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Optimized LSTM Model for Day-Ahead Solar Power Prediction

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Abstract
The effective integration of photovoltaic (PV) systems into the grid which facilitates better planning and resource allocation depends on accurate day-ahead solar power forecasts. This paper proposes a Long Short-Term Memory (LSTM) model for forecasting solar power generation one day in advance with the algorithm inspired by Ant Colony Optimization (ACO). A year's worth of real-time data for a 4.5 kW PV system is used to train and test the model with input characteristics including temperature, PV power production and solar irradiation. Over the course of three seasons—summer, winter, and monsoon—the performance of the ACO-optimized LSTM model is contrasted with that of a simple LSTM model and an LSTM model enhanced by particle swarm optimization (PSO). This encompasses metrics like R-squared (R^2) values, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The PSO-optimized LSTM model (MAE of 0.31 kW, RMSE of 0.38 kW and R^2 of 0.88) and the baseline LSTM model (MAE of 0.35 kW, RMSE of 0.42 kW and R^2 of 0.85) couldn't match the ACO-optimized LSTM model's summertime MAE of 0.27 kW, RMSE of 0.33 kW and R^2 of 0.92. Similar trends also surfaced throughout the monsoon and winter seasons, with the ACO-optimized model consistently outperforming the others. In the winter, for instance, it obtained an R^2 of 0.93, an RMSE of 0.26 kW and an MAE of 0.22 kW. With regard to hyper parameter optimization and overall performance, these findings demonstrate the ACO-optimized LSTM model's superiority over the baseline and PSO-optimized LSTM models highlighting its improved prediction precision for all seasons. The effectiveness of ACO in bolstering solar power forecast models is confirmed by this study and provides a solid basis for deep learning model improvement in practical PV applications.

Keywords: *PV system, LSTM, Hyper parameter tuning, PSO, ACO.*

1. Introduction

Accurate solar power forecasting for the coming day is fundamental to the seamless integration of Renewable solar systems into modern energy networks. With the increasing reliance on renewable energy sources, precise solar power output estimates are critical to grid stability, energy distribution optimization, and reducing reliance on non-renewable backup power. An energy infrastructure that is more robust and sustainable may be achieved by better planning and management of energy resources, which is made possible by accurate forecasting, the potential to forecast solar power generation contributes significantly to the stability of the grid, planning for energy, and resource allocation. Solar power is inherently volatile, dependent on weather patterns like temperature, cloud cover, and humidity, which makes forecasting particularly difficult for grid operators. Erroneous forecasts can cause inefficiencies in the distribution and management of energy, and therefore raise the demand for accurate forecasting models [1], [2]. In response to these issues, researchers have proposed several models broadly classified as physical, statistical, and machine learning-based approaches, each having different strengths and weaknesses. Physical models mimic the process of converting solar irradiance into electricity using site-specific weather information. Though these models proved useful in stable weather conditions, their dependence on precise weather information like Numerical Weather Prediction (NWP) restricts them from performing well in highly variable climates, tending to bring in large forecasting biases [3]. Time-series forecasting frequently uses The Autoregressive

Moving Average model (ARMA) is a statistical model used to describe time series data by combining auto regression and moving average components. ARMA prototype combine moving average (MA) components that take historical error terms into account with autoregressive (AR) components that rely on the series' history values. Since ARIMA adds differencing to ARMA, it may be used with non-stationary time-series data that exhibits seasonality or patterns. Compared to machine learning or deep learning models, these models cannot handle complex, non-linear patterns, but they perform well for linear connections and short-term projections have improved upon physical models in that they recognize patterns within historical data, but they still experience difficulties in addressing abrupt changes in weather, e.g., under cloudy or stormy conditions [4] [5]. Through precise modeling of the intricate, non-linear relationships between weather and photovoltaic (PV) generation, machine learning (ML) and artificial intelligence (AI) techniques have transformed solar power forecasting. Long Short-Term Memory (LSTM) networks and Gated Recurrent Unit (GRU) networks are among the most powerful deep learning architectures for modeling the temporal patterns of time series data. [6], [7]. LSTMs can learn long-term relationships in sequential data, which makes them especially well-suited for time-series forecasting. Fortunately LSTM models' success is heavily reliant on optimizing hyper parameters such the number of hidden units, learning rate, batch size, and training epochs. These factors are crucial in establishing the model's learning capacity and generalization ability [8]. Hyper parameter tuning plays a crucial role in improving the effectiveness of LSTM models in forecasting solar power. The conventional manual techniques are time-consuming and tend to result in suboptimal performance. This has triggered the use of optimization strategy optimization algorithms, including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) are used to fine-tune and streamline the hyper parameter selection process. [9], [10]. PSO has been effectively utilized to optimize LSTM hyper parameters for numerous forecasting tasks, including water level forecasting and energy consumption forecasting, with the result being more accurate and efficient [11]. ACO recently showed potential as a better alternative, providing a better balance between searching vast spaces and exploring them through imitating ant colonies' behavior, where the hunt for the best answers is guided by pheromone trails [12]. The use of ACO in the optimization of LSTM's hyper parameters has proven to be significantly better compared to conventional approaches. ACO has been specifically impressive in optimizing combinatorial optimization challenges, such as the Quadratic Assignment Problem (QAP), which showcases the capability to explore vast search spaces effectively and obtain high-quality solutions [13]. ACO has been used recently in LSTM models for time series forecasting, with it being utilized to avoid over fitting and enhance model generalization, especially in cases where there are complicated datasets such as solar power production [14]. Additionally, hybrid techniques that combine Ant Colony Optimization (ACO) with other optimization algorithms, including Particle Swarm Optimization (PSO) techniques have been designed to improve solution quality and accelerate convergence in energy management and solar power applications [15], [16]. In spite of the considerable merits of ACO, there are issues, including computational complexity and algorithm parameter tuning like pheromone evaporation rates and the number of ants. In spite of these, ACO's better exploration-exploitation trade-off renders it an appealing option for hyper parameter optimization for solar power prediction. With better day-ahead prediction accuracy of solar power, ACO-optimized LSTM models are capable of furnishing more robust solutions for real-world PV operations, supporting grid operators in efficiently balancing supply and demand. In conclusion, ACO for the optimization of LSTM hyper parameters is of great potential to improve the forecasting ability of solar power prediction models. With the capability to overcome the weakness of conventional techniques and provide an efficient mechanism to fine-tune deep learning models, ACO has the potential to greatly enhance the scalability and performance of the models and, therefore, promote a greater level of integration of renewable energy into contemporary energy systems.

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2. ACO-LSTM Optimization

ACO is a bio-inspired Optimization strategy that mimics the foraging process of ants. ACO works by mimicking how ants communicate through pheromone trails to discover the shortest routes between their nests and food sources. Every ant in the algorithm builds a solution by transitioning from one state to another based on the intensity of pheromone deposited by the ants before it and the visibility or desirability of the next state [1], [2]. The probability of state transition is given by:

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{k \in \text{allowed}} [\tau_{ik}(t)]^{\alpha} \cdot [\eta_{ik}]^{\beta}}$$

The algorithm will seek to maintain a balance of exploration (probing new parts of the solution space) and exploitation (stepping up search around the highest-rated solutions) [1]. Evaporation of pheromones keeps the algorithm from rapidly converging toward poor solutions, and the rule for updating the pheromones is:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}$$

Where ρ is the pheromone evaporation rate.

Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), are designed to capture long-term dependencies in sequential data. Unlike traditional RNNs, LSTMs employ memory cells that store information for extended periods, addressing the vanishing gradient problem. An LSTM consists of three primary gates: the input gate, forget gate, and output gate, each of which regulates the flow of information through the memory cell. The LSTM's functionality is governed by the following update equations. To ensure that important context is stored and redundant or irrelevant information is discarded in order to achieve efficiency and accuracy, the LSTM network's gates allow it to pay close attention to which informational chunks to remember and which to forget while processing lengthy data strings and this makes LSTMs extremely effective for time-series forecasting applications such as solar power prediction [4]. Adjusting the LSTM model's hyper parameters (such as the number of hidden units, learning rate, and batch size) is crucial for improving the model's precision and generalizability in solar power forecasting. By using Ant Colony Optimization (ACO) for hyper parameter tuning, the hyper parameter space may be searched more methodically [2], [5].

1. Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

2. Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

3. Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

4. Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

ACO stands for every set of hyper parameters as a candidate solution, and ants search for various configurations in each iteration [5]. The effectiveness of each solution is evaluated in terms of the LSTM model's quality, which is often assessed using metrics such as R-squared (R^2) values, Mean Absolute Error (MAE), or Root Mean Square Error (RMSE) [5, 6]. In every iteration, ACO updates the levels of pheromone on the hyper parameter configurations that were explored. Good-performing configurations are reinforced with more pheromone, which makes the ants in the future explore them [5]. This helps in ensuring that ACO maintains a balance between exploitation of good areas and exploration of the hyper parameter space, and this enhances convergence and performance [7]. The strength of ACO for hyper parameter optimization is that it can efficiently search in large, intricate search spaces. In contrast to grid search or random search, which use pre-specified hyper parameter ranges, ACO adapts in exploring the search space utilizing pheromone trails [7], [8]. Empirical results indicate that ACO-optimized LSTM networks perform better than conventional LSTM networks, especially in avoiding over fitting and enhancing generalization [6]. ACO's capacity to trade exploration and exploitation results

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in improved convergence and performance in practical solar forecasting applications [9]. By utilizing ACO, LSTM-based solar power forecasting models can be optimized to better predict day-ahead solar power output. This technique has been reported to perform better than other met heuristics, including PSO, in a number of applications [7], [10]. Because of ACO's iterative approach, the algorithm may constantly enhance the search for optimal hyper parameters, which enables the LSTM model to successfully learn and adjust to variations in solar conditions throughout the year [10].

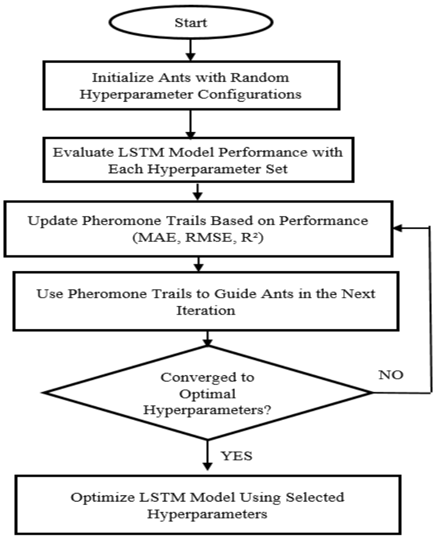

Figure 1 Data Gathering and Preparation

The data for the present study has been obtained from a 4.5 kW solar photovoltaic (PV) system that is installed at Kanchipuram, Tamil Nadu, India (12.8373° N, 79.7042° E). The database covers one-year duration and the hourly fluctuations in the major meteorological parameters of solar irradiance, temperature, and wind speed, along with the respective output of PV power generation. This abundant dataset, recorded at hourly frequencies, captures various seasons—summer, winter, and monsoon—thereby offering a perfect platform to create and validate a predictive model that can take into consideration the variability of weather conditions. The addition of multiple meteorological parameters, particularly wind speed, adds to the complexity of the data set, thus making it a good candidate to test the generalization capability and robustness of sophisticated machine learning algorithms like Long Short-Term Memory (LSTM) networks. Preprocessing of the dataset is essential to enabling the LSTM model to learn optimally and also make the most accurate predictions. Raw data sometimes have missing values, noise, or outliers, which, when not removed or handled, tend to impede the performance of the model. Hence, the data was thoroughly preprocessed through several steps involving the treatment of missing values via interpolation techniques, scaling the numerical attributes (e.g., solar irradiance and temperature) into a standard scale, and the splitting of data into relevant training and testing datasets. The temporal aspect of the dataset, particularly the seasonality, also called for meticulous management of how data was partitioned for training the LSTM. A seasonal split was utilized to make sure that the model would be able to predict PV power generation well for three seasons—summer, winter, and monsoon—thus capturing the inherent variability in solar irradiance and weather patterns characteristic of each season in Kanchipuram. The LSTM model, which is suitable for time-series forecasting, was fine-tuned with Ant Colony Optimization (ACO) for hyper parameter tuning. The most important hyper parameters that were adjusted include the size of hidden units, the learning rate, batch size and number of epochs. These hyper parameters are significant since they have a direct impact on the ability of the model to learn from past data and make precise future predictions. ACO was selected because it is robust in tackling combinatorial optimization problems by simulating the natural process of ants, with pheromone trails influencing the search for optimal solutions. For every season, individual hyper parameter tuning was conducted, taking into consideration the unique features of solar irradiance and meteorological conditions during summer, winter, and monsoon. This approach ensures that the LSTM model is both seasonally adaptable and robust across various weather conditions, providing high accuracy in day-ahead solar power forecasting, shown in Figure 1.

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3. Experimental Setup and Evaluation Metrics

Long Short-Term Memory (LSTM) models were trained and tested in a setting that took seasonality and variations in solar power output into account. Hourly sun irradiance, temperature, wind speed, and PV production records were collected for a year from a 4.5 kW photovoltaic (PV) plant in Kanchipuram, Tamil Nadu (12.8373° N, 79.7042° E). To allow for efficient model learning while conserving a portion for validation, the data was divided into 80% training and 20% test sets. To account for the impact of seasonal weather, the data was divided into three categories: summer, winter, and monsoon. LSTM models were used with hyper parameters such hidden units, learning rate, batch size, and epochs that were tuned using the Ant Colony Optimization (ACO) technique because of its suitability for handling time-series data. The ACO method experimented with several hyper parameter setups to optimize the LSTM's predicting capabilities. Several assessment metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2), were used in the current study to thoroughly assess the LSTM model's prediction capacity for distinct seasons. Regardless of the direction of the forecast, MAE calculates the average magnitude of error. The RMSE calculates the model's error magnitude, with larger mistakes carrying more weight. The accuracy of projected values compared to real data is determined by the value of R^2, where a larger number denotes greater accuracy. When taken as a whole, these steps ensure that the model's forecasting capabilities are properly examined. MAE is computed using the following formula

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where yi represents the actual PV power output, y^i is the predicted value, and n denotes the number of observations.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

RMSE places greater emphasis on large errors and is often utilized when large errors are especially undesirable. It is calculated by:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Lastly, the R-squared (R^2) metric measures how well the model predicts the data; it performs better when the numbers are near The calculation of the R^2 statistic is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

the mean of the actual values is represented by y BAR. These three measures were assessed for all seasons so that the ACO-optimized LSTM model could be comparatively evaluated with a PSO-optimized LSTM model and a baseline LSTM model. The experimental framework and measures enabled the ACO-optimized LSTM model to be precisely tested for different seasonal scenarios, proving to be robust and effective in day-ahead solar power generation forecasting.

4. Findings and Analysis

The performance of the models in three distinct seasons—summer, winter, and monsoon—showcases the benefits of the ACO optimized LSTM model over the baseline LSTM and the PSO-optimized LSTM models when comparing the models for day-ahead solar power forecasting. The accuracy and resilience of each model are quantitatively indicated by the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 values. The performance of the models in three distinct seasons—summer, winter, and monsoon—showcases the benefits of the ACO optimized LSTM model over the baseline LSTM and the PSO-optimized LSTM models when comparing the Accurately calculating the quantity of solar power that will be created in the next 24 hours given a variety of inputs is the main focus of models designed to estimate one-day solar power production. The accuracy and resilience of each model are quantitatively indicated by the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R2 values. As seen in Fig (2), the ACO-optimized LSTM has the consistently achieves the lowest RMSE and MAE values, implying and showing its better

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performance in reducing prediction errors throughout the year. For instance, during the summer season, the ACO-optimized LSTM attains an MAE of 0.27 kW and an RMSE of 0.33 kW, performing far better than the baseline LSTM (MAE: 0.35 kW, RMSE: 0.42 kW) and the PSO-optimized LSTM (MAE: 0.31 kW, RMSE: 0.38 kW). Equally good enhancements are seen during winter and monsoon, wherein ACO-optimized model consistently retains an upper hand in the value of MAE as well as RMSE, Figure 2.

SESONS	MODEL	MAE	RMSE	R square value
SUMMER	LSTM	0.35	0.42	0.85
	LSTM-PSO	0.31	0.38	0.88
	LSTM-ACO	0.27	0.33	0.92
WINTER	LSTM	0.28	0.34	0.87
	LSTM-PSO	0.25	0.3	0.89
	LSTM-ACO	0.22	0.26	0.93
MONSOON	LSTM	0.3	0.37	0.84
	LSTM-PSO	0.27	0.34	0.87
	LSTM-ACO	0.24	0.31	0.91

Figure 2 Comparison of LSTM, LSTM-PSO & LSTM- ACO Models

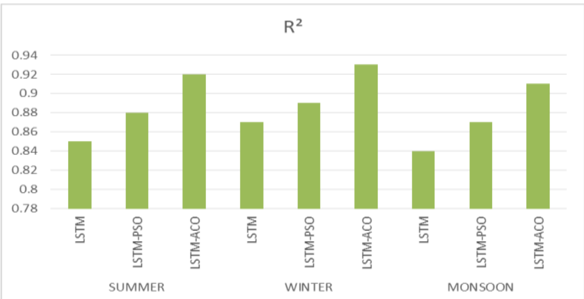

Figure 3 Chart Comparison

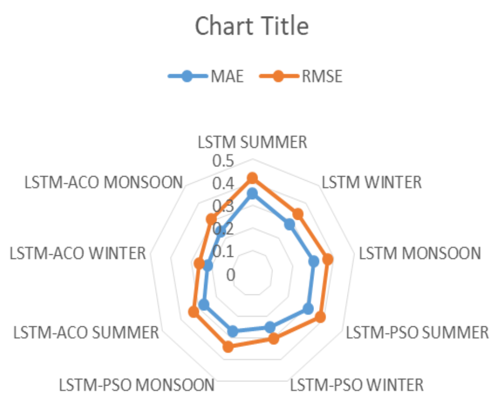

Figure 4 Charts Comparing R², MAE & RMSE Values in LSTM, LSTM-PSO & LSTM-ACO Models

The ACO-optimized LSTM performs well in all seasons, as shown in Fig (3), and the R^2 measurements highlight the models' predicting capabilities. As can be shown, the ACO-optimized LSTM exhibits more precision with an R^2 value of 0.92 for the summer. This demonstrates how well ACO optimizes LSTM for seasonal prediction. While the baseline LSTM produces an R^2 of 0.85 and the PSO-optimized LSTM produces an R^2 of 0.88. These enhancements in R^2 values show that the ACO-optimized model is more capable of explaining the variance in the solar power data, leading to more accurate and trustworthy predictions. The radar chart in Fig (3) offers a visual representation of the MAE and RMSE values for each model over the three seasons, clearly showing the exceptional functionality of the ACO-optimized LSTM, Shown in Figure 3 & Figure 4.

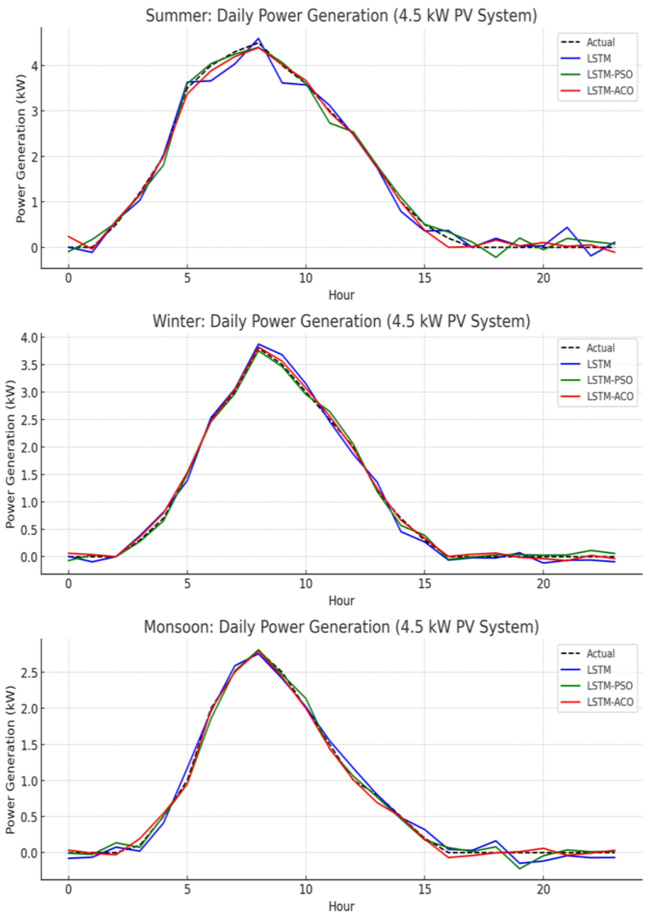

Figure 5 Daily Power Generation Plots for Summer, Winter & Monsoon

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The daily power generation plots for summer, winter, and monsoon, as shown in Fig (4), further validate these findings by comparing the actual PV power generation data with the predictions from each model. The ACO-optimized LSTM closely follows the actual power generation curve in all three seasons, particularly during peak solar hours, where prediction accuracy is most critical. On the other hand, the baseline LSTM and PSO-optimized With regard to seasonal patterns, the model's ability to adapt to fluctuating solar irradiance and power levels is significantly improved by the ACO hyper parameter tuning based on the previously listed features, such as hidden units, learning rate, and batch size. The model is tuned to better fit changes, particularly those that take place in the mornings and afternoons. The predictions become more accurate when these parameters are adjusted because the LSTM model becomes more sensitive to changes in the patterns of solar energy throughout the day. The model's capacity to track variations in power output during peak and off-peak times is enhanced by the fine-tuning procedure. As a result, the optimized LSTM model performs better by effectively adjusting to seasonal variations in solar energy, Shown in Figure 5.

Conclusion

The ACO-optimized LSTM model consistently outperforms both the PSO-optimized LSTM and baseline LSTM models across all key performance metrics and showcases its superior predictive accuracy. This is reflected in the significantly lower MAE and RMSE values alongside higher R^2 scores which validate the effectiveness of Ant Colony Optimization (ACO) in fine-tuning the hyperparameters of LSTM models for accurate day-ahead solar power forecasting. By harnessing historical data patterns and weather trends, the model effectively predicts solar energy output over a 24-hour period. These results can confirm that ACO is a highly efficient optimization method and enhances the precision of machine learning models in real-world photovoltaic applications. Looking ahead, there are several promising directions for further research. Incorporating real-time data streams and investigating hybrid optimization strategies could elevate prediction accuracy even further. Additionally, expanding the model's scope to account for longer-term solar generation forecasts and integrating advanced weather prediction models could provide more actionable insights for energy management. Exploring more sophisticated deep learning techniques such as attention mechanisms or ensemble models hold the potential to push the boundaries of model performance especially in extremely variable and dynamic environments.

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