaining concentrated solar thermal power systems. The DNI may be reduced by as much as 30% due to environmental conditions such as dust storms, air pollution, and cirrus clouds. As a result of the greater tolerance for error that “GHI” measurements provide compared to DNI measurements, it is the principal metric for use in evaluating non-concentrated solar PV systems.

Statement of the Problem

The globe, including India, is experiencing an energy crisis. The gap between energy demand and supply is relatively large. This chasm is widening as our nation moves steadily forward in the path of development, and closing it is crucial if we maintain this trend. Several potential solutions are discussed, with a focus on those that use renewable energy sources. In today's solar system, many researchers and academics are hard at work creating new instruments, models, and algorithms. Forecasting has become an increasingly important aspect of modern business planning with the increase in renewable energy sources and the adoption of electricity deregulation in the industry. Solar power forecasting has emerged as a critical concern for grid operators. Various methods are used to predict the Sun's radiation following market demands. This comprehensive study will provide academics and utility companies with a better understanding of the need to develop accurate models for predicting solar power generation and minimizing associated risks. The information gleaned may also aid policymakers and energy market players in making better, more informed choices about installing solar power systems.

Motivation

In order to run operations effectively and prepare for the future, accurate forecasting is essential.

The need for predicting, however, is explained below:

- Because of the unpredictable nature of the sky, solar power production is not a stable source of energy.
- For Suppliers and Customers to Reach Mutually Beneficial Contract Terms, Bilateral Negotiation is a Must
- Economic location, kind, and size of solar power facilities are all described by operational planning decisions.
- Grid operators may use solar forecasts to predict better and coordinate power generation and demand.
- Making calls on the future of regional power transmission, production, distribution, and trading

Review of Literature

According to the research results, the deterioration and performance significantly depend on the installation's location. Degradation of CdTe installations, for instance, is more severe in the center of India because of the region's higher average temperature and more significant daily temperature variation. Discoloration of the encapsulant is the most typical form of deterioration. This linear assumption of deterioration rates may not be as precise as it formerly was as PV performance modeling advances. In one of our investigations, we identified a range of output power loss from 0.9% to 42.8% while analyzing the effect of polycrystalline PV microcracks utilizing 4000 damaged solar cells.[3]

Microcracks in the dark regions of PV modules indicate power loss. Parallel and centered fractures between busbars caused less than a 4% loss of power, according to research by Grunow et al. However, the power output would decrease by 60% if the fractures were parallel. The research was completed by evaluating 31 operational PV samples from 2012. Oblique and parallel fissures affect PV power performance when present in enough cells and over enough area.[4]

The current PV system's dependability is accurately represented in research that analyzed yearly production data from 100,000 systems and comments about their performance. Consistent with our findings, we discovered that the more cell breaks there were, the greater the performance reductions. Snail trails have been shown to have a minor impact on PV module performance; nevertheless, long-term behavior analysis has shown that these effects do not evolve rapidly enough to pose a significant danger in terms of power losses. The effect of a microcrack on the power output of a PV solar cell depends on its location, direction, and severity. The next step was to compile a summary of the research on PV solar installation performance to better grasp its mechanisms and the factors that might affect it. It was shown that the complexity of simulating microcracks hampers precise modeling performance.

The use of renewable energy sources to lessen the impact of environmental problems has grown dramatically in recent years. Photovoltaic (PV) power production is one method of transforming solar energy into usable electricity. Grid scheduling, dispatching, and regulation face several technical issues due to the unpredictability of ground-level irradiance. Many efficient methods are necessary to lessen the impact of PV power plants linked to the grid. Methods like multi-scale PV power forecasting, demand response, battery reserves, peaking units, and others fall under this category.[5]

A new method of forecasting PV output at many scales and during multiple periods was presented based on correlations between nearby solar sites. Using data from the past at PV sites in California and Colorado, we compared the suggested method's performance to that of the traditional persistence model and investigated the increased prediction quality. The movement of clouds and the daily variation in sunlight cause random and periodic fluctuations in solar PV power production. The forecasting model has to include more in-depth data capable of following the volatility. The link between two PV power time series from the target and surrounding plants is initially studied.

Available forecasting methods are often classified as physical, statistical, or ML-based. ML-based models are the most accurate and promising in hourly resolution and solar power projections. Methods in machine learning (ML) often depend on AI's capacity to infer new patterns and associations from existing data. Due to the iterative nature of their training, these approaches often have large computing requirements. We have zeroed down on five ML models that will provide reliable predictions.[6]

Additional characteristics capture the connections inside a PV's physical domain, but they might be distracting if too many exist. Better accuracy is achieved than traditional approaches since the model can understand the underlying physical correlations between the many features. The accuracy was highest for models that used exogenous factors not included in the original data set and lowest for those that relied only on intrinsic features. Despite being the top performance, RF's memory requirements may make it less appealing than alternative approaches that use fewer resources. It allows us to provide a performance baseline for the ML and statistical approaches mentioned in this research, which the forecasting community may use.

Numerical weather forecasts are used to evaluate 24 machine learning models for predicting photovoltaic (PV) electricity one day in advance (NWP). The data from 16 ground-mounted PV plants in Hungary are used to put the models through their paces, and they are then assessed using five standard verification measures. Kernel ridge (KR) is the most accurate model overall, but it takes an exceptionally long time to train and uses much memory. Compared to traditional neural networks, multilayer perceptron (MLP) achieves about the same level of accuracy with far less effort required during the training phase. The RMSE is just 1.5% higher when using the daily mean GHI predictions and the sky position angles as predictors.[7]

These 24 models were validated for accuracy and hyperparameter sensitivity and may be used as guidelines in real-world settings. While this research focuses on NWP-based irradiance-to-power conversion, the findings should also hold for other irradiance projections. The accuracy of the power forecasts has been dramatically improved by the addition of even fundamental theoretically generated data, such as the sky view. As the objective of the ML models, i.e., describing the functioning of the PV plants, is the same as per the source of the irradiance data, it is assumed that the findings of this research will be comparable for different sources of irradiance predictions.[1]

The research team behind this study wanted to show off their new solar irradiation forecaster, which can anticipate the amount of sunlight a solar power plant would get up to 10 minutes in advance. Training and validation RMSEs for this model are 36.93 and 35.77 W/ m2, respectively, for an accuracy increase of 37.08% and 37.52%. Regarding root-mean-squared error (RMSE), Daubechies wavelet transformations enhance forecaster accuracy from 50.80 to 35.77 W/m2, a 25.59% gain. Furthermore, this study's mean error cumulative percentage is 1.46 percent, whereas the error percentage for a Spatio-temporal FFNN forecaster is 2.40 percent. In addition, the developed forecaster has been compared against forecasters.

An enhanced deep learning method that makes use of ANN, LSTM, and XGBoost is suggested in this research. Combining strong base learners rather than weak learners allowed the DSE-

XGB approach to beat the separate deep learning algorithms. This research has combined the two methods of modeling with interpretable machine learning To decipher how the meta-learner acquires knowledge about the basic model's predictions. Each base learner sequentially constructs a tree to decrease the error rates of the preceding trees. Using a boosting technique called XGBoost, we merged the predictions of the individual base learners.

The suggested DSE-XGB model can manage uncertainty in the prediction from separate models since it does not depend only on the input characteristics. The suggested stacking ensemble method may be influential when applied to challenges in other domains, such as health, control engineering, and the financial markets. The trade-off between improved forecast accuracy and longer calculation times is another factor that should be addressed while choosing the basic models.[2]

In order to enhance ML-based PV power predictors, the article suggests augmenting a given dataset with PV-performance models and other physically relevant factors. The most common patterns held across all of our models and timeframes, and they tracked with our physics-informed search space. Some suggested measures may need to perform better due to their sluggish thermodynamic behavior. Therefore, future research should focus on determining whether or not this approach is suitable for more excellent sample rates.

In order to estimate the PV power from input factors such as solar PV panel temperature, ambient temperature, solar flux, and relative humidity, many ML methods were explored. These included support vector machine (SVM) and Gaussian process regression (GPR). There was a strong indication from the data that Matern 5/2 GPR performs best among the offered ML algorithms.[8]

Hypothesis

Most research in solar irradiance/PV power forecasts concentrates on a single power plant. For minute-by-minute irradiance and PV power predictions, sky photos are often employed for cloud characteristic extraction.

This approach is analyzed and tested using several statistical characteristics to forecast beam irradiance, diffuse irradiance, and global irradiance, with the results showing an improvement over the previous method.

This study uses a technique for ultra-short-term PV power forecasting that combines Spatio-temporal correlation with sky information from the nearby plant.

Methodology

The mapping between cloud characteristic indices derived from nearby satellite photos and the target plant's solar power data is then shown. The suggested strategy has improved the precision of ultra-short-term solar PV power forecasts in simulations using real-world data.

With careful feature selection and tuning, ANN can be surpassed by techniques like RF and SVR. The scientific literature has lately begun to take notice of ML-based models. The primary facilitator in lowering RES uncertainty is accurate forecasting. We suggest a physics-informed dataset extension and feature selection approach to enhance the precision of high-resolution PV power forecasts based on ML models. Combining a convolutional neural network with a long short-term memory is likely more successful at capturing spatial and temporal data.

Classifying solar forecasting methods is determined by the days that predictions are made into the future. Grid operators may achieve consumption and output parity with the help of accurate forecasts. Intra-hour, daily, and weekly perspectives are different time frames.

Several time series models, including an artificial neural network, an autoregressive integrated moving average, and a persistence model, are used to predict solar irradiance over concise time scales.

Solar irradiance, which is highly dependent on observations based on the changes of clouds utilized as a foundation for short-term irradiance forecasting:

- Ground-based, high-resolution sky photos may capture cloud data, which can predict the sky's irradiance in the sub-hour range.
- The cloud motion vector from satellite images determines the amount of solar irradiance available from 30 minutes to 6 hours.

Numerical weather prediction models outperform satellite-based predictions over extended periods (4-6 h ahead). Furthermore, unified methods are available for deriving an optimal prediction for a 2-horizon period.

Physical Methods

“Total Sky Imagers (TSI)," “Numerical Weather Prediction (NWP)," and physical characteristics like ‘temperature,' cloud cover, and ‘humidity’ are relied on by the physical approaches.

Table 1: Correlations among horizon length, prediction accuracy, and associated tasks

Horizon type	**Forecast horizon**	**Granularity time step**	**Events**	**Forecasting models**
Intra hour	2 min – 55 min	2 minutes	Ramping events, variability-related operations	Total sky imagers models, time series models, NWP models, and satellite imagery
Intraday	1-8 hr	2 hours	Load following forecasting	
Day ahead	1-3 days	8 hours	Unit commitment, transmission scheduling, day-ahead markets	

Numerical Weather Prediction

Atmospheric physics is essential to the process of numerical weather prediction. Assimilation predicts future weather conditions based on the present weather measurements. For forecasts ranging from one day out to many days out, NWP models perform well.

The procedure for NWPs:

- First, data on the present state of the atmosphere is gathered using satellite and ground-based sky photographs. Assimilation is utilized to process the present weather status, which is a crucial and complicated process in and of itself.

- In Step 2, we integrate and solve the most critical equations describing the atmosphere, including the thermodynamic equation and Newton's second rule of fluids.

The World Weather Atmosphere Model (WWAM), the Regional Climate Atmosphere Model (RCM), & the "Weather Research and Forecasting Model (WRF)" are all examples of NWP models. The input parameters and the spatial resolution are two ways in which we may distinguish between them.
Cloud imaging with a high spatial resolution is used to examine cloud circumstances. They can detect cloud variation and forecast global irradiance up to 6 hours in advance. Both cloud cover and cloud optical depth have significant impacts on solar irradiance. In order to anticipate solar irradiance accurately in the near term, total sky imagers rely on cloud information. Some researchers create their own TSIs, and some utilize commercially available TSIs like TSI-800.

Statistical Methods
The prediction approach is independent of the internal model phase and uses historical time data of solar irradiation. The statistical technique incorporates several other approaches, such as the persistence model, ARIMA, ANN, and Fuzzy logic.

Table 2: Models of the NWP: A Comparison

Models	Time Step	Layers	Resolution (km)	Source
HRRR	15 min	50	3	NOAA
NAM	6 hr	60	12	NCEP
RAP	1 hr	50	13	NOAA
WRF	Depends	Depends	1	NCAR
ECMWF	3 hr	91	25	-
GFS	6 hr	64	28	NOAA

Results and Discussion

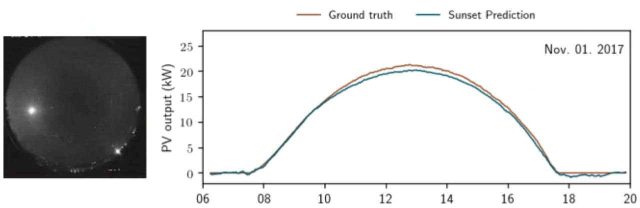

Figure 1: Data Analysis of the Sky in winters

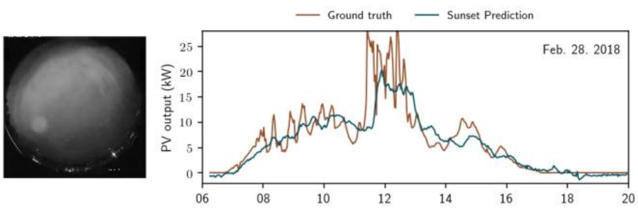

Figure 2: Analysis of the sky in Early Springs

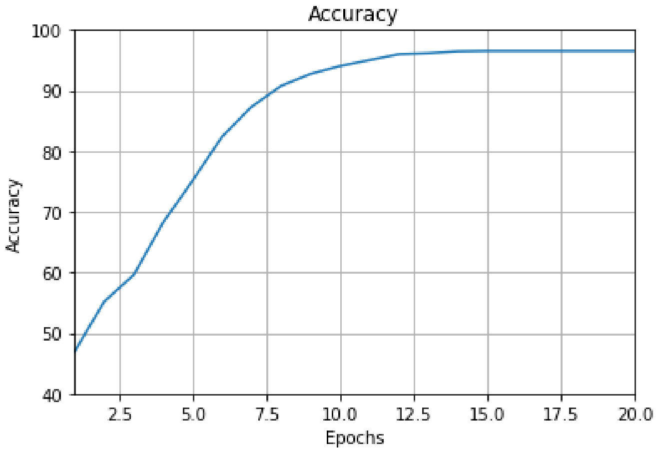

Figure 3: Accuracy Analysis

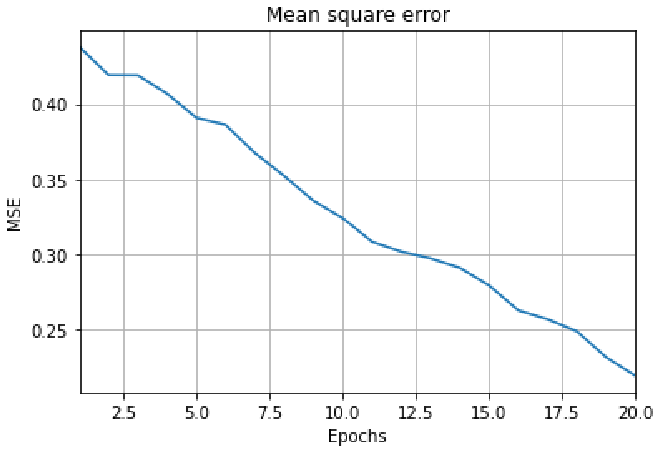

Figure 4: Mean Square Root of the complete images

Conclusion
In winter, as per figure 1, the output power of PV is highest in the afternoon at around 20 kW, whereas it is minimum at sunrise and sunset at around 0 kW. In early springs in figure 2, the output power of PV is highest in the afternoon at more than 25 kW, but at that time, it fluctuates due to the formation of clouds in that season. It is a minimum at sunrise and sunset of around 0 kW. The output power is calculated concerning time in which we have considered the time between 6:00 AM to 8:00 PM in figure 1 and figure 2.
The correlation ratio for overall accuracy calculated of the experimented model compared to the predictive model is 65.5. When the repeated iterations go above 7.5, the accuracy becomes stable at more than 90%. The changes in the environment affect the value of accuracy in the analysis. As per figure 4, the mean square plot is in depleting mode from 0.4 to 0.25 as the iterations increase. The correlation ratio for MSE is calculated as 56.33. The overall MSE Score is calculated as 52.42. Similarly, the R^2 Score is calculated as 0.106.

References

[1] G. Goudelis, P. I. Lazaridis, and M. Dhimish, “A Review of Models for Photovoltaic Crack and Hotspot Prediction,” Energies, vol. 15, no. 12, p. 4303, Jun. 2022, doi: 10.3390/en15124303.

[2] F. Wang et al., “A satellite image data based ultra-short-term solar PV power forecasting method considering cloud information from neighboring plant,” Energy, vol. 238, p. 121946, Jan. 2022, doi:10.1016/j.energy.2021.121946.

[3] D. V. Pombo, P. Bacher, C. Ziras, H. W. Bindner, S. V. Spataru, and P. E. Sørensen, “Benchmarking physics-informed machine learning-based short term PV-power forecasting tools,” Energy Reports, vol. 8, pp. 6512–6520, Nov. 2022, doi: 10.1016/j.egyr.2022.05.006.

[4] D. Markovics and M. J. Mayer, “Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction,” Renewable and Sustainable Energy Reviews, vol. 161, p. 112364, Jun. 2022, doi:10.1016/j.rser.2022.112364.

[5] F. Rodríguez, I. Azcárate, J. Vadillo, and A. Galarza, “Forecasting intra-hour solar photovoltaic energy by assembling wavelet based time-frequency analysis with deep learning neural networks,” International Journal of Electrical Power & Energy Systems, vol. 137, p. 107777, May 2022, doi:10.1016/j.ijepes.2021.107777.

[6] W. Khan, S. Walker, and W. Zeiler, “Improved solar photovoltaic energy generation forecast using deep learning-based ensemble stacking approach,” Energy, vol. 240, p. 122812, Feb. 2022, doi:10.1016/j.energy.2021.122812.

[7] D. V. Pombo, H. W. Bindner, S. V. Spataru, P. E. Sørensen, and P. Bacher, “Increasing the Accuracy of Hourly Multi-Output Solar Power Forecast with Physics-Informed Machine Learning,” Sensors, vol. 22, no. 3, p. 749, Jan. 2022, doi: 10.3390/s22030749.

[8] B. Zazoum, “Solar photovoltaic power prediction using different machine learning methods,” Energy Reports, vol. 8, pp. 19–25, Apr. 2022, doi: 10.1016/j.egyr.2021.11.183.