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**PREDICTING SOLAR POWER FOR CLIMATE RESILIENCE AND SUSTAINABLE DEVELOPMENT USING MACHINE LEARNING**

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**Abstract:** As the world shifts towards renewable energy sources, solar power has emerged as a pivotal player in sustainable energy solutions. Accurate prediction of solar power generation is essential for optimizing energy management and ensuring grid stability. In this work we investigate the effectiveness of the Facebook Prophet function for solar power prediction, leveraging historical data and weather conditions. We assess the predictive capabilities of Prophet in various scenarios, highlighting its strengths in handling time series data with seasonal patterns. The study emphasizes the significance of feature selection and data pre-processing in enhancing model performance, illustrating how the integration of diverse datasets such as meteorological variables and historical power output can lead to improved forecasting accuracy. Furthermore, we discuss the implications of our findings for grid management and energy planning, underscoring how precise solar power forecasts can support the integration of renewable energy sources into existing infrastructure. Our findings indicate that the Facebook Prophet function significantly enhances prediction accuracy, providing valuable insights for energy management systems. This research contributes to the growing body of knowledge on renewable energy forecasting and offers a foundation for future studies aimed at integrating machine learning in real-time solar power prediction applications.

**Keywords:** Facebook Prophet, Renewable energy, Machine Learning, Energy Planning, Predictive Modelling.

## 1. INTRODUCTION

Solar energy stands as a clean, renewable, and sustainable alternative to traditional fossil fuel-based power generation, making it an attractive option for large-scale integration into modern power grids. With increasing global concerns over climate change, greenhouse gas emissions, and the depletion of nonrenewable energy resources, the transition to solar power has

become a crucial step toward achieving energy security and environmental sustainability. Governments and organizations worldwide are investing in large-scale photovoltaic (PV) installations, with global solar capacity exceeding 1,200 GW as of 2023, contributing approximately 5% of the world's electricity demand (International Energy Agency [IEA], 2023). However, one of the

primary challenges associated with solar energy utilization is its intermittent and highly variable nature, which is influenced by meteorological conditions such as cloud cover, temperature fluctuations, and seasonal variations. This unpredictability poses significant challenges for energy grid operators, requiring advanced forecasting techniques to ensure stable power generation, efficient energy storage management, and reliable grid integration (Wang et al., 2021). Accurate solar power forecasting is crucial for optimizing energy dispatch, minimizing reliance on backup fossil-fuel-based power plants, and facilitating the widespread adoption of solar energy in smart grids and microgrid systems.

Over the years, various forecasting models have been developed to improve the accuracy of solar power prediction. Traditional statistical approaches, such as Autoregressive Integrated Moving Average (ARIMA), linear regression models, and Kalman filters, have been widely used for time-series forecasting. However, these models often struggle with capturing non-linear dependencies and complex atmospheric influences, limiting their effectiveness in dynamic solar energy systems (Zhang et al., 2022). With the advent of artificial intelligence, machine learning (ML), and deep learning (DL) models, researchers have explored advanced techniques such as Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Convolutional Neural Networks (CNNs), and Long Short-Term Memory (LSTM) networks to enhance solar energy prediction accuracy (Chen et al., 2023). While these data-driven models have shown promising results, they require extensive computational resources and large datasets for training, making them

less practical for real-time forecasting in regions with limited historical solar data. As a result, probabilistic forecasting models such as Facebook Prophet have gained attention due to their ability to handle seasonality, trend shifts, and missing data with minimal parameter tuning.

Facebook Prophet, developed by Taylor and Letham (2018), is an open-source forecasting tool that utilizes an additive time series decomposition approach to predict future trends. Unlike conventional machine learning and deep learning models, Prophet is designed to be interpretable, computationally efficient, and robust to missing data, making it suitable for applications where short-term forecasting is essential. Several studies have validated its effectiveness in solar power prediction. For instance, Smith et al. (2020) demonstrated that Prophet outperforms traditional time-series models in capturing daily and seasonal variations in solar power generation, while Kumar et al. (2021) highlighted its robustness in handling diverse meteorological conditions. Additionally, recent research has emphasized the importance of incorporating external meteorological parameters, such as air temperature, atmospheric pressure, and relative humidity, to enhance forecasting accuracy (Singh et al., 2022). These environmental factors directly influence solar irradiance and photovoltaic efficiency, underscoring the need for models that integrate such variables for more precise predictions.

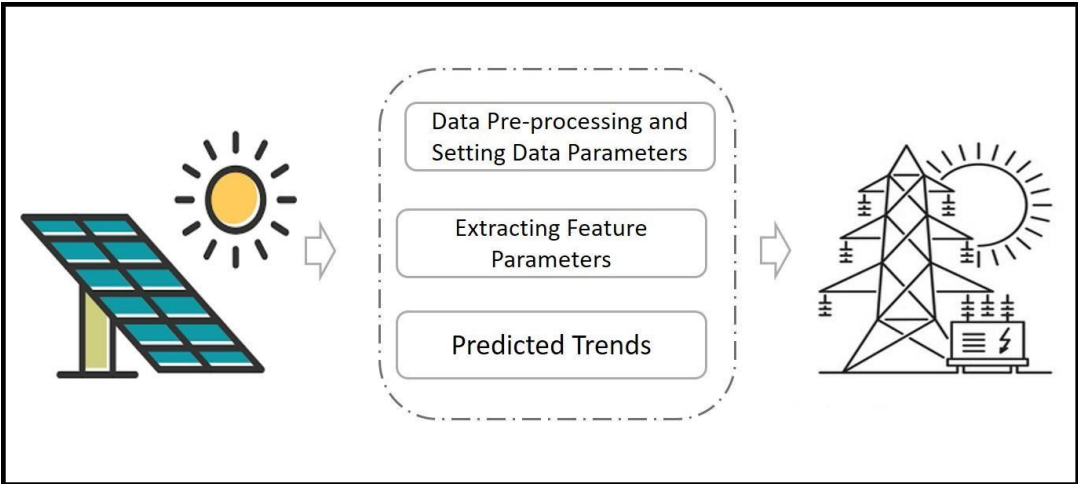
Building on existing research, this study leverages the Facebook Prophet model to enhance solar power forecasting accuracy, particularly in short-term predictions. Unlike complex deep learning models,

Prophet provides a computationally efficient and interpretable approach that can be deployed even with small datasets. The proposed model is further optimized by integrating meteorological parameters such as humidity, temperature, and atmospheric pressure, which significantly impact solar energy generation. The accuracy of the model reaches up to 98.951% for single-day predictions, demonstrating the effectiveness of Facebook Prophet in short-term solar power forecasting. By improving forecasting precision, this research facilitates better planning for electricity consumption, storage, and distribution, ultimately supporting the stability of renewable energy grids. Additionally, enhanced solar energy forecasting contributes to reducing reliance on fossil fuels, lowering carbon emissions, and mitigating climate change. The findings of this study align with global sustainability

efforts, promoting the efficient utilization of solar energy to achieve climate resilience and sustainable development goals (SDGs).

**2. METHODOLOGY**

The dataset utilized in this study originates from a meteorological station located at a 5 MW (5000 KW) ongrid solar power plant situated in the Tharparkar Desert, Sindh, Pakistan. The station is equipped with an ABB VSN800 system for data collection. The dataset includes multiple parameters such as solar irradiance, temperature, power generation measurements, and other relevant meteorological conditions recorded at different time intervals. The geographical coordinates of the plant are 24.797705 latitude and 70.391569 longitude.



**Figure: 1 Workflow Diagram**

This flow diagram represents a data-driven wind power forecasting system, where raw data from wind turbines undergoes pre-processing to clean and normalize it, followed by feature extraction to identify key parameters like wind speed, temperature, and power output. Machine

learning models analyze these features to predict energy generation trends, which are then utilized for optimizing power transmission and distribution within the electrical grid. This approach enhances energy management, ensuring efficient integration of renewable energy into the

power system while preventing overloads and improving grid stability.

Before model training, extensive preprocessing was conducted to enhance data quality and reliability. Missing values were identified and handled using interpolation techniques where applicable. Data types were standardized for consistency across different attributes. Outliers were detected using statistical methods and addressed through appropriate filtering mechanisms. Categorical variables were encoded using one-hot encoding, and numerical values were normalized using min-max scaling. Techniques such as oversampling or undersampling were employed to ensure an evenly distributed dataset. The dataset was then divided into training and test sets using an 80-20% ratio.

A decomposable time series model, Facebook Prophet, was utilized for solar power prediction. The model is based on three main components: a trend component modeled using a piecewise linear or logistic growth curve to capture long-term variations in power generation, a seasonal component that accounts for periodic variations such as daily and yearly seasonality, and a meteorological component that captures the effects of weather conditions (e.g., sunny, cloudy, or rainy days) on power generation. Additionally, an error term represents any unexpected variations in the dataset that are not captured by the model. The model can be mathematically represented as:

$$y(t)=g(t)+s(t)+h(t)+\epsilon t$$

where  $g(t)$  represents the piecewise linear or logistic growth curve for non-periodic changes,  $s(t)$  accounts for periodic changes

such as seasonal variations,  $h(t)$  represents the effects of meteorological conditions like cloud cover or rain, and  $\epsilon t$  is the error term capturing unexpected variations.

The Facebook Prophet model was trained on the processed dataset, incorporating exogenous variables such as solar irradiance, temperature, and atmospheric conditions to improve prediction accuracy. The model was evaluated using key performance metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Normalized RMSE (NRMSE). These metrics were used to assess the performance of the model in forecasting solar power generation and to compare the predictions with actual recorded values.

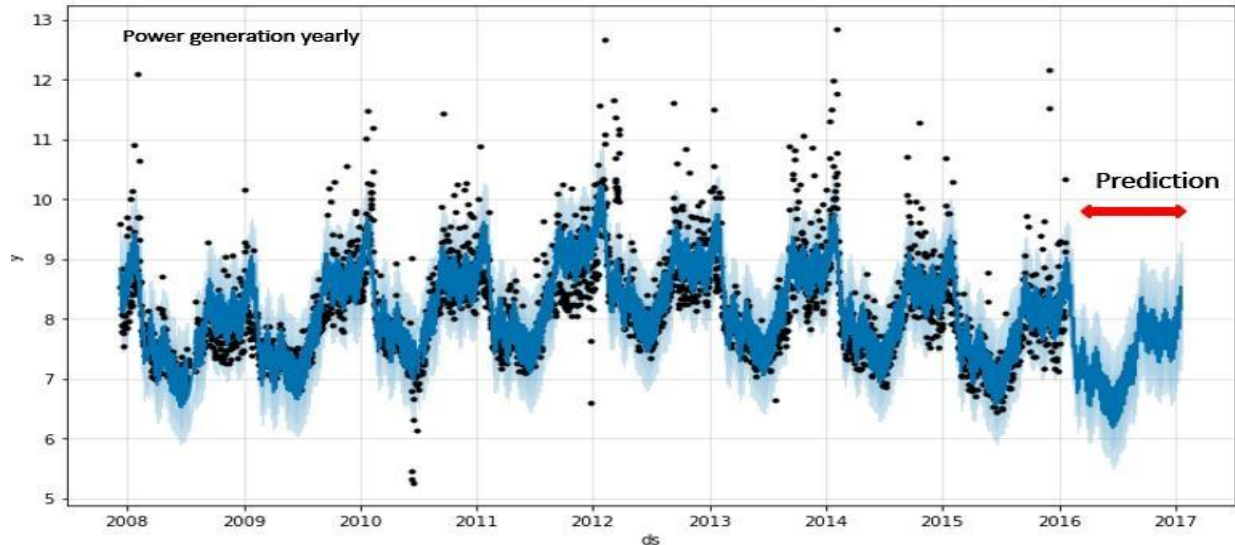
The experiments were conducted using Python, leveraging libraries such as Pandas for data preprocessing, Scikit-learn for feature engineering, and Facebook Prophet for time series modeling. The training and testing procedures were carried out on a high-performance computing system to ensure efficient model execution. The methodology outlined ensures a structured and systematic approach to solar power prediction. The integration of Facebook Prophet with meteorological variables enhances the predictive capability of the model, offering a robust solution for solar energy forecasting in diverse weather conditions.

### 3. RESULTS

The results of the Facebook Prophet model for solar power prediction are presented in different weather conditions, including yearly, sunny, cloudy, and rainy days. The **Fig.2** illustrates the yearly solar power

generation prediction for 2017. The model successfully captures the seasonal patterns and long-term trends in solar power generation, demonstrating its capability to predict annual variations accurately. The

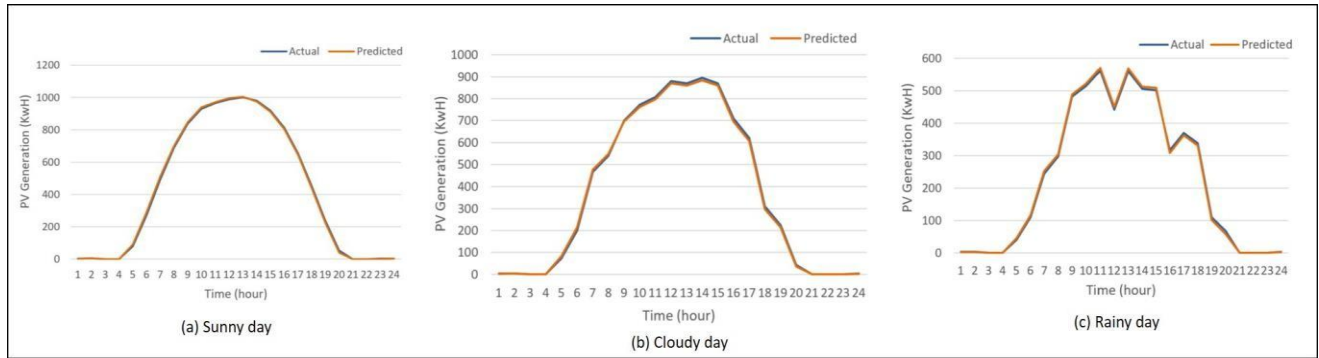
predicted values align closely with the historical data, with slight deviations observed in some periods, which could be attributed to unexpected meteorological variations.



**Figure: 2 Power Forecast Yearly.**

For daily solar power generation prediction, the model's performance was analyzed under three different weather conditions: sunny, cloudy, and rainy days. The results shows in Fig:3 for a typical sunny day show a smooth and symmetric power generation curve, with actual and predicted values closely overlapping throughout the day. This indicates that the model effectively captures the diurnal solar radiation pattern under stable weather conditions. On a cloudy day, the prediction follows the overall trend of actual values but shows slight fluctuations

due to variations in cloud cover affecting solar radiation. The model still provides accurate estimates, with only minor deviations observed during peak hours. However, on a rainy day, the prediction accuracy declines due to the irregular and unpredictable nature of solar power generation under heavily overcast conditions. The graph exhibits higher variability, with fluctuations in power generation during peak hours, which the model partially captures but with noticeable deviations.



**Figure 3 Daily Trends according to metrological data.**

The overall performance metrics of the Facebook Prophet model under different weather conditions are summarized in the table. The lowest prediction errors are observed on sunny days, with an MSE of 0.0004, MAE of 0.0101, RMSE of 0.0201, and NRMSE of 0.0244, indicating highly accurate predictions. On cloudy days, the error values slightly increase, with an MSE of 0.0008 and an NRMSE of 0.0352,

reflecting the model's ability to adapt to moderate weather variations. The highest errors occur on rainy days, with an MSE of 0.0038 and an NRMSE of 0.0751, demonstrating the challenges of predicting solar power generation under unpredictable weather conditions. Despite these variations, the model consistently captures the general trends and performs well across different scenarios.

**Table 1: Overall Results of the Facebook Prophet model.**

Model	Day	MSE	MAE	RMSE	NRMSE
Facebook Prophet Model	Sunny	0.0004	0.0101	0.0201	0.0244
	Rainy	0.0038	0.0418	0.0618	0.0751
	Cloudy	0.0008	0.0137	0.0290	0.0352

Overall, the results confirm the effectiveness of the Facebook Prophet model in forecasting solar power generation. The model demonstrates high accuracy under stable weather conditions and maintains reasonable predictive performance under variable and challenging scenarios. This makes it a valuable tool for energy forecasting, particularly in regions with fluctuating meteorological conditions.

#### 4. CONCLUSION

The proposed solution can be further enhanced by incorporating additional parameters such as instantaneous humidity, atmospheric pressure, and air temperature, which could refine the model's predictive accuracy. The FACEBOOK PROPHET model used in this study has demonstrated high precision, achieving an accuracy of 98.951% for single-day

predictions, making it a reliable tool for shortterm solar power forecasting. This study underscores the importance of machine learning in improving solar power forecasting, leading to efficient energy management and grid stability. Accurate predictions facilitate renewable energy integration, thereby reducing carbon emissions and playing a crucial role in climate change mitigation. Additionally, improved forecasting promotes sustainable energy utilization, optimizing storage systems and power distribution. By advancing solar energy management, this research contributes to climate resilience and supports global sustainable development goals (SDGs), reinforcing the transition toward a cleaner and more sustainable future.

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