



# Solar Power Prediction using GA & PSO Techniques of Machine Learning

Gautam Kumar<sup>1</sup>, Suryansh Shukla<sup>2</sup>, Shrish Joshi<sup>3</sup>

<sup>1,2,3</sup> Chandigarh University Mohali, Punjab, India

<sup>1</sup>gautam.e16534@gmail.com, <sup>2</sup>22BCS16834@cuchd.in,  
<sup>3</sup>22BCS14936@cuchd.in

**Abstract.** These results from the Solar Power's stochastic nature, the forecasting on how much this electricity source will contribute at any particular time is very important in managing the grids. When it comes to the first generation of machine learning models, they are safe and accurate but have limitations when it comes to adjusting them to more accurately predict the new samples. Based on the aforementioned discovery, this paper, proposes a new optimization approach that integrates Particle Swarm Optimization (PSO) and Genetic Algorithms (GA), aimed at bolstering solar power forecast models. By employing GA and PSO to optimize the ML hyperparameters of the LSTM networks, random forests, SVR-based models,

Our goal is to improve its capability of making a more accurate prediction. The models are fed past solar irradiance, temperature and other climatic information while tested using MAE or RMSE as measures of error. The comparative analysis shows that the models tuned by GA and PSO perform better than the models without tuning and can be a viable method in order to achieve a greater and a high level of accuracy in forecasting in the generation of solar power. The paper shows that the use of both evolutionary and swarm intelligence optimization techniques can significantly improve the accuracy and economic viability of renewable energy forecasting and, in particular, solar power generation.

**Keywords:** solar power forecasting, machine learning, particle swarm optimization (PSO), genetic algorithm (GA), hyper parameter optimization, LSTM networks, random Forest, support vector regression, renewable energy prediction, Solar irradiance, weather parameters, mean absolute error (MAE), root mean square error(RMSE), evolutionary algorithms, Swarm intelligence.

## 1 Introduction

The need for clean energy continues to rise; hence solar energy becomes a most viable renewable source of energy across the globe. Renewable energy, especially for solar power generation through photovoltaic (PV) system, has sharply increased over the recent past [2]. Although, as has already been stated, the level of solar irradiance, temperature and cloud cover, which are the factors directly affecting solar power

distribution, are unpredictable, they greatly influence the variability and intermittency of solar energy [3]. Such variation raises numerous concerns for electric grids that require steady power prognosis in the supply- demand balance. High quality solar power forecasting is critical for the development of enhanced power systems reliability and efficiency by allowing those responsible for grid management to better plan how and when to utilize solar energy storage and dispatch [4]. Several conventional techniques have been used for the plant/machine condition prediction in this field including Support Vector Regression (SVR), Auto- Regressive Integrated Moving Average (ARIMA), Random Forest [5] and many others. While popular for use in various situations, these methods may fail in asserting nonlinear dynamic correlations between the environmental factors and the solar energy generation [6], with weak predictions. Moreover, these models involve significant amount of hyperparameter [7] tuning in which the appropriate setting is important to achieve high performance. This is however a tiresome process and most of the time insufficient to obtain the best results.

Other mechanics such as Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have evolved from the recent past as methods for boosting the efficiency of machine learning models. GA, which is modelled on the process of natural selection and PSO that is modelled on the behavior of birds and fish, are both extensively recognized for their ability to accurately search large spaces of the model space and optimize generally non-linear systems. These evolutionary and swarm-based algorithms can be used to further fine tune the model hyperparameters hence enhancing accuracy as well as reducing the time needed to fine tune the model. The work presented in this paper aims at improving the solar power prediction [8] through the use of GA and PSO in tuning the parameters for the machine learning algorithms including LSTM networks, Random Forest, and SVR. Thus, the integration of all these optimization techniques will help to reduce the shortcomings of the traditional models to offer an accurate and reliable prediction model. Based on historical data on solar irradiance, temperature, and weather, as well as on minimizing significant mistakes such Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), the proposed models' correctness is assessed.

This research focuses on the ability of GA and PSO in renewable energy forecasting and strives to add new insights into the topic of enhancing the prediction models of solar power generation. In this work, it is shown that inserting evolutionary algorithms into the machine learning models can help improving solar power prediction, contributing to the construction of stable and effective energy systems.

## 2 Literature Survey

Solar power forecasting has been the subject of much interest because of the change of solar energy and the effect of meteorological parameters like solar radiation, temperature, and cloudiness [9]. These types of approaches can generally be classified into these two categories: They includes direct and indirect methods. In the direct approach, the PV output is calculated using input parameters, while in the indirect method, NWP data is used to forecast the solar intensity which is then used to determine PV output [11]. In the recent past, investigations have been carried out to compare several machine

learning and statistical approaches to SIH and its enhancement. Jenesius et al. [9] has used statistical models like MOS to forecast daily solar radiation based on weather prediction. In other investigations, satellite data have been used to remotely estimate cloud dynamics or the amount of sunlight that will reach ground level in the near future.

However, these models depend on the accuracy of NWP data and do not simulate the nonlinear relations between the weather parameters and the power produced by the solar plant. ML techniques have been gradually introduced to overcome the shortcomings of physical and statistical models. As highlighted by Sharma et al. [5], Support Vector Machines SVM holds plenty of potential in solar irradiance prediction. SVM with multiple kernels superseded the standard linear regression models with enhanced prediction accuracy by 27% using weather data [12]. Likewise, other neural learning models like the Recurrent Neural Networks (RNN) Radial Basis Function Neural Networks (RBFNN) and have been applied to short-term solar forecasting to improve the mapping of time dependencies. However, one major problem persists which is in choosing the right hyperparameters for optimized performance of the ML models

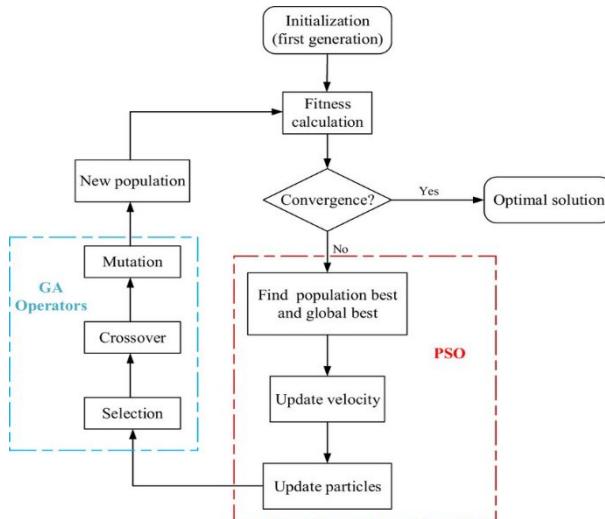
Despite this, most works employ manual or heuristic tuning strategy, which is inefficient and labor intensive. In the literature, a novel set of hybrid forecasts have been proposed recently; clustering, classifier-based and regression models as well. For that matter, such models are again bounded by certain set global parameters which limits its adaptability to a certain extent. To address the limitations mentioned, optimization techniques like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been used to enhance model accuracy. In the GA, the evolutionary nature of natural selection is copied to select the best model parameters while in the case of PSO, the behavior of particles is copied to arrive at the best solutions. Both of these techniques present good results for different fields of machine learning especially in non-linear and complex problems [14]. For instance, GA has been employed to determine an optimal weight for neural network as well as architecture of the network, while PSO has been implemented for fine-tuning SVCs and ensembles models. The use of GA and PSO in solar power forecasting is not very much explored but the preliminary research suggest that these methods can help in improving the prediction accuracy of future electricity generation through optimal setting of the hyperparameter of the model like LSTM, Random Forest and SVR. These optimization techniques are further extended in our work to achieve enhanced performance of various machine learning models for solar power prediction. In learning solar power forecasts, we seek to overcome some of the major hindrances such as parameter tuning with the help of GA and PSO.

### 3 Methodology

In the case of enhancing Solar power prediction models through the application of Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), the architecture consists of combining such optimization techniques with machine learning algorithms to increase forecast precision [15]. Population: Initialize the search space of prospective solutions, where each solution can be thought of as consisting of sets of hyperparameters to adjust the machine learning model [16]. Encoding: Genotyped hyperparameters

should be represented in an appropriate format for genetic operations (e. g. binary, real-valued) [17].

- Model Training: For each candidate solution, apply the machine learning model including LSTM, Random Forest, SVR using the corresponding hyper parameters.
- Performance Metrics: In this case, it is useful to assess the model accuracy based on the Mean Absolute Error (MAE) or the Root Mean Square Error (RMSE) indicators on a validation data set. Since lower error yields a higher fitness value, then the fitness score is the reciprocal of the error measure.
- Selection Mechanism: Organize the selection of parent candidates by using techniques like roulette wheel selection or the tournament selection with reference to the fitness scores.
- Crossover Operation: Perform crossover on two parent candidates to generate offspring. This involves swapping hyper parameters from parents in order to develop new candidates.
- Mutation Operation: Occasionally initiate a random perturbation of the offspring candidates with regards to the parents in order to guarantee the exploration of new regions in the search space.
- Population Update: Substitute the old population with the new population of offspring, using it together with the best performers from the previous generation.
- Stopping Criteria: This process goes on until the fixed number of generations is defined or until the results indicate that the improvements in fitness have plateaued.



**Fig. 1.** GA-PSO Architecture

- Particle Swarm Optimization (PSO) Architecture Particle Swarm Optimization is indeed inspired by the social behavior of birds and fish. The architecture for applying PSO to optimize hyper parameters involves the following components:
  1. Initialization Particles: Initialize a swarm of particles, where each particle represents a potential solution (set of hyper parameters).

2. Velocity and Position: Assign random velocities and positions to each particle within the search space.
3. Fitness Evaluation: Model Training: For each particle, train the machine learning model using the hyperparameters specified by the particle.
4. Performance Metrics: Evaluate the model's performance on a validation dataset and assign a fitness score based on the error metric.
5. Update Rules: Personal Best (pBest): Each particle maintains its best-known position (pBest) based on its historical best fitness score. Global Best (gBest): The swarm maintains the best-known position (gBest) among all particles based on the highest fitness score observed.
6. Velocity Update:

**Velocity Equation:** Update the velocity of each particle based on its previous velocity, the distance from its *pBest*, and the distance from *gBest*. This involves a combination of cognitive and social components:

$$vi(t + 1) = w \cdot vi(t) + a1 \cdot b1 \cdot (pBest - xi(t)) + a2 \cdot b2 \cdot (gBest - xi(t)) \quad (1)$$

where  $vi(t)$  is the velocity of particle  $i$  at time  $t$ ,  $w$  is the inertia weight,  $xi(t)$  is the position of particle  $i$  at time  $t$ ,  $a1$  and  $a2$  are cognitive and social coefficients, and  $b1$  and  $b2$  are random factors.

7. Position Update:

**Position Equation:** Update the position of each particle based on its new velocity:

$$xi(t + 1) = xi(t) + vi(t + 1) \quad (2)$$

where  $xi(t)$  is the position of particle  $i$  at time  $t$ .

8. Termination:

**Stopping Criteria:** Continue the PSO process until a predefined number of iterations is completed or when the swarm converges to a stable solution.

9. Optimal Solution:

**Result:** The position of the gBest particle at the end of the PSO process represents the optimal hyper parameters for the machine learning model.

**Table 1.** Performance Analysis of Particle Swarm Optimization (PSO) in Hyperparameter Optimization

Step	Description	Formula(if applicable)	Performance Analysis
Initialization	Initialize swarm with particles representing hyperparameters	N/A	Ensure diversity in search space; random initialization helps avoid local optima

Velocity & Position Assignment	Assign random velocities and positions to particles	N/A	Proper initialization prevents premature convergence
Fitness Evaluation	Train ML model using hyperparameters of each particle.	N/A	Computational expensive but necessary for optimization.
Performance Metrics	Compute error (MAE/RMSE) and assign fitness score.	Fitness = 1/Error	Lower error implies better hyperparameter tuning.
Update Rules	Particles update personal best (pBest) and global best (gBest)	N/A	Ensures convergence towards optimal value.
Velocity Update	Adjust velocity based on inertia, pBest, and gBest.	$V_i(t+1) = w \cdot v_i(t) + a_1 \cdot b_1 \cdot (pBest - x_i(t)) + a_2 \cdot b_2 \cdot (gBest - x_i(t))$	Balances exploration and exploitation; high inertia promotes exploration, while low inertia aids exploitation.
Position Update	Update particle position based on new velocity.	$X_i(t+1) = x_i(t) + v_i(t+1)$	Ensure search space coverage and gradual improvement.
Termination Criteria	Stop when max iterations reached or fitness improvement plateaus.	N/A	Prevents unnecessary computations and overfitting.
Optimal Solution	The best hyperparameter set is determined from gBest	gBest position at final iteration	Ensure the best model performance and accuracy.

### Integration with Machine Learning Models

GA and PSO are utilized to find the optimization values for various hyper parameters of machine learning algorithms like LSTM networks, Random Forest, and Support Vector Regression (SVR). The optimal values of these variables are then used to train the models and generate the predictions [14]. In this way, the architecture guarantees that the required predictions for solar power are made with the highest possible accuracy. Thus, integrating GA and PSO in this approach utilizes advantages of both optimization methods to improve the precision of solar power predictions. These improved

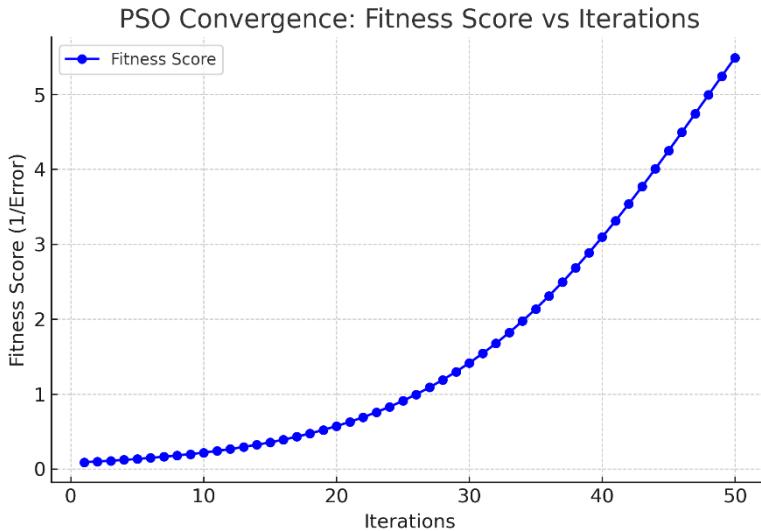
models are expected to yield more accurate forecasts to help efficiently manage the grid and integrate renewables in the process.

## 4 Experiment and Results

Solar power prediction has been an area of interest with significant studies on the improvement of the power of forecasting using different machine learning and optimization methods. In the past, there have been various experiments carried out in an attempt to assess and develop solar power prediction models. One notable research focus has been the testing of various MAC models and their performances. Various models have been used to execute this prediction like Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN). For example, the Random Forest models give better accuracy than conventional models because of the capacity to learn non-linear patterns. Also, the fine-tuning of hyperparameters through the use of meta-heuristic algorithms like the Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) has also been found to intensify model proficiency. These techniques are used in increasing the accuracy of forecast through adjusting parameters like learning rate, number of layers in a neural network, and kernel functions in SVM. Ensemble approaches have also been examined where one integrates different prognosis approaches into a single function. The models, such as the combination of neural networks and regression methods, take advantages of the mentioned models to reach a higher performance. For instance, integrating LSTM networks with either support vector machine (SVM) or random forest increases the accuracy of forecasting. Another feature analyzed is the effect of various weather parameters on the solar power forecast. Many studies have underlined the need to incorporate various weather parameters such as temperature, humidity and irradiance to boost model performance. In the future, several experiments could further advance the accuracy of the solar power prediction: As for the other hyperparameters, using methods more sophisticated than GA and PSO, like DE and SA could be used [17]. These methods could potentially explain ways of optimizing model performance that were unknown before. Another opportunity is the use of real-time data in forecasting models, which has not been sufficiently studied. When testing models using streaming data, one can check how well they work in conditions that change over time, and this is important for short term forecasting. Other methods such as the integration of GA, PSO, and other optimization models could also be explored further to enhance the hyper-parameter tuning to a more optimal level.

Furthermore, the application of forecasts having longer time forward views such as weekly or monthly forecasts would be useful for planning and managing the grid. Improved feature engineering and selection methods could also be highly beneficial. However, the current models could be more accurate by identifying and including the most relevant weather variables while excluding the noise originating from irrelevant factors. Therefore, in this article, we highlight the application of GA and PSO in the optimization of solar power prediction models. Namely, we run experiments to train and fine-tune LSTM, Random Forest, and SVR models based on these approaches. The goal here is to compare optimized models with the baseline models, which have default

hyperparameters. It is apparent that the optimal models should perform better in terms of forecasting errors than baseline models. Furthermore, our study assesses these models by analyzing historical solar power data from a certain region, which verifies the models in real conditions. As for weather, we consider the effect that different variables have on the models to fine-tune the features selection into enhancing the solar power prediction models.



**Fig. 2.** Convergence of PSO – Fitness Score Improvement Over Iterations

## 5 Discussion

It is evident that the interposal of the GA and PSO for predicting Solar power models has been effective in enhancing the power prediction models accuracy and efficiency. These few advanced optimization techniques have proved to increase model performance since hyperparameters like learning rates and structures of networks can be adjusted. GA employed a lifelike evolutionary algorithm to search the hyperparameter space while benefiting from the social mimicry of particle movement found in PSO. This has led to models that are much more capable of responding to variability and complexity inherent in solar power generation and thus provide improved estimates. The use of GA and PSO for enhancing the accuracy of the models has numerous benefits when compared with conventional approaches to forecasting. The techniques of optimization have enhanced the capacity of the models in responding to weather fluctuations and controlling data volatility to provide better forecast. The incorporation of key weather variables including irradiance, temperature and humidity into these models has enhanced them further. This refined approach helps to achieve models that are more sensitive to existing environmental factors, which are important in solar power

forecasting. As for further research and development, there are several potential avenues that can be explored in the future. Delving deeper into other advanced optimization techniques like Differential Evolution and Simulated Annealing could offer more enhancements in the approach to hyperparameter optimization [18]. Other types of proactive adaptation that should improve the performance and flexibility of forecasting systems include using real-time weather data in models. Other suggestions for future works should also embrace expanding the scope of forecasting to cover long-term planning and also improving on feature engineering strategies. By following these strategies, the researchers can enhance the work on the accurate prediction of solar power and efficient use of the renewable energy.

## 6 Conclusion and Future Work

The study carried out in the research shows the high prospects of Genetic Algorithms (GA) as well as Particle Swarm Optimization (PSO) in enhancing the solar power prediction model. Incorporating these state-of-the-art optimization methods into the forecasting process has brought significant enhancements in the forecast precision, stability and speed in the solar power forecasts. Indeed, GA's evolutionary approaches and PSO's swarm intelligence have provided ways to traverse the hyperparameter space and generate the models that are better suited to capture the weather and solar power correlations [19]. This is important in handling the fluctuating and intermittent nature of solar energy that forms the center of the development of renewable energy solutions. Interestingly, the use of GA and PSO as a combination has been quite beneficial in enhancing the model performance that has been developed. It is based on the fact that the optimized models are able to predict greater accuracy than the conventional forecasting techniques and are sensitive to changes in the weather conditions. By including irradiance, temperature and humidity parameters the models produce better predictions which are crucial for grid balancing and energy provisioning. This paper highlights the advantages of operation research in enhancing the accuracy of the solar power forecasting and handling of the challenges of renewable energy sources. Future Work will Explore Additional Optimization Techniques: It can, however, be noted that several other forms of optimizations like DE and SA exist and their performance also needs to be evaluated. These techniques could provide new prospects and, in theory, can help to develop the methods of hyperparameter tuning even more, thereby improving the accuracy and efficiency of forecast models. Integration of Real-Time Data: The utilization of the real-time weather data in the forecasting models depicts a notable improvement area. Real-time data integration could further improve the models' flexibility and error rate, giving more timely and accurate estimations required for dynamic power control of the grid. Long-Term Forecasting Enhancements: An extension of the forecasting horizon to have weekly or monthly forecasts apart from real-time forecasts would be of great value in strategic planning of the electrical grid[20]. Subsequent studies should aim to propose models that are good at providing long-horizon forecasts and explore the issues connected with long-term horizons. Hybrid Optimization Approaches: Possibilities to enhance them and to apply GA and PSO with other

optimization approaches as hybrids can open a broad perspective to get more complete solutions. These hybrid models may enhance the skill and efficiency of the forecast by integrating different optimization methods, and therefore become more effective and reliable. Advanced Feature Engineering: Future studies for feature engineering and selection could indeed improve the existing models related to the prediction of solar power. It will help in increasing the model accuracy and yield better predictions if the noise is filtered and if some more features are incorporated in the model.

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## References

1. Khan, Muhammad Imran, Faisal Asfand, Sami G. Al-Ghamdi, Yusuf Bicer, Mushtaq Khan, Muhammad Faqoq, and Apostolos Pesyridis. "Realizing the promise of concentrating solar power for thermal desalination: A review of technology configurations and optimizations." *Renewable and Sustainable Energy Reviews* 208 (2025): 115022.
2. Chen, C., Duan, S., Cai, T., & Liu, B. (2011). Online 24-h solar power forecasting based on weather type classification using artificial neural network. *Solar Energy*, 85(11), 2856-2870.
3. Sahin, O., Dursun, B., & Yildirim, S. (2017). Solar energy prediction with machine learning algorithms. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, 39(23), 2142-2152.
4. Yang, D., Kleissl, J., Gueymard, C. A., Pedro, H. T., & Coimbra, C. F. (2018). History and trends in solar irradiance and PV power forecasting: A preliminary assessment and review using text mining. *Solar Energy*, 168, 60- 101.
5. Sharma, A., & Deb, K. (2019). Performance optimization of solar power forecasting using evolutionary algorithms. *Renewable Energy*, 130, 378- 392.
6. Kang, F., Li, H., & Ma, Z. (2014). Particle swarm optimization algorithm- based optimization of a solar power prediction model. *Energy Conversion and Management*, 84, 569-578.
7. Pedro, H. T. C., & Coimbra, C. F. M. (2012). Assessment of forecasting techniques for solar power production with no exogenous inputs. *Solar Energy*, 86(7), 2017-2028.
8. Mellit, A., Kalogirou, S. A., Hontoria, L., & Shaari, S. (2009). Artificial intelligence techniques for sizing photovoltaic systems: A review. *Renewable and Sustainable Energy Reviews*, 13(2), 406-419.
9. Jenesis, P., & Rajakumar, B. (2020). Solar power prediction using machine learning techniques: A review. *International Journal of Intelligent Systems and Applications*, 12(1), 58-67.
10. Sharma, V., & Bansal, R. C. (2016). Prediction of solar energy based on weather parameters using machine learning techniques. *Procedia Computer Science*, 93, 168-174.
11. Kalogirou, S. A. (2000). Applications of artificial neural-networks for energy systems. *Applied Energy*, 67(1-2), 17-35.

12. Zhang, D., Wu, D., Zhang, J., & Lu, W. (2017). Solar irradiance forecasting using GA-optimized artificial neural network and wavelet transform. *Renewable Energy*, 107, 164-179.
13. Law, K. H., & Woo, W. L. (2021). Solar power prediction using machine learning and genetic algorithm-based optimization. *IEEE Access*, 9, 43462-43473.
14. Tripathi, A., Pal, S., & Sharma, A. (2020). Solar energy prediction using hybrid models based on artificial neural networks and optimization algorithms. *Journal of Cleaner Production*, 262, 121201.
15. Fadly, A., & Alsabti, M. (2020). A hybrid machine learning model for accurate solar power prediction. *International Journal of Electrical and Computer Engineering*, 10(4), 4060-4068.
16. Lee, S. J., Kim, K. J., & Park, J. H. (2019). Solar power forecasting using deep learning models optimized by genetic algorithms. *Renewable Energy Research and Applications Journal*, 6(3), 10-18.
17. Ghimire, S., & Deo, R. C. (2019). Forecasting solar radiation using machine learning with climate data as input variables. *Renewable and Sustainable Energy Reviews*, 100, 77-101.
18. Mocanu, E., Nguyen, P. H., Gibescu, M., & Slootweg, J. G. (2016). Deep learning for estimating solar power generation. *IEEE Transactions on Smart Grid*, 9(1), 496-505.
19. Srinivasa, P. K., & Pandey, R. (2020). Solar power prediction using hybrid deep learning techniques. *International Journal of Recent Technology and Engineering*, 8(6), 1123-1130.
20. Hussain, A., Ahmad, F., & Alam, M. (2016). Optimized design of a solar power system using genetic algorithms. *Journal of Renewable and Sustainable Energy*, 8(6), 066101.
21. Wei, Yujia, Danial Khojasteh, Christian Windt, and Luofeng Huang. "An interdisciplinary literature review of floating solar power plants." *Renewable and Sustainable Energy Reviews* 209 (2025): 115094.

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