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Renewable Solar Energy Prediction in India: 2025–2030

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Abstract

As India endeavors to realize its objective of achieving 500 GW of renewable energy capacity by the year 2030, the precise forecasting of solar power generation is rendered increasingly essential. This scholarly article conducts a comprehensive review of the utilization of machine learning (ML) methodologies in the prediction of solar energy across diverse Indian states, underscoring their potential to address the complexities associated with the variability of solar irradiance. Conventional forecasting techniques frequently fall short of capturing the intricate non-linear relationships that exist between meteorological variables and solar energy output. In contrast, ML methodologies, such as artificial neural networks and hybrid models, have demonstrated considerable potential in enhancing the accuracy of predictions. Recent developments indicate that the amalgamation of historical meteorological data with sophisticated algorithms can result in superior forecasting performance. This review accentuates the transformative capacity of machine learning in the optimization of solar energy management and bolsters India's renewable energy aims by offering insights into effective forecasting strategies. The results highlight the imperative of embracing innovative methodologies to improve the reliability of solar power forecasts, thus enabling a more effective integration of solar energy into the national grid.

Keywords: Solar energy, prediction, machine learning, renewable energy, India, Indian States, artificial intelligence

INTRODUCTION

India's dedication to renewable energy is exemplified by its ambitious objective of attaining 500 GW of installed renewable energy capacity by 2030, with solar energy serving as a pivotal element in this transition. The country's extensive and varied geographical landscape results in considerable spatial and temporal fluctuations in solar irradiance, thereby necessitating the implementation of precise forecasting methodologies to optimize energy management and maintain grid stability. Conventional forecasting methodologies frequently encounter challenges in effectively capturing intricate non-linear interrelationships between meteorological parameters and solar power generation [1, 2].

In recent years, machine learning (ML) has emerged as a promising methodology for enhancing solar power forecasting precision. Raja et al. [3] illustrated the efficacy of various ML methodologies for predicting solar power generation in Uttar Pradesh, underscoring their potential to surpass traditional forecasting techniques [4, 3]. Sheoran [5] conducted a thorough review of ML methodologies specifically utilized for solar energy forecasting in India, accentuating the significance of integrating historical datasets and sophisticated algorithms to achieve enhanced accuracy. Nair et al. (2022) further investigated the utilization of deep learning models, uncovering insights from multiple Indian states that highlight the ability of these models to discern complex patterns within solar irradiance

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datasets [6]. Moreover, Bhutta et al. examined hybrid machine learning models, demonstrating that the amalgamation of diverse techniques can markedly improve predictive efficacy [7].

Machine learning is becoming essential for forecasting solar power generation, particularly in India, where solar energy is vital for meeting renewable energy objectives. As India strives to achieve its 2030 objective of constructing a solar capacity of 280 GW, the necessity for precise solar power forecasts and optimization is critical. Based on several factors, such as meteorological conditions, geographical location, and seasonal variations, solar energy generation presents difficulties in sustaining grid stability, regulating energy supply, and incorporating renewable sources into the national system. Machine learning is an unconventional and innovative way to analyze the current situation and predict future scenarios.

A prominent application of machine learning is the accurate forecasting of solar energy production, including hourly estimates, and effective grid management. There are algorithms in supervised machine learning, such as regression, support vector machines, and other algorithms that can evaluate historical meteorological data, real-time satellite imagery, and local solar radiation levels to produce precise forecasts regarding the energy output of a solar facility. Factors such as temperature, cloud cover, solar irradiance, and humidity were used for time-series forecasting [8].

One example is the application of neural networks, particularly long short-term memory (LSTM) networks, which are adept at handling time-dependent data such as meteorological patterns. By analyzing extensive historical weather and solar energy data, these models can forecast variations in solar power generation, enabling grid operators to prepare for shifts in energy supply and demand more effectively. This predictive capability is crucial, as India grows its dependence on intermittent renewable energy sources, such as solar power [9].

In addition to forecasting, machine learning is employed to enhance solar panel performance and augment the efficiency of solar farms. Machine learning techniques can be utilized to assess the status of photovoltaic (PV) panels by detecting inefficiencies or flaws in real-time. Through the analysis of data from sensors affixed to solar panels, machine learning can identify performance irregularities, forecast probable system breakdowns, and suggest maintenance schedules, thus maintaining optimal energy generation. Predictive maintenance enhances the longevity of solar installations while minimizing downtime and operational expenses. Hence, solar power generation is more dependable and economical.

Moreover, machine learning is essential for optimizing energy storage. A primary difficulty in solar energy is its intermittency, necessitating energy storage systems to retain surplus energy produced during peak sunshine hours for utilization during periods of low generation. Integrating machine learning driven energy storage management systems with solar power generation can boost the reliability of India's renewable energy grid [10].

This study aims to scrutinize the progress in machine learning applications for solar power forecasting in India, focusing on the methodologies employed, the predictive accuracy attained, and the ramifications for energy policy and grid integration. Through this inquiry, we aim to underscore the transformative capacity of machine learning in enhancing solar energy forecasting and bolstering India's renewable energy aspirations.

LITERATURE REVIEW

The utilization of machine learning methodologies in the domain of solar power prediction has undergone substantial advancements in recent years, exemplifying a plethora of pioneering strategies. In 2024, Krishnan et al. investigated ensemble learning methodologies, with a particular emphasis on Gradient Boosting Machines (GBM), for the prediction of solar power within the context of

Maharashtra. Their research demonstrated that GBM surpassed other machine learning methodologies by proficiently accommodating heterogeneous data distributions [11]. Concurrently, Bakhashwain et al. [12] employed Support Vector Machines (SVM) to model solar radiation levels, showcasing the proficiency of SVM in accurately capturing non-linear interrelations, which facilitated dependable predictions. There is no doubt that there are multiple options for understanding data patterns, but linear regression is the most renowned way to predict or estimate future paths or future values [12].

In the subsequent year 2021, Khan et al. concentrated on the comparative analysis of various machine learning algorithms, including Random Forest and support vector regression, forecasting solar energy output in Punjab. Their results indicated that Random Forest achieved a prediction accuracy exceeding 90%, particularly when meteorological variables were incorporated. Singh et al. similarly contributed to this field in 2021 by applying deep learning methodologies, specifically long short-term memory (LSTM) networks, to forecast solar power generation in Southern India [13]. Their findings suggested that LSTM effectively assimilates temporal dependencies, culminating in diminished prediction errors [4]. Furthering this trajectory in 2022, Singh et al. investigated the application of artificial neural networks (ANN) for solar power forecasting in Gujarat, attaining a mean absolute error of less than 5%. Their research underscored the capability of ANN to model non-linear interdependencies within data [1]. In 2019, Yadav et al. examined hybrid models that integrated various machine learning methodologies, such as ANN and Genetic Algorithms, for short-term solar power forecasting in Rajasthan. Their hybrid approach surpasses isolated methods, indicating a synergistic advantage derived from the amalgamation of diverse algorithms [14].

In the same year, Choi et al. introduced an innovative methodology employing convolutional neural networks (CNNs) to predict solar power generation using satellite imagery. This synthesis of image processing with conventional meteorological data yielded a high prediction accuracy, underscoring the potential associated with diverse data sources [15]. Borunda et al. also concentrated on geographical aspects in 2023, discovering that models such as Random Forest and XGBoost exhibit superior performance across various Indian states [16].

In, researchers propelled the field forward by leveraging reinforcement-learning algorithms to enhance solar power predictions in real-time scenarios. Their adaptive learning framework refines its predictions over time by assimilating incoming data, thereby demonstrating the significance of dynamic modeling in solar energy forecasting [17]. Furthermore, Munawar contributed to the ongoing discourse in 2020 by scrutinizing feature selection techniques, concluded that the selection of features profoundly affected model performance, and advocated specific strategies to augment predictive accuracy [7].

Scholarly discourse has continued to evolve, with Rakholia exploring multioutput regression models for solar power forecasting. They applied machine learning techniques, including Random Forest and ANN, and achieved promising outcomes while emphasizing the necessity of accounting for interdependencies among outputs [18]. Paleta et al. adopted an alternative approach by investigating hybrid models that fuse machine learning with statistical methodologies, demonstrating that their hybrid model outperformed individual techniques [19].

As the field progresses, the amalgamation of hybrid modeling strategies and inventive data utilization will play a pivotal role in enhancing the predictive capabilities for solar energy generation. However, because linear regression is the most timely, reliable, and authentic way of generating or predicting data values, proceeding with the same is most suitable and appropriate in this study.

RESEARCH METHODOLOGY

As discussed previously, linear regression is the best way to predict future (2025) values for each state, based on prior data; hence, we should follow this path and proceed with it. Agrawal et al. (2022) used the following best techniques for implementing regression for solar power forecasting [18].

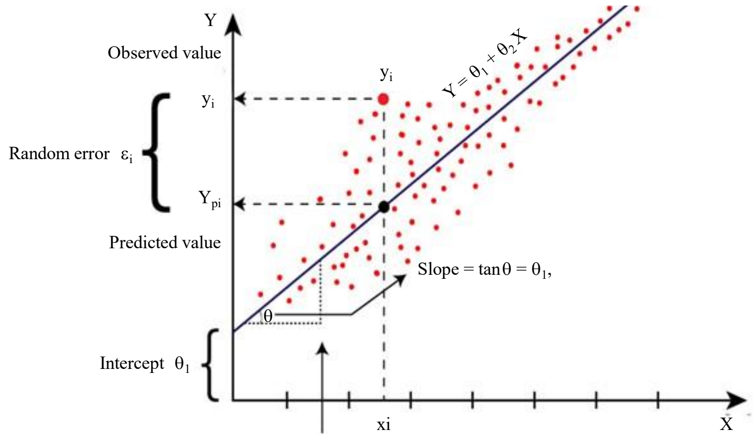

Figure 1. Intercept and slope.

The formula used in regression:

$$y = a + bx1 + cx2 + dx3 \quad (1)$$

$$a = \frac{[(\Sigma y)(\Sigma x^2) - (\Sigma x)(\Sigma xy)]}{[n(\Sigma x^2) - (\Sigma x^2)]} \quad (2)$$

$$b = \frac{[n(\Sigma xy) - (\Sigma x)(\Sigma y)]}{[n(\Sigma x^2) - (\Sigma x^2)]} \quad (3)$$

The interception and slope illustrations are shown in Figure 1.

Python was used to clean the state-wise solar power generation data provided in CSV format on the Government of India website. Although the data was originally in a monthly format, it was aggregated to yearly data for the period from 2021 to 2024. Regression analysis was then applied to forecast data for 2025. Null and zero production entries were identified and appropriately addressed.

RESULTS AND FINDINGS

Table 1 provides the best description of the input data and final output, that is, 2025 prediction, state-wise. The study conducts a detailed examination of multiple regression and factors responsible for forecasting solar energy consumption at the state level in India, held in million units (MU). The study looks at numerous methods and evaluates how accurate, dependable, and appropriate they are for predicting trends in energy consumption in various states. The study includes data cleaning, preprocessing, and final analytics using multiple regression. The data were collected from the Government of India renewable energy website, processed monthly data to convert it to yearly data, and applied to linear regression.

Table 1. Comparison of input and output data.

States	2021	2022	2023	2024	2025
Andaman and Nicobar Islands	562	1098	1400	1763	1967.52612
Andhra Pradesh	100	300	600	990	1575
Arunachal Pradesh	20	25	35	67	131
Assam	0	3	6	8	10
Bihar	150	170	226	357	723.8
Chandigarh	0.96	1	0.9	1	0.75
Chhattisgarh	20	40	60	80	100
Dadra and Nagar Haveli	250	1000	2254	4984	9548.56
Daman and Diu	269	1000	2378	4368	8119.32695
Goa	0	205	309	506	605.941463

States	2021	2022	2023	2024	2025
Gujarat	700	800	1200	1600	3200
Haryana	20	29.567	28.666	50.78	48.6973499
Himachal Pradesh	0	6	7.56	7.34	7.2828
Jammu and Kashmir	0	1.6	1.78	1.7	1.691
Jharkhand	1000	2879	3768	4999	5581.41565
Karnataka	0	765	1400	2000	2498.03922
Kerala	0	1200	2000	2900	3500
Lakshadweep	3000	5000	7056	10843	14736.036
Madhya Pradesh	2400	3000	4890	6815	12878.75
Maharashtra	552	789	1200	2400	4481.01266
Manipur	67	100	196	290	563.454546
Meghalaya	0	2	2	4	4
Mizoram	70	120	209	220	239.58
Nagaland	205	390	590	600	601.810811
NCT of Delhi	11.04	25.89	22.5	33.64	31.0969293
Odisha	0	10	20	30	40
Puducherry	1000	1490	2300	3000	4157.14286
Punjab	100	160	168	207.45	212.71
Rajasthan	560	1400	1900	2100	2219.04762
Sikkim	23	50	78	109	141.148148
Tamil Nadu	0	200	350	400	437.5
Telangana	1500	1900	2400	2698	3070.5
Tripura	0	0.3	0.6	0.7	0.8
Uttar Pradesh	200	400	500.564	567.32	600.886252
Uttarakhand	267	390	490	300.98	147.305203
West Bengal					

It also emphasizes the importance of choosing the correct predictor variables and statistical methods to guarantee reliable forecasts. The results will aid in the creation of data-driven models that can be used for national and regional energy policy and resource allocation. In addition, how less dependent can we be on conventional energy sources and move to non-conventional sources such as solar energy, wind energy, hydropower, etc.?

LIMITATIONS

The study identified various strategies for multiple regression and used the best techniques for predicting state-wise MU in India. However, more factors can be included, such as power consumption, population, and energy-spending patterns.

CONCLUSION

As the use of electricity and its allied usage continues to grow, both in commercial and domestic usage, there is a constant need for alternative energy resources. Renewable energy such as solar power is a correct substitute for providing answers to all energy crisis questions. This paper focuses on how much solar power is being generated and uses machine learning and linear regression to understand the increasing pattern of power generation. Finally, the energy generation for the period 2025–2030 was predicted. This is done state-wise and is beneficial in multiple ways as to what is the overall dependency on non-renewable energy, such as coal. The best-performing states or best power generation are Lakshadweep Islands and Madhya Pradesh, each with more than 12 K + MU of power generation.

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