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Solar irradiation intensity forecasting for solar panel power output analyze

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ABSTRACT

Accurate forecasting of global horizontal irradiance (GHI) is critical for optimizing solar power plant (SPP) output, particularly in tropical locales where solar potential is high yet underutilized due to forecasting challenges. This research aims to enhance GHI prediction in one of the major cities of Indonesia, where existing models struggle with the area's natural climate unpredictability. Our analysis harnesses a decade of data 2011-2020, including GHI, temperature, and the Sky Insolation Clearness Index, to calibrate and compare these methodologies. We evaluate and contrast the exponential smoothing method versus the more complicated artificial neural network (ANN). Our findings reveal that the ANN method, notably its fourth iteration model with 12 input and hidden layers, substantially outperforms exponential smoothing with a low error rate of 1.12%. The use of these methodologies forecasts an average energy output of 252,405 Watt for a solar panel with specification 15.3% efficiency and 1.31 m^2 surface area throughout the 2021 to 2025 timeframe. The work offers the ANN method as a strong prediction tool for SPP development and urges a further exploration into more advanced forecasting methodologies to better harness solar energy.

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1. INTRODUCTION

Indonesia, as a tropical nation, is drenched in solar radiation throughout the year, delivering a plentiful supply of solar energy with an average intensity of roughly 4.8 kWh/m^2 [1], [2]. This plentiful resource is at the heart of the country's agenda for renewable energy growth. The promise of solar energy, a clean and sustainable resource, matches nicely with national goals, as it offers No. environmental hazards and is limitless. These properties make solar power a highly viable choice for energy generation, positioned to meet a range of societal needs [3], [4].

With the nation's cf forecast to increase between 7% to 10% yearly until 2025, a comparable spike in power demand is anticipated [5]. The National Energy Policy, issued by Presidential Decree No. 5 of 2006, requires the growth of alternative and renewable energy sources, such as microhydro, biomass, wind, and solar to fulfill this expanding need [6]. The government regulation of 2014 further encourages this tendency by calling for energy diversification, establishing a target for renewable energy to contribute at least 23% of total consumption by 2025. In this context, Solar Power Plants emerge as a strategic alternative, lowering dependency on fossil fuels [7].

Despite more steady solar radiation compared to nations like Germany and Japan, reliable forecasting remains a major concern in Indonesia. Previous research has utilized artificial neural network (ANN) approaches for estimating sun radiation across thirty Indonesian cities, providing a broad spectrum of intensities with Kupang recording the highest and Bandung below the average. Such research underlines the variety in solar radiation and the necessity for precision forecasting systems [8], [9].

Forecasting accuracy has been investigated thoroughly, with a range of methodologies demonstrating varied degrees of effectiveness. Techniques such as fuzzy logic and the gated recurrent unit (GRU) have been investigated, each with its strengths and limitations [10], [11]. Specifically, in Java Island, the efficiency of ANN models in predicting solar irradiance and power generation has been validated, albeit with recognized faults in the estimate process [12], [13].

Recognizing Indonesian tremendous solar potential and the important necessity of accurate solar radiation predictions in utilizing this resource, this research tries to bridge the knowledge gap in forecasting approaches. It analyzes the performance of the ANN approach versus the exponential smoothing method for estimating solar radiation intensity in Bandung City over a five year horizon. This research not only seeks to boost forecasting precision but also to offer a rigorous analytical framework for the construction of solar power plants, enabling the country's transition to a sustainable energy future. By undertaking a comparative examination of various methodologies, the study intends to offer forecasts of better accuracy, therefore influencing strategic energy planning and allowing the best usage of Indonesia’s solar resources.

2. METHOD

2.1. Tools

In this research, we conducted a thorough conceptual development, consulting a wide range of reputable international journals and books available through digital libraries. These resources gave us a solid grasp of the theoretical aspects of solar irradiance forecasting and how it can be applied in the renewable energy industry. In order to tackle the forecasting challenge, we implemented a dual strategy. The first method that was used is exponential smoothing, a statistical technique commonly used for analyzing time series data. it was selected for its simplicity and ability to calculate weighted averages based on previous observations. We used Microsoft Excel for the implementation of this method, taking advantage of its built-in functions and data analysis tools to model and forecast the global horizontal irradiance (GHI) data. The second technique involved the ANN, selected for its ability to model non-linear relationships and its robustness in dealing with complex variables [14]. The ANN analysis was conducted using the zaitun time-series application, which was selected for its specialized features in time series forecasting and its user-friendly interface for building and validating neural network models.

Our analysis relied on data obtained from NREL and NASA POWER, well known sources of open source climatology data. These platforms were chosen because of their extensive datasets on GHI, along with other important meteorological variables. We collected relevant data for Bandung City over the next five years to gather empirical evidence on the potential of solar energy generation in the region. With the approach using a comprehensive analysis of solar irradiance patterns and forecasting accuracy was conducted, providing valuable insights to the field of solar energy analytics [15].

2.2. Research design

The research conducted herein falls under the category of experimental studies, which are defined by a systematic method aimed at testing the precision of forecasting models using preset variable data. This research is created on an experimental basis, where the focus point is the validation of prediction model accuracy against known data variables [16]. The findings generated from the forecasting method will be examined to calculate the output power of solar panels inside a photovoltaic solar power system. This explicit methodological route is demonstrated in Figure 1, which sets out the flow of the research design.

Harnessing solar energy, crucial to the renewable energy grid, relies substantially on the exact measurement and forecasting of GHI. GHI estimates the solar energy accessible at the earth’s surface and is crucial for evaluating the potential output of photovoltaic (PV) systems. This research is based on projecting GHI to discover the energy that solar panels in Bandung City could potentially generate from 2021 to 2025.

Our methodology comprises a dual approach forecasting framework. Initially, we employed the exponential smoothing approach to project GHI, leveraging on its proficiency in smoothing time series data and revealing underlying patterns. Complementarily, the ANN technique was applied to capture the nonlinear complexity of climatic factors affecting GHI. The juxtaposition of various approaches, as indicated in the Figure 1, allows for a full examination of their predicting accuracy.

The flowchart shows the research pathway, starting with the assimilation of temperature data and the Sky Insolation Clearness Index, with GHI values, to input into the forecasting models. After the use of exponential smoothing and ANN approaches, the research moves to a rigorous comparison examination of their performance. This stage is crucial in determining the most trustworthy model based on the lowest error index. Subsequently, the ideal GHI forecasting informs the research of the solar panels power production. This phase add precise factors such as the panels efficiency and surface area to approximate real world energy output [17]. These calculations are vital for determining the achievable energy production of a solar power plant in the context of Bandung City geographic and climatic circumstances.

The findings produced from this thorough analytical method will give significant evidence to inform policy choices and strategic planning for solar energy adoption in the region. The succeeding parts will go deeper into the model construction, validation techniques and the significance of the anticipated results for future energy solutions.

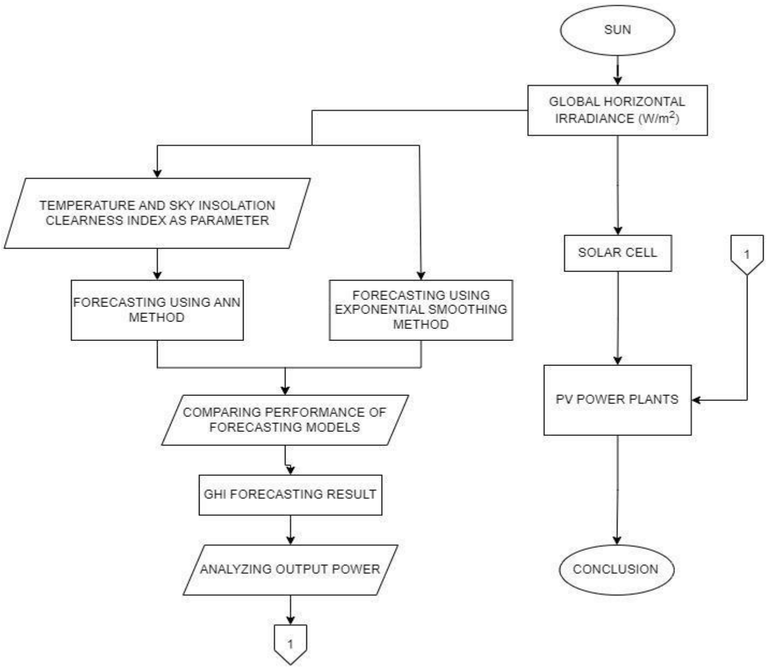

Figure 1. Research design flowchart

2.3. Forecasting methods

Ensuring the accuracy of GHI forecasts is crucial for maximizing the efficiency of solar power systems. This research utilized two separate techniques in order to achieve the most precise forecasting model for GHI intensity from 2021 to 2025. The selection of these techniques was based on their established proficiency in meteorological forecasting and their specific aptitude in managing the intricacies of solar radiation data. Through a comparative analysis of these two forecasting methodologies, our goal is to determine and improve the most dependable strategy for projecting solar irradiance [18]. This will ultimately contribute to the overall purpose of increasing solar energy technology and its practical implementation.

2.3.1. Exponential smoothing method

To enhance the accuracy of solar irradiance forecasts, we utilized exponential smoothing, a widely recognized technique for analyzing trends in time series data. Using the features with Microsoft Excel, we analyzed a dataset including solar radiation intensities measured in watts per square meter $\left(W/_{m^2}\right)$ [19].

The strategic deployment of exponential smoothing is laid out in Figure 2, where a succession of models was produced, each applying a distinct damping factor within the range of 0.1 to 0.9. This spectrum was chosen to extensively assess the method's sensitivity to changes in trend adjustment and its influence on the accuracy of the forecasts [20]. The ideal model, defined by the lowest error measure, is designated for a comparison evaluation against the ANN model's findings.

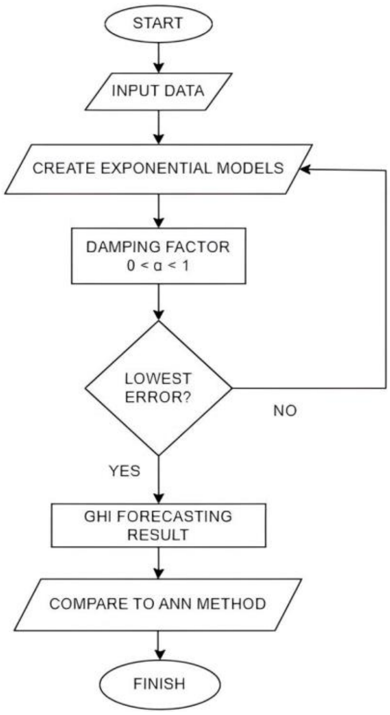

Figure 2. Exponential smoothing flow

Error quantification was a crucial component of this procedure, with the mean absolute percentage error (MAPE) acting as the main indicator for assessment. The MAPE formula, as follows gives a clear indicator of the model's performance [21]:

$$MAPE = \left(\frac{1}{n}\right)\sum\frac{|F_t - Y_t|}{Y_t} \times 100\% \quad (1)$$

Through this technique, we could discover the model's departure from real values, enabling us to fine-tune our approach to obtain a model synonymous with both dependability and precision in predicting [22].

2.3.2. Artificial neural network method

ANN are a highly advanced methodology in predictive analytics, specifically designed to handle the complexities of climatological data. The research utilized the ANN method to predict the intensity of GHI. The ANN methodology was chosen because it is capable of effectively dealing with intricate relationships between variables, such as temperature and cloud cover, which greatly influence the fluctuation of solar irradiance [23].

As shown in Figure 3, the process of developing the ANN model started with choosing and preparing the input dataset. The data were processed using the zaitun time-series application, which has neural network modeling capabilities. Our ANN architecture was created using a backpropagation algorithm and a bipolar sigmoid activation function, which is ideal for handling continuous input data such as irradiance levels [24]. During the model training phase, we performed nine different experiments to optimize the ANN structure, testing out different combinations of input and hidden layers. The experimental design aimed to calibrate the network to minimize the error rate [25]. In order to maintain consistency across experiments, we kept the momentum and learning rate value fixed at 0.5 and 0.05, respectively.

After conducting these experiments, the ANN model that produced the lowest error was selected for a comparative analysis with the exponential smoothing model. This evaluation is essential for determining the most effective forecasting method in terms of accuracy and reliability for GHI prediction within the context of our research [26].

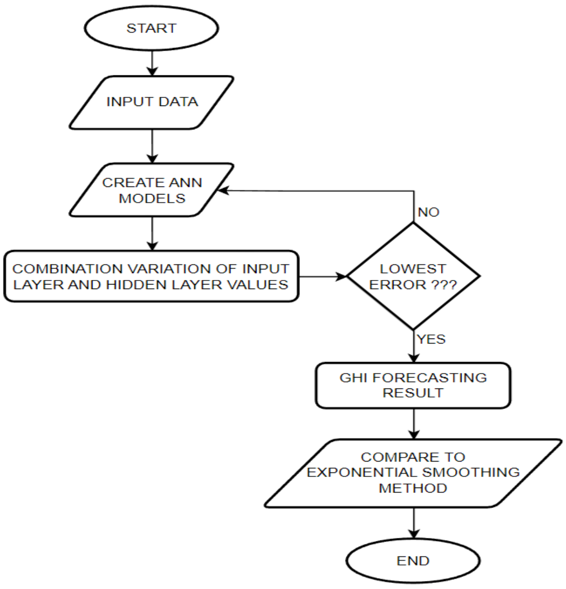

Figure 3. Artificial neural network algorithm flow

2.4. Output power calculation

The practical application of our research ends in the power output calculation, which is reliant on the projected GHI data produced from the most exact forecasting model identified. These calculations are crucial since they transform theoretical GHI values into actionable data regarding the energy generation of solar panels [27]. For our research, we combined the solar panels unique attributes namely, an efficiency rate of 15.13% and a surface area of 1.31 m^2 into the power output calculation. This is in accordance with industry standards for solar panel specs widely utilized in comparable climes to Bandung City. The calculation of power output was eased using the following [28].

$$Power\ (W) = GHI\left({}^{W}/_{m^2}\right) \times \eta(\%) \times A(m^2) \tag{2}$$

Employing this equation allows us to approximate the energy production during the anticipated time frame, giving a baseline for the prospective power generation from solar arrays. It’s via this essential phase that we can analyze the feasibility and efficiency of solar energy solutions adapted for the geographic and economic context of the location.

3. RESULTS AND DISCUSSION

This study contributes to existing research on predicting the intensity of (GHI) by conducting a comparison between exponential smoothing and artificial neural network techniques in Bandung City [29], [30]. This issue has not been extensively studied in the context of variable tropical climates. The results of our research demonstrate that artificial neural network achieves higher accuracy compared to exponential smoothing. Our findings indicate that ANN outperforms exponential smoothing in accuracy, reflecting its superior capability to handle the complex dynamics of solar irradiance in this region. Therefore, utilizing a more accurate artificial neural network model will improve the accuracy of our estimates for solar panel power production, thereby increasing the dependability of solar energi predictions from 2021 to 2025 [31].

3.1. Exponential smoothing method result

Prior to estimating Bandung City GHI intensity for the 2021 to 2025 period using the exponential smoothing approach, it was important to first determine the data set that would serve as the foundation for our forecasts. For this method, only GHI data from 2011 to 2020 were evaluated. The GHI data utilized, as illustrated in the following graph at Figure 4, demonstrates that sun irradiance in Bandung has a changing tendency. Notably, the maximum irradiance intensity was recorded in 2015 at 1,942,286 W/m^2, while the lowest was reported in 2011 at 1,670,978 W/m^2. This undulating trend illustrates the fluctuation of solar irradiance in Bandung, with intensity rising and declining year by year.

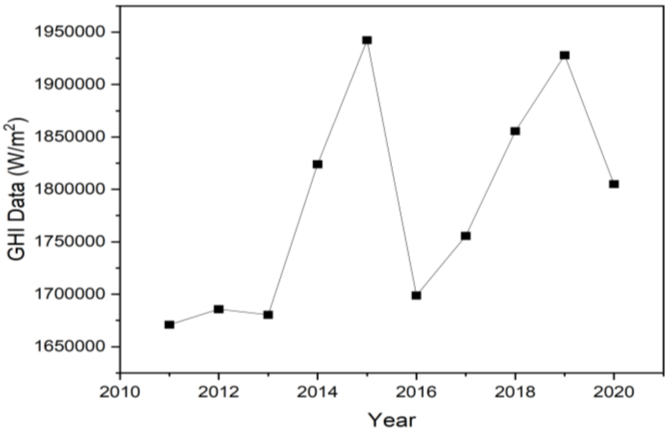

Figure 4. GHI data trend

Upon studying the forecasted results as they correspond with the damping factors in Table 1, we observed that the variation in the predicted values lowers as the damping factor increases. Forecasts with lower damping factors revealed more significant variations, whilst those with damping factors closer to 1 offered a more stable trend, as is shown with a damping factor of 0.9, which demonstrated negligible changes.

Table 1. Forecasted GHI results and error rates by damping factor

Year	GHI data	Damping factor								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
2011	1,670,978	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
2012	1,685,750	1,670,978	1,670,978	1,670,978	1,670,978	1,670,978	1,670,978	1,670,978	1,670,978	1,670,978
2013	1,680,336	1,684,273	1,682,796	1,681,318	1,679,841	1,678,364	1,676,887	1,675,410	1,673,932	1,672,455
2014	1,823,959	1,680,730	1,680,828	1,680,631	1,680,138	1,679,350	1,678,266	1,676,888	1,675,213	1,673,243
2015	1,942,286	1,809,636	1,795,333	1,780,961	1,766,431	1,751,655	1,736,543	1,721,009	1,704,962	1,688,315
2016	1,698,736	1,929,021	1,912,895	1,893,888	1,871,944	1,846,970	1,818,840	1,787,392	1,752,427	1,713,712
2017	1,755,609	1,721,765	1,741,568	1,757,282	1,768,019	1,772,853	1,770,799	1,760,795	1,741,689	1,712,214
2018	1,855,589	1,752,225	1,752,801	1,756,111	1,760,573	1,764,231	1,764,723	1,759,239	1,744,473	1,716,554
2019	1,927,958	1,845,253	1,835,031	1,825,746	1,817,583	1,809,910	1,801,069	1,788,144	1,766,696	1,730,457
2020	1,805,003	1,919,687	1,909,373	1,897,294	1,883,808	1,868,934	1,851,825	1,830,088	1,798,948	1,750,207

Figure 5 further illustrates that a damping factor of 0.7 results in the lowest error rate of 4.44%, showing the best level of predicting precision. This discovery is crucial because it indicates that selecting an appropriate damping factor may greatly enhance the precision of solar irradiance forecasts, which is essential for optimizing the operation of solar power plants. Due to the proven efficacy of the 0.7 damping factor, it was chosen to project future GHI values. The projections for the period from 2021 to 2025 are shown in Table 2.

Table 2 shows a consistently steady GHI intensity expected over the next five years, with an average yearly value of 1,824,032 W/m^2. The regularity of solar energy availability in Bandung is advantageous for energy planning, as it provides a dependable foundation for optimizing the usage of solar energy. This portion of the research not only confirms the usefulness of the exponential smoothing approach in tropical environments but also emphasizes the crucial need of adjusting model parameters to obtain reliable forecasts. Further improving these parameters, particularly the damping factor, might boost the accuracy and dependability of solar irradiance estimates in similar environmental situations.

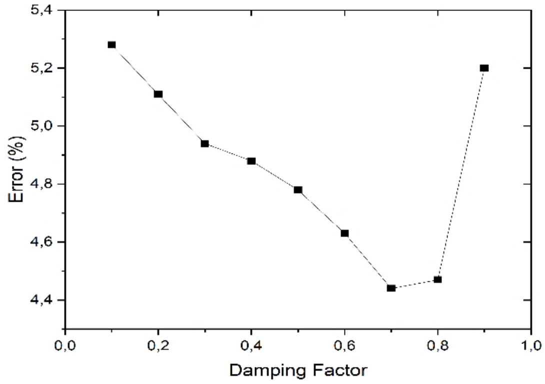

Figure 5. Error rates across damping factors

Table 2. Forecasted GHI intensity for 2021-2025

Year	Forecasting result (W/m^2)
2021	1,822,563
2022	1,824,820
2023	1,824,143
2024	1,824,346
2025	1,824,285
Average	1,824,032

3.2. Artificial neural network method result

Prior to implementing the forecasting of GHI intensity using the ANN method, a detailed review of the key input data GHI (W/m²), temperature (°C), and Sky Insolation Clearness Index (SICI) was required. These inputs constitute the core of our ANN model, which attempts to boost the accuracy of solar irradiance forecasts in Bandung City.

Figure 6 demonstrates the interdependencies within the data. The GHI, temperature, and SICI statistics from 2011 to 2020 show significant variations that are crucial for training the ANN model. Notably, while the temperature remains relatively stable with an average of approximately 23 °C, the SICI index fluctuates more substantially, reaching its peak in 2019 and its lowest in 2016. This variability indicates the complex nature of the climatic factors influencing solar irradiance, which the ANN method is well-equipped to handle due to its ability to model non-linear relationships.

During the training process of the ANN, different combinations of input and hidden layer values were tested, while keeping other parameters such as the learning rate and momentum constant. This approach of random combination in the trials was crucial to establishing the configuration that produced the lowest error index in predicting output. Nine iterations were undertaken to identify the model configuration with the smallest error, as summarized in Table 3. Each iteration explored varying arrangements of the input and hidden layers to refine the accuracy of our forecasts, demonstrating the adaptive capability of the ANN method to optimize based on the intricate patterns observed in the input data.

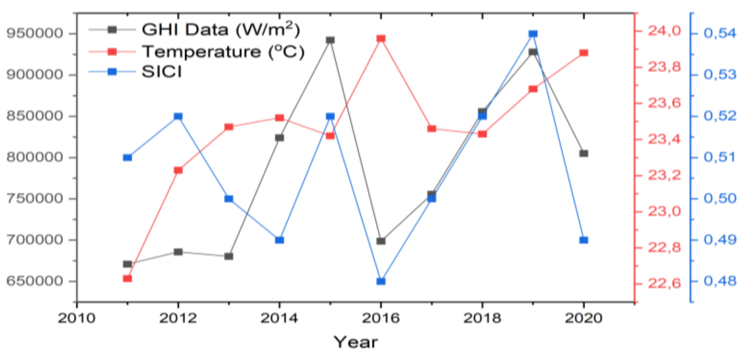

Figure 6. Bandung City GHI, temperature, and SICI data trend

Table 3. ANN model error rates during training

Training	Learning rate	Momentum	Input layer	Hidden layer	Error
Iterate 1	0.05	0.5	12	10	0.025940
Iterate 2			10	10	0.198387
Iterate 3			10	12	0.120557
Iterate 4			12	12	0.011986
Iterate 5			10	11	0.061338
Iterate 6			12	11	0.032094
Iterate 7			11	10	0.050909
Iterate 8			11	11	0.036640
Iterate 9			11	12	0.062182
Average					0.066670

Upon completing the ANN training trials, abroad range of error values was recorded, with the average error rate throughout all iterations at 6.67%, peaking at 19.84% and decreasing to a low of 1.12%. These numbers will be contrasted against the outputs of the exponential smoothing approach for a comparative assessment. The forecasted GHI for the next five years, as predicted using the ANN method demonstrated varying error rates and forecast values.

Table 4 offers a complete review of the anticipated GHI values for each year from 2021 to 2025, across several experimental models. The data suggests that the maximum expected GHI intensity is anticipated in 2023 during the fifth iteration at 1,954,519 W/m², suggesting that this model configuration would produce the most robust forecast for that time. Conversely, the lowest anticipated GHI emerges in 2025 during the seventh iteration at 788,107 W/m², showing possible areas for model development.

These results indicate the ANN aptitude to adapt to complicated datasets and its promise for refining solar irradiance estimates. However, the changes in forecast accuracy over multiple iterations imply that more in-depth investigations are needed to tune model parameters constantly. By expanding our understanding of the linkages between input variables and their influence on GHI forecasts, future versions of the model might possibly minimize forecasting errors and boost dependability for solar energy planning.

Table 4. Forecasted GHI by ANN method trials

Training	GHI forecasting (W/m^2)					Average (W/m2)
	2021	2022	2023	2024	2025	
Iterate 1	1,855,139	1,862,693	1,193,512	1,607,539	943,908	1,492,558
Iterate 2	1,690,979	951,625	1,820,017	967,781	1,448,812	1,375,843
Iterate 3	1,845,512	1,549,038	1,277,297	1,553,750	1,298,327	1,504,785
Iterate 4	1,744,827	1,427,517	1,108,571	1,028,482	987,178	1,259,315
Iterate 5	1,852,266	1,704,135	1,954,519	1,845,500	1,940,916	1,859,467
Iterate 6	1,833,816	1,466,897	1,327,083	1,285,378	1,247,794	1,432,194
Iterate 7	1,902,674	1,352,195	1,800,412	1,862,011	788,107	1,541,080
Iterate 8	1,804,211	1,880,268	1,215,772	1,703,149	1,807,426	1,682,165
Iterate 9	1,898,526	1,893,945	1,944,579	1,201,746	1,404,789	1,668,717

3.3. Comparison performance of method

The performance comparison between the exponential smoothing and ANN approaches is dependent on the models that attained the lowest error index from each approach. The exponential smoothing model with a damping factor of 0.7 and the ANN model from the fourth iteration with 12 input and hidden layers were identified for this comparative study. These picks were based on the superior error indices produced in their respective approaches.

The statistics from Table 5, showed the diverse predicting outcomes achieved by the exponential smoothing and ANN method. The exponential smoothing method gave rather steady GHI forecasts year over year, averaging an expected value of around 1,824,032 W/m^2. In comparison, the ANN technique gave more variable projections, with the GHI peaking at 1,744,827 W/m^2 and plummeting to 987,178 W/m^2, demonstrating a considerable divergence in the predicting outcomes.

Table 5. Comparison of forecasting results by method

Year	Exponential smoothing	Artificial neural network
2021	1,822,563	1,744,827
2022	1,824,820	1,427,517
2023	1,824,143	1,108,571
2024	1,824,346	1,028,482
2025	1,824,285	987,178
Average	1,824,032	1,259,315

As seen in Figure 7, the error rates differed dramatically between the two strategies. Exponential smoothing maintained a constant error rate between 4-6%, whereas ANN displayed changing error rates, culminating at 19.84%. This variance is related to the intrinsic disparities in their processing processes. The stability of exponential smoothing implies a close alignment with the actual GHI data, while the flexibility of ANN, controlled by the arrangement of its layers and neurons, allows it to capture more complicated patterns, albeit at the risk of overfitting. Our analysis reveals that while the average error rate was lower for exponential smoothing (4.86%) compared to ANN (6.67%), the latter's best model in the fourth iteration had the lowest error rate of 1.12%, indicating its potential when optimally adjusted. This shows that ANN models, with their capacity to include various parameters and alter their learning process, could give an edge in capturing the fluctuations of solar irradiance more effectively than exponential smoothing.

Future research may consider modifying ANN configurations to boost stability and minimize variability in forecasts. Investigating how different configurations effect the learning process and prediction accuracy might lead to more robust forecasting models capable of responding to altering environmental variables without overfitting. Recent data imply that the resilience of forecasting models is vital for trustworthy solar power production estimate. Our findings give clear evidence that the choice of model and its configuration considerably influences prediction accuracy, underscoring the need of selecting and modifying forecasting models based on unique geographical and climatic variables.

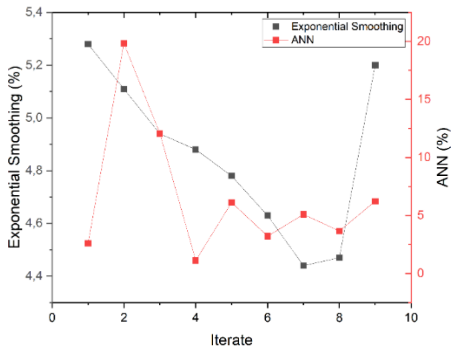

Figure 7. Error comparison across methods

3.4. Analyze output power

The potential output of solar panels in Bandung City has been quantitatively analyzed using the GHI values anticipated by the ANN approach. A solar panel power generation is largely controlled by the solar irradiation it receives, which in conjunction with the panels characteristics, sets the foundation for output power calculations. Such assessments are crucial for estimating the performance of a photovoltaic solar power plants. Using the forecasted GHI data and applying the details of the solar panel, we have estimated the prospective power production using (2), as indicated in Table 6.

Table 6. Forecasts between GHI and power

Efficiency	Cross section area	Year	GHI (W/m^2)	Power (W)
15.3%	1.31 m2	2021	1,744,827	349,716
		2022	1,427,517	286,117
		2023	1,108,571	222,191
		2024	1,028,482	206,139
		2025	987,178	197,860
Average output power (W)				252,405

Table 6 presents the power output estimations based on the ANN projected GHI values, using the characteristics of a typical GH200M48 solar panel with an efficiency of 15.3% and a cross-sectional area of 1.31 m^2. These specs give a detailed view into the power potential, eliminating other essential elements such as operational temperature, inclination angle, power loss, and extra component specifications. From the data, we find a steady fall in yearly output, strongly associated with the GHI values where greater annual GHI leads to an increase in electrical power generation potential. Thus, the performance of the solar panels is essentially connected to the intensity of GHI. Over the forecast period from 2021 to 2025, the average annual energy production is expected at 252,405 watts, with the total potential power output estimated at 1,262,023 watts.

This study highlights the direct association between GHI and the output power of solar panels, stressing the necessity of exact and dependable solar irradiance predictions. Future study should aim on boosting the accuracy of GHI forecasts, potentially using more advanced ANN models or alternative forecasting approaches that combine wider climate data components. Additionally, evaluating the performance implications of different solar panel efficiencies and configurations across diverse environmental circumstances might further enhance energy production projections and solar plant performance. The findings from this investigation clearly illustrate that the effectiveness of solar panels in converting solar irradiance to electricity is directly controlled by the varying levels of GHI, rather than just by technological elements of the panels or external climatic variables. This association is essential for regulators and investors in the solar energy sector, as it stresses the necessity for sophisticated forecasting methods to optimize the utility and profitability of solar energy installations.

4. CONCLUSION

This research set out to test the usefulness of the exponential smoothing and ANN method in forecasting the GHI for Bandung City. The exponential smoothing method exhibited encouraging results in its seventh iteration, applying a damping factor of 0.7 and obtaining an error rate of 4.44%. The GHI values varied from a low of 1,822,5663 W/m^2 in 2021 to a maximum of 1,824,820 W/m^2 in 2022, averaging 1,824,032 W/m^2 yearly. The ANN method, however, surpassed this performance in its fourth iteration, with a complicated design of 12 input and hidden layers, obtaining a considerably reduced error rate of 1.12%. The GHI ranged from a low of 987,178 W/m^2 in 2025 to a high of 1,744,827 W/m^2 in 2021, averaging 1,259,315 W/m^2 yearly.

The comparison research indisputably reveals the greater accuracy of the ANN method in predicting GHI, as indicated by its reduced error rate. The ramifications for solar power generation are enormous, with the anticipated GHI values directly guiding the possible energy yield. Over the 2021–2025 period, the average power production is predicted to be 252, 405 watt with a high of 349,716 watt in 2021 and a low of 197,860 watt in 2025. Consequently, a solar panel with a specification of 15.3% efficiency and 1.31 m^2 surface are could generate a total of 1,262,023 watt throughout this five year timeframe.

While the conclusions of this research are informative, the limitations owing to the dataset's breadth and the range of characteristics employed should be acknowledged. Future study could examine increasing the dataset and including a larger array of factors to boost the precision of the projections. Additionally, employing a more comprehensive trial and error approach with several iterations may enhance the models further. It is also encouraged to study and integrate more complex forecasting approaches to enhance the accuracy of GHI forecasts. This work seeks to act as a springboard for ongoing research in this sector, seeking to progressively perfect the forecasting models for solar irradiance and contribute to the optimization of solar energy harnessing systems.

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