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Enhancing solar power generation through AC power prediction optimization in solar plants

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ABSTRACT

As the world embraces sustainable energy solutions, the accurate prediction of AC power generation in solar power plants becomes imperative for efficient energy management. This research endeavors to address this critical need through a meticulous exploration of five distinctive predictive algorithms: linear regression, gradient boosting, neural networks, support vector regression (SVR), and ensemble techniques. Leveraging a merged dataset comprising environmental parameters like ambient and module temperatures, irradiation, and historical yield, our study embarks on a comprehensive evaluation journey. The essence of this endeavor lies in the recognition that renewable energy sources, particularly solar power, are instrumental in mitigating environmental concerns associated with traditional energy generation. To unleash the full potential of solar power, a nuanced understanding of predictive methodologies is indispensable. Linear regression serves as a cornerstone, validating its foundational role. However, the crux of innovation lies in the advanced algorithms – gradient boosting, neural networks, SVR, and ensemble methods – each striving to optimize prediction accuracy. A novelty of this research stems from its holistic approach to predictive modelling. By meticulously comparing the performance of multiple algorithms, we uncover insights that transcend mere theoretical applications. Our findings assume significance in the context of renewable energy's societal impact.

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1. INTRODUCTION

Solar power plants frequently confront the challenge of unpredictable energy outputs, primarily due to fluctuating environmental conditions such as irradiation, temperature, and weather patterns. These inconsistencies in power generation predictions pose a significant hurdle in ensuring stable and reliable energy supply. Furthermore, solar power plants operate under a myriad of environmental and operational conditions, each presenting unique challenges in accurately forecasting power output [1]. This diversity necessitates a method that is adaptable and robust enough to handle various real-world scenarios [2]. Additionally, the efficient solar power combination into the power grid, a critical aspect of modern energy management, depends heavily on the precision of power predictions [3]. This precision is vital for effective load balancing, energy storage, and implementing demand-response strategies [4]. Finally, the decision-making process regarding the selection of predictive technology for AC power generation in solar plants is crucial, as it directly impacts efficiency and cost-effectiveness [5].

Fatemi *et al.* [6] delved into the parametric methods, a crucial aspect of predicting solar power generation. However, their focus on solar irradiance forecasting did not extend to a comprehensive approach for AC power prediction in solar power plants. Meanwhile, Ahmad *et al.* [7] conducted research on comparing various algorithms such as support vector regression and random forests. According to Krishnan *et al.* [8] though insightful, was limited to solar thermal systems and did not encompass the broader scope of solar photovoltaic power plants.

Krechowicz *et al.* [9] explored machine learning (ML) based predict electricity from renewable energy sources, highlighting the effectiveness of these models in renewable energy. Yet, their study did not specifically focus on AC power prediction in solar plants, a gap that your research addresses. Similarly, Rafati *et al.* [10] concentrated on forecasting using data-driven methods. Although valuable, their study was more narrowly focused on short-term forecasting and did not cover a comprehensive set of environmental and operational parameters.

In another significant contribution, Alaraj *et al.* [11] investigated energy production forecasting from solar photovoltaic plants based on meteorological parameters for the Qassim region in Saudi Arabia. Their research, while important, predominantly centered on meteorological parameters and did not integrate a broader range of data for AC power prediction. Lastly, Huang *et al.* [12] developed a point prediction method with multi-region photovoltaic plants. While this was a step forward in day-ahead forecasting, it potentially lacked in addressing the need for long-term predictive consistency, an aspect that your research seeks to enhance [13], [14]. Each of these studies has contributed to the field of solar power prediction, yet there remain gaps related to comprehensive data integration, long-term predictability, and adaptability across various operational scenarios [15], [16].

- Problem statement

Proposed research addresses several key challenges in solar power generation: Firstly, it tackles the unpredictability of AC power output in solar plants, a crucial factor for consistent energy generation [17], [18]. Secondly, it confronts the issue of maintaining stable and efficient energy production amidst variable environmental conditions [19]. Thirdly, the research focuses on improving the integration of solar energy into power grids, which is often hindered by inconsistent energy outputs [20]. Finally, it addresses economic feasibility issues that arise due to the irregular nature of solar power generation, aiming to make solar energy more viable and cost-effective [21]. Existing methods in solar power prediction mostly focused on general aspects like solar irradiance and solar thermal systems, using models such as support vector regression and random forests [22]. These methods, however, did not directly address AC power output prediction in photovoltaic solar power plants [23]. The current research fills this gap by applying a range of advanced predictive algorithms - linear regression, gradient boosting, neural networks, support vector regression (SVR), and ensemble methods - specifically to AC power prediction in solar PV plants [24]. This approach represents a substantial advancement in predictive modeling for solar energy, enhancing the accuracy and applicability of forecasts for AC power output [25].

2. THE PROPOSED METHOD

The proposed methodology in this study aims to address these challenges by employing a range of advanced predictive algorithms, including linear regression, gradient boosting, neural networks, SVR, and ensemble techniques. These algorithms are applied to a comprehensive dataset that merges environmental and operational data, enhancing the accuracy and adaptability of power predictions. Through this approach, the study endeavors to provide more consistent and reliable power generation forecasts, improve the adaptability of predictive models to diverse operational conditions, optimize energy management for grid integration, and offer valuable insights for decision-making in technology selection.

This method is novel with respect to three aspect, first comprehensive data integration, employing a merged dataset that includes a wide range of environmental and operational parameters such as ambient and module temperatures, irradiation, and historical yield. This approach allows for more nuanced and accurate predictions of AC power generation, considering various factors influencing solar power output. Additionally, the research introduces a diverse array of predictive algorithms, including linear regression, gradient boosting, neural networks, SVR, and ensemble techniques, enabling robust comparative analysis across different predictive models, from foundational statistical methods to advanced machine learning techniques. The methodology's focus on specific evaluation metrics, like deviation and mean difference, for assessing the performance of each predictive algorithm, is a technically innovative approach, ensuring that the assessment is grounded in practical and relevant measures of accuracy and reliability, enhancing the applicability of these findings in real-world solar power plant operations [13]. The dataset used in the study is an amalgamated dataset, which includes comprehensive data from a solar power plant. This dataset is sourced from The Kaggle Solar Power Plant dataset and merges two specific subsets of data: the generation data and the weather sensor data. The generation data, often referred to as "Plant_2_Generation_Data," provides detailed insights into the operational aspects of the solar power plant, including the historical power yield. The weather sensor data, known as "Plant_2_Weather_Sensor_Data," encompasses crucial environmental parameters such as ambient and module temperatures, along with irradiation levels.

These values given in Table 1 reflect the operational status of the solar power plant during sunlight hours. The irradiation, DC power, and AC power values are greater than zero, indicating active solar power generation. The increase in module temperature is also consistent with exposure to sunlight. These daytime readings are crucial for understanding and predicting the solar power generation capacity of the plant under varying environmental conditions.

Table 1. Dataset parameters description with their technical details

Parameter	Description	Range /technical specification
Date/time	Timestamp of the data entry	2020-05-15 06:00 to 06:45
Ambient temperature (°C)	Temperature of the surrounding environment	24.7 °C to 25.0 °C
Module temperature (°C)	Temperature recorded by the solar modules or panels	23.8 °C to 25.7 °C
Irradiation (kW/m²)	The amount of solar irradiance received	0.0028 kW/m² to 0.1035 kW/m²
DC power (kW)	Direct current power output from solar panels	14.77 kW to 15.41 kW
AC power (kW)	Alternating current power output after conversion	14.25 kW to 14.86 kW
Daily yield (kWh)	Total energy produced in a day	0.73 kWh to 1.87 kWh
Total yield (kWh)	Cumulative energy output since installation	1.70M kWh to 2.25B kWh

3. MATERIALS AND METHODOLOGY

Initiating a cutting-edge approach to predict solar power output, the study implements a multifaceted and technically advanced methodology. The process begins with the careful loading and pre-processing of historical data, which includes both generation and weather sensor information, ensuring a robust foundation for analysis. The data is then subjected to a series of pre-processing steps, such as normalization and feature selection, to refine the dataset for predictive modelling. This leads into the core of the methodology - the application of a suite of diverse predictive algorithms. The study strategically employs linear regression as a baseline model, providing a foundational comparison for other techniques. This is followed by more complex algorithms, including gradient boosting, which is known for its effectiveness in handling non-linear relationships and offering high prediction accuracy. Neural networks are also utilized for their ability to model complex patterns through interconnected layers of nodes, making them suitable for the intricate dynamics of solar power generation. SVR is another key method, leveraging its capability to perform regression in high-dimensional spaces, ideal for the multifaceted nature of the data involved. Finally, an ensemble approach is adopted, synthesizing outputs from multiple models to enhance overall predictive performance. The flow diagram, illustrated in Figure 1, elucidates the sequential process of AC power prediction through diverse predictive algorithms.

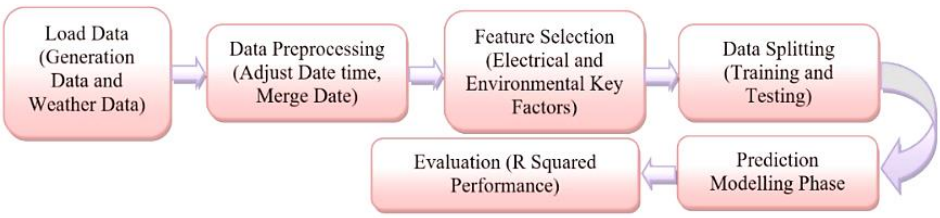

Figure 1. Linear regression (LR) prediction flow diagrams

- Linear regression (LR)

Linear regression serves as a basic method for predictive modeling, aiming to determine a straight-line correlation (in this context, AC power). The objective is to identify an optimal linear equation that effectively reduces the sum of squared deviations between forecasted and real outcomes. The equation representing a straightforward linear regression model is articulated as (1).

$$y = b_0 + b_1 x \tag{1}$$

Where y is the predicted AC power; b_0 is the intercept (bias) of the linear model; b_1 is the coefficient of the linear model; and x represents the input features (ambient temperature, module temperature, and irradiation).

- Gradient boosting regression (Grad)

Gradient boosting is a technique in ensemble learning that constructs a predictive model through the sequential incorporation of weak learners, typically decision trees. This method emphasizes correcting the inaccuracies of prior iterations. The culmination of this process is a comprehensive prediction derived from the aggregate, weighted sum of the outputs of all the constituent trees. The formula to represent the predictive output in gradient boosting is structured as (2).

$$F(x) = \sum_{m=1}^{M} \gamma_m h_m(x) \tag{2}$$

Where $F(x)$ is the final prediction; M is the number of trees; γ_m is the weight of the m-th tree's prediction; and $h_m(x)$ is the prediction of the m-th tree.

- Neural network (NN)

Complex model comprises numerous interconnected layers of nodes, commonly referred to as neurons. In each layer, every node undertakes the processing of input data and subsequently transmits it to the subsequent layer for further information processing. Ultimately, the final layer culminates in producing the prediction. The mathematical depiction of a neural network can be broadly defined as (3).

$$\dot{y} = f_3\left(w_3 f_2\left(w_2 . f_1(w_1 x)\right)\right) \tag{3}$$

Where ẏ is the predicted output (AC power); x represents the input features; f_1, f_2, f_3 are activation functions; and w_1, w_2, w_3 are weights of the neural network layers.

- Support vector regression (SVR)

SVR is a regression methodology that draws upon the principles of SVR. The fundamental objective of SVR is to locate a hyperplane that optimally accommodates the data points while concurrently allowing for a pre-determined margin of error. The SVR model can be mathematically represented as (4).

$$f(x) = \sum_{i=1}^{n} (\propto_i - \propto_i^*) K(x, x_i) + b \tag{4}$$

Where $f(x)$ is the predicted output; $\propto_i, \propto_i^*$ are Lagrange multipliers; $K(x, x_i)$ is the Kernal function; and b is the bias term.

- Ensemble of models (ENS)

Ensemble methods have emerged as a powerful approach in enhancing prediction accuracy and mitigating over fitting by amalgamating the outputs of multiple individual models. A prevalent manifestation of this technique is the weighted average of predictions. The representation of the ensemble prediction can be succinctly expressed as (5).

$$Ensemble(x) = \sum_{i=1}^{N} w_i Prediction_i(x) \tag{5}$$

Where $Ensemble\ (x)$ is the final ensemble prediction; $Prediction_i(x)$ is the prediction of the i-th individual model; and w_i are the weights assigned to each individual model's prediction.

3.1. Detailed methodology description

Stage 1: Data collection and preprocessing: The study begins by loading historical data, which includes both generation and weather sensor data (Step 1). This data is critical as it encompasses key variables like power output and environmental conditions that influence solar power generation. Feature selection is also conducted in this phase to identify the most relevant variables for predictive modeling.

Stage 2: Predictive algorithms employed: The modeling phase (Steps 3 to 5) includes the application of five distinct predictive algorithms: linear regression, gradient boosting, neural network, support vector regression, and an ensemble approach. Each algorithm is chosen for its unique strengths and suitability in handling different aspects of solar power prediction. Linear regression serves as a baseline, while advanced methods like gradient boosting and neural networks cater to complex non-linear relationships in the data.

Stage 3: Data analysis techniques: Post-modeling, the evaluation phase (Step 6) involves calculating R-squared scores for each model to compare their performance. This metric is crucial for understanding how well the models can explain the variance in the observed data. The final step (Step 7) visualizes the results, juxtaposing actual AC power values with predictions from each model, providing an intuitive understanding of each model's predictive accuracy.

3.2. Predicting AC power output

Suppose we have historical data points for ambient temperature, module temperature, irradiation, and DC power. Let's assume the ambient temperature is 25 °C, module temperature is 27 °C, irradiation is 0.5 kW/m², and the DC power at that time is 100 kW. The gradient boosting algorithm is trained with historical data. In this training process, the model learns the complex relationships between the selected features (like temperature and irradiation) and the target variable, which is AC power output. Gradient boosting works by sequentially adding predictors (trees), where each one corrects its predecessor, minimizing the prediction error over iterations. Once trained, the model can predict AC power output based on new input data. For example, if the current ambient temperature is 28 °C, module temperature is 30 °C, irradiation is 0.6 kW/m², and DC power is 120 kW, the model will use these inputs to predict the AC power.

3.3. Outcomes and relation to prediction

The predictive modeling of AC power output in solar energy management leverages algorithms including linear regression (LR), gradient boosting (GRAD), neural networks (NN), support vector regression (SVR), and ensemble (ENS) techniques. These models digest data on factors like irradiation and temperature fluctuations to anticipate power generation. Understanding these correlations is pivotal, as accurate predictions ensure optimal energy grid functioning and the efficient harnessing of solar resources. The precision of these forecasts underpins key operational decisions in solar power facilities, encompassing maintenance planning, load distribution, and the seamless integration of solar power into the overall energy supply, thereby highlighting the substantial impact of predictive analytics in renewable energy sectors.

4. RESULTS AND DISCUSSION

The predictive outcomes of the examined algorithms were distinct in their alignment with the actual AC power values. Linear regression (LR) exhibited predictions that subtly deviated from the actual values, hinting at a cautious approach. Conversely, gradient (GRAD) predictions showcased a parallel yet distinctive trend compared to the actual values, introducing an intriguing perspective. In contrast, neural network (NN) predictions closely mirrored the actual values, demonstrating a high degree of concordance. Support vector regression (SVR) predictions unfolded with noticeable deviations from the actual values, implying a more pronounced divergence. Notably, ensemble (ENS) predictions amalgamated insights from a composite of methods, culminating in predictions that encapsulated the inherent data essence. According to Figure 2, we present a visual representation of the predicted value differences when compared to the actual AC power values across all implemented methods. This depiction offers a comprehensive overview of how each method's predictions deviate from the true AC power values. The spread and distribution of points provide insights into the consistency and accuracy of the predictive algorithms. The chart aids in identifying trends and patterns in the deviations, which can help inform decisions regarding model refinement and selection for optimal AC power prediction. Figure 3 delves into a more focused comparison, specifically analyzing the predicted value differences for the linear regression (LR) and gradient boosting (GRAD) methods. Fundamental to this analysis were two pivotal metrics: "Mean Difference" and "Deviation." While specific numerical values are omitted, these metrics stood as quantitative indicators of the extent of deviation between predicted and actual values as given in Table 2. The "Mean Difference" metric provided an average portrayal of the disparity, encompassing both overestimations and underestimations.

In tandem, the "Deviation" metric illuminated the consistency of these deviations, underlining the stability of predictive trends across methods. Figure 4(a) gives visually represents the disparities between predicted and actual AC power values across all implemented prediction methods. This graphic provides an insightful overview of the prediction accuracies of various methods, helping to assess their performance consistency and the extent of deviations from actual values. Figure 4(b) offers a clear snapshot of how LR and GRAD approaches perform individually in terms of predictive accuracy. This targeted analysis aids in understanding the specific strengths and limitations of these methods and assists in informed decision-making when choosing between LR and GRAD for AC power prediction in solar power plants.

Table 2. Performance comparison of prediction methods

Methods	Deviation	Mean difference
LR	6.29	0.125
GRAD	-6.26	-0.125
NN	10.56	0.211
SVR	76.25	1.525
ENS	27.21	0.544

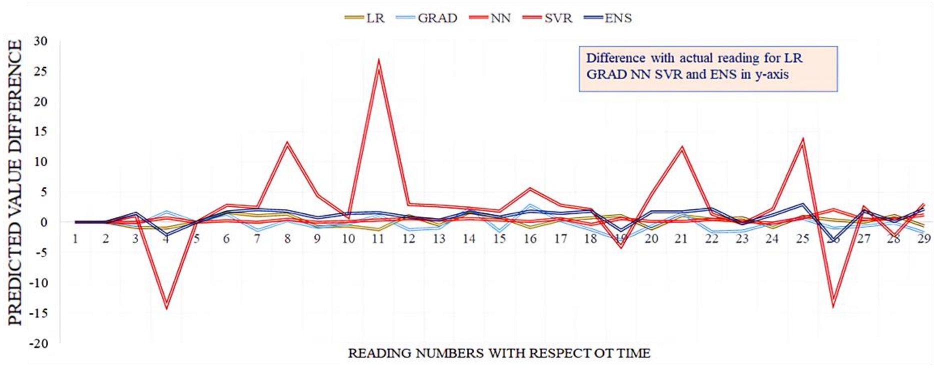

Figure 2. Predicted value difference with actual for all methods

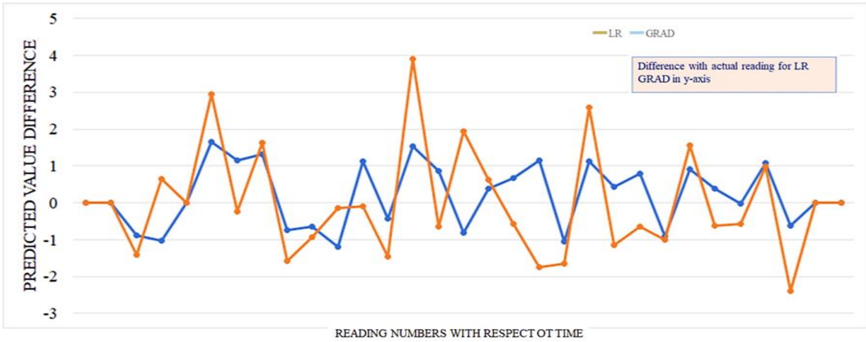

Figure 3. Predicted value difference with actual for LR and GRAD methods

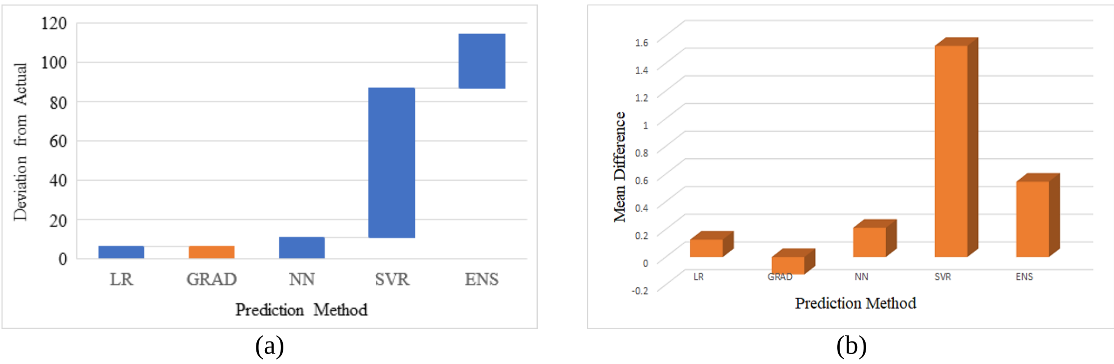

Figure 4. Comparative analysis of prediction accuracy and deviation for different methods (a) predicted value differences with actuals and (b) mean differences with actuals

In our research, while primarily centered on large-scale solar plants, the methodologies proposed are adaptable for domestic solar power systems. The adaptation involves recalibrating the predictive models, such as linear regression and gradient boosting, to align with the smaller scale and unique environmental conditions of residential settings. This would entail adjusting the data analysis to account for factors like smaller solar arrays, varying rooftop orientations, and localized shading effects typical in-home installations. By refining the models to reflect these residential-specific parameters, the methodologies can be effectively applied to optimize solar power generation in domestic environments. The research achieved significant advancements in AC power prediction in solar plants by implementing advanced predictive algorithms like linear regression, gradient boosting, neural networks, SVR, and ensemble methods. Prior work mainly focused on solar irradiance forecasting or solar thermal systems, often employing fewer comprehensive methods like support vector regression and random forests. This study uniquely applied these sophisticated algorithms to solar photovoltaic plants, enhancing prediction accuracy, and offering a novel approach in the field of renewable energy management.

5. CONCLUSION

The work implements accurate prediction of AC power in solar power plants by employing a range of advanced predictive algorithms. The study's methodology leverages these diverse algorithms to interpret the complex relationships within the solar power generation data. The ultimate goal is to identify the most accurate method for predicting AC power, thereby enabling more efficient operation and integration of solar energy into power grids. The findings from this analysis provide valuable insights for optimizing solar power generation and enhancing the overall efficiency of solar power plants. These methods, including linear regression, gradient boosting, neural networks, SVR, and ensemble techniques, mark a significant departure from traditional models like support vector regression and random forests used in prior research. The proposed study applies to solar PV plants and the comprehensive integration of various environmental and operational data, resulting in enhanced accuracy and reliability.

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