Development Of An Ai-Based Model With Low Computational Complexity For Accurate Solar Energy Forecasting

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ABSTRACT

This paper introduces a short-term solar energy forecasting model that is designed with a focus on low computational complexity and addresses the challenges posed by fluctuations in solar energy generation, which are significantly influenced by environmental factors. These fluctuations can lead to instability when solar power generation systems are integrated into national energy grids, creating difficulties in maintaining a balanced supply and demand. If solar energy generation can be accurately forecasted before fluctuations occur, potential issues can be identified in advance, allowing for better management of the energy system, including optimizing storage facilities when energy generation is high. Current solar energy forecasting systems face significant challenges due to their high computational complexity, which results in increased power consumption and lower accuracy. To address these issues, this study focuses on the development of an artificial intelligence (AI)-based forecasting model using an Artificial Neural Network (ANN). The goal is to reduce the computational complexity of the model while maintaining high accuracy. To achieve this, various data analysis and complexity reduction techniques, such as variable reduction, pruning, and quantization, were applied. The performance of the optimized AI model was evaluated by comparing the forecasted values to actual solar energy generation data. The results demonstrate that the proposed model successfully reduces computational complexity while maintaining a satisfactory level of accuracy. This optimization makes the model more suitable for real-time forecasting, particularly in resource-constrained environments, and provides a more efficient approach to solar energy management. The findings of this study suggest that AI-based forecasting models can play a critical role in enhancing the integration of solar energy into national grids, ensuring a more reliable and sustainable energy supply. Further research could explore additional optimization techniques and the introduction of generalization techniques to improve transferability of the model and applicability across diverse geographical regions. Additionally, focus on utilizing AI techniques that minimize computational complexity without compromising the accuracy of the model, aiming to maintain high forecasting precision while optimizing the efficiency of the system.

KEYWORDS: *Solar forecasting, artificial intelligence, computational complexity, simulation, optimization, machine learning.*

INTRODUCTION

A significant amount of energy is utilized in daily lives, with conventional methods of energy generation, such as hydro power generation and the burning of fossil fuels, being commonly employed. However, as the demand for energy continues to rise, there has been a growing emphasis by researchers and other responsible entities on exploring alternative sources of energy. Among these, solar energy is particularly promising due to its inherent qualities it is a clean, eco-friendly, and renewable source of power. Its potential to provide sustainable energy solutions has garnered much attention as a viable

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alternative to traditional energy generation methods.

The integration of solar power generation has led to increased recognition within the community of its numerous advantages, particularly its environmental sustainability and potential for long-term energy cost reduction. As awareness of these advantages grew, both small and large-scale investors became increasingly interested in contributing to the expansion of solar power infrastructure. Consequently, a significant number of solar power generation systems have now been integrated into the national grid. However, the management of these systems has become more challenging due to the fluctuations in solar power generation, which are influenced by varying environmental factors such as weather conditions. These fluctuations can complicate efforts to maintain a stable and reliable energy supply, posing a challenge to the smooth operation of the overall energy system(Chodakowska et al., 2024).

Forecasting solar power generation is of utmost importance for maintaining a well-balanced and reliable national energy system. Accurate forecasts are vital for ensuring that supply and demand are harmonized, storage management is optimized, and the overall system remains dependable. However, traditional forecasting methods, while effective in some respects, present certain challenges. These methods tend to be resource-intensive and may not always provide the level of precision required for efficient decision-making. They often demand significant computational resources, rely on complex machine learning models, and require the collection and management of large datasets. Moreover, real-time systems can struggle to accommodate such heavy models, leading to delays in processing and a time-consuming forecasting process. As a result, the accuracy of traditional methods may fall short, potentially affecting the effectiveness of the forecasts and the smooth functioning of the energy system.

Advancements in AI have significantly improved solar energy forecasting, offering solutions to overcome the limitations of traditional methods. AI models provide more accurate and reliable forecasts of solar energy generation, which enhances overall system performance. However, despite these advancements, AI models also face certain challenges. One major issue is computational complexity, especially when scaled for large datasets or deployed in environments with limited resources. Additionally, when operating in real-time systems, these models can become difficult to manage, as they require substantial computational power and can impact the efficiency of the forecasting process. These challenges highlight the need for further innovations to make AI-driven solar forecasting more efficient and applicable in various settings.

This research aims to address the challenges posed by datasets that require substantial computational resources, as well as other factors such as algorithmic complexity, data dimensionality, and system limitations, all of which contribute to increased computational complexity. Short-term forecasting (within a 0–48-hour timeframe) facilitates efficient grid scheduling, optimize solar plant dispatch, and enhances participation in energy markets. It will examine various AI techniques designed to reduce this complexity, thereby improving efficiency. The study will provide a comprehensive overview of the behavior of the different complexity-reduction variables, analyzing each one individually to better understand their impact. Furthermore, the research will explore strategies to achieve the highest level of accuracy in a complexity-reduced Neural Network model, focusing on how to optimize performance while minimizing computational demands.

LITERATURE REVIEW

Past approaches to solar forecasting have evolved from traditional statistical methods to more advanced machine learning (ML) and deep learning techniques. Traditional forecasting relied on manual calculations, empirical formulas, and simplified assumptions based on historical data and meteorological parameters. These methods were often time-consuming, error-prone, and limited in capturing the complex, non-linear relationships inherent in solar energy production. As solar power generation depends heavily on fluctuating meteorological factors such as solar radiation, temperature, and cloud cover, forecasting became increasingly challenging(Chodakowska et al., 2024; Sammar et al., 2024). In response, machine learning methods, including neural networks (NN), support vector regression (SVR), and time-series models, emerged to enhance prediction accuracy(Amer et al., 2023). More recently, deep learning approaches such as long short-term memory (LSTM) networks, convolutional neural networks (CNN), and hybrid methods like extreme gradient boosting trees (XGBT) have been applied to improve solar irradiance forecasting. These advanced techniques offer more precise and reliable predictions by better capturing the dynamic behavior of solar energy generation in relation to changing environmental conditions.

Several models are commonly used in solar energy forecasting, leveraging the advancements in machine learning (ML) and deep learning to improve prediction accuracy. Among these, Artificial Neural Networks (ANN) are widely used due to their ability to capture complex, non-linear relationships between weather variables and solar energy production. Support Vector Machines (SVM), particularly Support Vector Regression (SVR), are also popular, as they can efficiently predict solar energy generation by identifying optimal patterns in the data. Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN), are particularly effective for time-series forecasting, as they can learn sequential dependencies in data, making them ideal for predicting solar energy generation based on historical weather and irradiance data. Additionally, other deep learning models like Convolutional Neural Networks (CNN) and hybrid approaches such as Extreme Gradient Boosting Trees (XGBT) have been introduced to improve the accuracy and efficiency of solar irradiance predictions. These models offer a more reliable and precise forecasting method compared to traditional approaches, particularly in handling the complexity and volatility of solar energy generation.

The main challenge with existing solar forecasting and real-time prediction systems is their high computational demand. These systems, which often rely on complex models such as statistical methods, machine learning (ML), and deep learning techniques, require substantial computational resources. The intricate nature of these models, combined with the vast amount of data they process, makes it challenging to deploy them in resource-constrained environments. The need for significant processing power can result in delays and inefficiencies, especially in real-time applications, where timely predictions are crucial.(Hossain et al., 2023)

If the AI model is designed with low computational complexity, several significant benefits can be achieved. Data can be processed more rapidly, enabling faster real-time predictions. The consumption of resources and power can be minimized, leading to lower operational costs. The system's scalability is enhanced, allowing it to handle larger datasets or expanded infrastructure without difficulty. Latency can be reduced, ensuring quicker response times to new inputs. Additionally, cost efficiency is attained, as less computational power is required, reducing the need for expensive hardware and cloud services. The model can also be more easily adapted to changing requirements, making updates and modifications simpler and more efficient. Furthermore, small-scale generation stations, which may have limited resources, can benefit from the model's reduced complexity, as it allows for its deployment without the need for high-end infrastructure. These advantages demonstrate how a less complex model can make advanced forecasting systems more accessible, practical, and sustainable in various applications.

METHODOLOGY

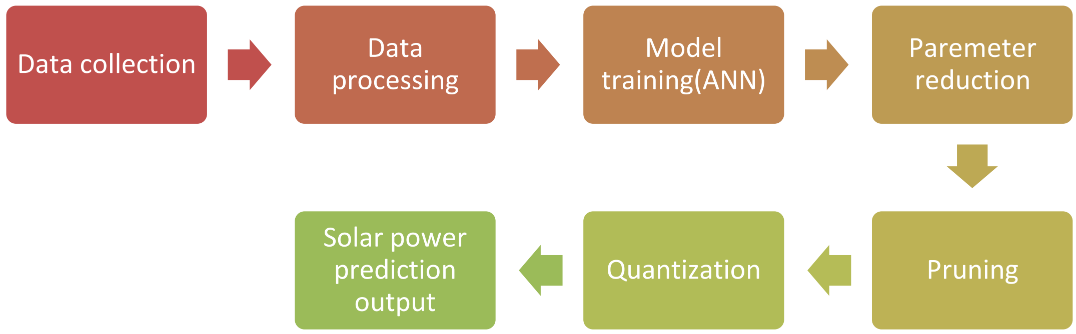

Figure 1. methodology

Data Collection

As the first stage of the development of the AI model, the data collection process is initiated. Throughout this research, the model is developed based on open-source datasets that are publicly available. For the initial dataset, a dataset containing data from the Northeast region of Brazil has been utilized. (*Solar Energy Northeast Brazil*, n.d.)This dataset includes around 4,000 data points collected over a period of five months, with a 5-minute interval between each data point.

After the collection of solar energy data, meteorological data that affects solar energy generation was identified. Meteorological factors such as weather patterns, wind speed and direction, humidity, solar radiation, ambient temperature, and module temperature, among others, have been recognized as influential through a review of past research(Amer et al., 2023). To gather the necessary weather data, efforts were made to collect this information using an open-source platform. In the initial stage, eight input variables were considered for analysis. The Historical Weather API was used to obtain the relevant data for these meteorological factors(🏛 *Historical Weather API | Open-Meteo.Com*, n.d.).

Due to the limited number of data points in the initial dataset, which could potentially affect the accuracy of the AI model and lead to improper training, a decision was made to transition to a different dataset. This new dataset was identified through research conducted on data collection in China. The dataset comprises approximately 70,000 data points, spanning two years (2019-2021), with a 15-minute interval between each data point (Chen & Xu, 2022)

The dataset effectively captures the solar power fluctuations of a 50MW solar station, providing a more comprehensive record of solar power generation. It includes six key input variables, Total Solar Irradiance (W/m²), Direct Normal Irradiance (W/m²), Global Horizontal Irradiance (W/m²), Air Temperature (°C), Atmospheric Pressure (hPa), and Relative Humidity (%). (*GitHub - Bob05757/Renewable-Energy-Generation-Input-Feature-Variables-Analysis*, n.d.)

Simulation Platform

The Artificial Neural Network (ANN) is a widely recognized and powerful method used to find solutions, particularly when other statistical techniques may not be applicable. Its advantages, such as the ability to learn from examples, operate in real-time environments, and forecast non-linear data, make it an invaluable statistical tool. One of the key strengths of ANN is its capacity to model complex, non-linear relationships between known input and output values.(Amer et al., 2023)

Additionally, ANN is well-suited for handling large datasets, making it particularly useful when working with vast amounts of data points and complex datasets.(Abuella & Chowdhury, n.d., 2015) This ability to process large quantities of data effectively sets it apart from linear models that may struggle with high-dimensional data or non-linear trends.(Amer et al., 2023)

MATLAB was chosen as the development environment for implementing the ANN model. MATLAB's Neural Network Fitting feature was employed to create and train the model, using 80% of the data for training and 20% for testing. This feature provides a comprehensive and efficient framework for building neural networks, allowing for accurate fitting of the data and effective prediction of solar energy generation. By utilizing ANN, the model is able to handle the intricacies of the data, including non-linear relationships, making it a powerful tool for accurate forecasting in this context.(*Deep Learning Toolbox - MATLAB*, n.d.)

Optimization methods

Before the first model was prepared, the dataset was arranged on an hourly basis, and data points with unexpected values were removed, provided the input variables were in optimal conditions. Eighty percent of the arranged dataset was used for training the model, while the remaining 20% was reserved for testing. However, after the model was trained on this dataset, an accuracy of only 30% was achieved. This low accuracy was attributed to the insufficient data and the inaccurate training of the model due to the limited dataset available.

To improve the dataset and accuracy, a decision was made to shift to the second dataset, which had been sourced from research conducted in China. This dataset, covering one year of data (2019-2020), was processed by removing zero output data when the input conditions were normal. The model's accuracy improved to 58% after this larger dataset was used. Subsequently, after the data was arranged on an hourly basis and the model was refined, an accuracy of 84% was achieved. This improvement in accuracy was attributed to the more comprehensive and reliable dataset, which allowed for better training and more accurate predictions.

As the next step in reducing computational complexity and improving accuracy, input variables with minimal correlation to the output were removed. The second model initially included six input variables: Total Solar Irradiance (W/m²), Direct Normal Irradiance (W/m²), Global Horizontal Irradiance (W/m²), Air Temperature (°C), Atmospheric Pressure (hPa), and Relative Humidity (%). Upon evaluating the correlation between these variables and the output, it was found that four of them exhibited a considerable correlation with the output, while two of them showed very little correlation and accuracy.

To improve the model's performance, the two variables with minimal correlation were removed, and the model was retrained. After this adjustment, the model's accuracy increased to 90.3%. This enhancement in accuracy was attributed to the removal of less relevant variables.

Table 20. Correlation ranges (Ratner, 2009)

Correlation	**Range**
Strong positive correlation	0.7 to 1
Moderate positive correlation	0.3 to 0.7
Weak or negligible correlation	-0.3 to 0.3
Moderate negative correlation	-0.7 to -0.3
Strong negative correlation	-1.0 to - 0.7

Table 21 . Variable and correlation

Input Variable	**Correlation**
Total Solar Irradiance (W/m²)	94.6%
Global Horizontal Irradiance (W/m²)	64.7%
Direct Normal Irradiance (W/m²)	57.8%
Air Temperature (°C)	22.6%
Relative Humidity (%)	18%
Atmospheric Pressure (hPa)	-0.8%

As the third method of complexity reduction, Pruning, or sparsity induction, was applied.(Fernandes & Yen, 2021) . The pruning threshold of 0.3 was selected after testing various values ranging from 0.1 to 0.5. This value provided the optimal balance between reducing network size and maintaining prediction accuracy(Molchanov et al., n.d.). This model optimization technique involves removing 15-25% of the smallest (near-zero) weights from a neural network. The aim was to enhance computational efficiency while maintaining accuracy. After applying this technique to the MATLAB model, the accuracy was slightly reduced to 89.7%. The slight decrease in accuracy was attributed to the impact of the complexity reduction technique, as some weights were removed to improve efficiency.

To measure the effectiveness of the complexity reduction, several parameters were used, Model Size (MB), Inference Time (ms), Total Time (s), RMSE (Root Mean Squared Error), and the Training Epoch. These parameters provided a comprehensive evaluation of the trade-off between reducing model complexity and preserving performance, ensuring that the model's accuracy remained acceptable while achieving improvements in computational efficiency (Pham et al., 2019).

The final method applied for computational complexity reduction was Quantization. This technique was used to reduce the computational complexity and memory usage of the model by approximating the weights and activations with lower precision. Instead of using 32-bit or 64-bit floating-point numbers to represent these values, quantization utilized fewer bits, such as 8-bit integers, to represent the model's parameters(Im & Dasari, 2022).

After applying quantization, the model's accuracy slightly decreased to 89.6% with respect to the actual values. During the research, it was observed that while the application of complexity reduction techniques consistently reduced model complexity, it also led to a reduction in accuracy. Given this trade-off, it was concluded that no further complexity reduction techniques would be applied beyond this stage, as the accuracy began to suffer with each additional reduction method. Thus, the model reached an optimal balance between reduced complexity and acceptable accuracy at this point.

COMPLEXITY EVALUATION MATRIXES

The level of complexity and the reduction in computational complexity were measured using several parameters of the model, including Model Size (MB), Inference Time (ms), Total Time (s), RMSE (Root Mean Squared Error), and the Training Epoch. When these values were high, it was understood that the computational complexity was also higher. It was important to maintain the Training Epoch at a moderate level to avoid excessive training time and overfitting. By observing the changes in these values, insights were gained into the reduction of complexity in the model and the behavior of each parameter with the application of different techniques. Each technique's impact on these values provided a clear understanding of the model's complexity was being reduced while balancing accuracy and performance.

Table 22 . Initial and final model parameters

Metrics	**Initial model**	**Final model**
Parameters	8	4
Model size (MB)	0.06	0.04
Inference Time(ms)	15.6	7.75
Total time (s)	19.718	5.23
RMSE	9.44	4.123
Training Epoch	330	18
Model accuracy(R^2)	30.3 %	89.6%

EVALUATION METRICS FOR PERFORMANCE

To measure the performance of the model, the RMSE (Root Mean Squared Error) value was calculated by comparing 20% of the actual values from the test dataset with the predicted values generated by the model. This comparison provided a quantitative assessment of how accurately the model was able to predict the data. A lower RMSE value indicated that the model's predictions were closer to the actual values, reflecting better performance, while a higher RMSE suggested a larger discrepancy between the predicted and actual values, signaling a need for improvement in the model's accuracy.(Pham et al., 2019)

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

R-squared (R^2), also referred to as the coefficient of determination, was understood to be a measure of the proportion of variance in the dependent variable that could be predicted from the independent variables in the model. After the model had generated the output, the deviation between the actual and predicted values was examined. It was expected that the R^2 value should be close to 1, indicating a high level of accuracy. When the R^2 value approached 1, it suggested that the model had explained a significant portion of the variance in the data, leading to better predictive performance. The closer this value was to 1, the more reliable the model was considered to be in terms of its accuracy in predicting the dependent variable.(Pham et al., 2019)

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

RESULTS

Model Performance

The accuracy of the model initially began at 30% and was improved to 90.3% due to the enhancement in the number of data points and the data analysis techniques that had been discussed previously. Subsequently, the accuracy slightly decreased from 90.3% to 89.6%, which was attributed to the application of computational complexity reduction techniques, such as pruning and quantization. However, the demand for computational resources was notably reduced as a result of these techniques.

Table 23. Model Performance

Metrics	**Initial model**	**Variable Reduction**	**Pruning**	**Quantization**
Parameters	8	4	4	4
Number of Layers	3	3	3	3
Model size (MB)	0.06	0.04	0.04	0.04
Inference Time(ms)	15.6	11.34	8.16	7.75
Total time (s)	19.718	9.42	5.61	5.23
RMSE	9.44	5.42	4.20	4.123
Training Epoch	330	43	21	18
Model accuracy(R^2)	30.3%	90.3 %	89.7%	89.6%

Computational Metrics

The time required for the full model training, measured in seconds, was reduced from 19.7 to 5.25. Additionally, the time for generating a single output with a single input was also decreased from 15.6 milliseconds to 7.75 milliseconds. The model size was reduced from 0.06MB to 0.04MB, and the number of variables was halved, leading to a corresponding reduction in input variables. These improvements collectively demonstrate a significant reduction in computational complexity, showcasing the effectiveness of the optimization techniques employed.

Forecasting Accuracy Visualization

The forecasting accuracy was measured using the R-squared (R^2) value, which improved significantly from 30.3% to 89.6%, reflecting the model's enhanced predictive performance in the final result. (Abuella & Chowdhury, n.d., 2015)

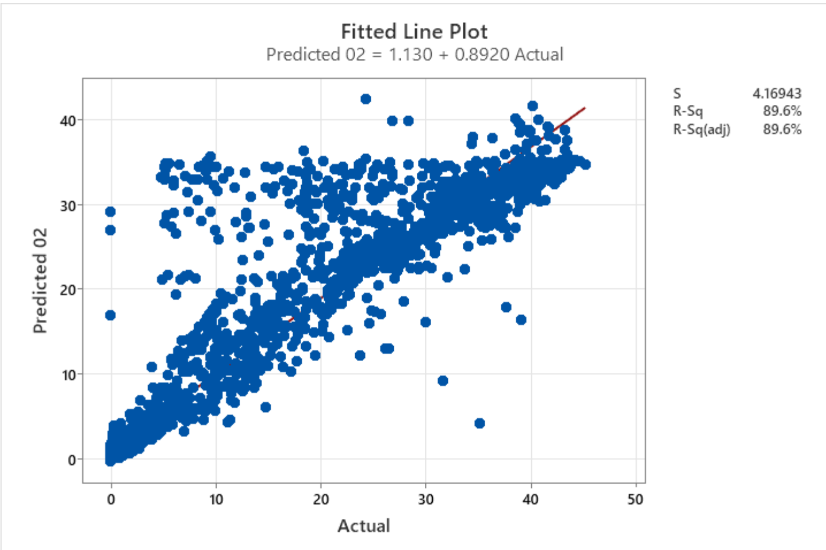

Figure 3. Final model accuracy

DISCUSSION

The results of this study demonstrate the successful development, optimization, and evaluation of an AI-based solar energy forecasting model. The initial objective of developing an AI model was achieved through the use of Artificial Neural Networks (ANN), which effectively captured the complex, non-linear relationships between meteorological data and solar power generation, leading to improved accuracy. The optimization goal was met by applying various techniques like variable reduction, pruning, and quantization, significantly reducing the model's computational complexity while maintaining high performance.

Forecasting accuracy increasing from 30.3% to 89.6%, interference time decreasing from 15.6ms to 7.75ms, total processing time reducing from 19.71 s to 5.2 s, and RMSE improving from 9.44 to 4.12. Additionally, the training epochs decreased from 330 to 18, model size reduced from 0.06 MB to 0.04 MB, and parameter count halved from 8 to 4, resulting in faster inference and a more compact architecture suitable for real-time and embedded systems. While a slight accuracy trade-off occurred during optimization, the balance between reduced complexity and maintained high prediction accuracy was deemed acceptable. Compared to similar studies, this work stands out by achieving a computationally efficient model without significantly compromising performance, addressing the high resource demands common in many forecasting models.

The study has limitations, including the need for further testing in diverse geographical regions and over different time horizons to assess the model's generalizability. Additionally, as further computational complexity reduction techniques were applied, there was a slight decrease in accuracy. Therefore, it is crucial to apply computational complexity reduction techniques that do not compromise the model’s accuracy. Real-world integration and testing in live solar power systems could further validate the model's performance and adaptability, ensuring its broader applicability and potential for sustainable solar energy solutions.

CONCLUSION

This research focused on the development of a low-complexity ANN-based short-term solar forecasting model. The model achieved an impressive 89.6% accuracy with a significant reduction in computational time, including inference time (from 15.6ms to 7.75ms) and total processing time (from 19.71s to 5.2s). The results demonstrate the model's suitability for deployment on low-power embedded devices, ensuring efficient real-time solar energy forecasting even in resource-constrained environments. Future work will involve testing the model under a wider range of weather conditions to further enhance its robustness and adaptability.

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