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Integrating Temporal and Feedforward Models for Solar Energy Prediction: LSTM and ANN Hybrid Approaches

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Abstract: The growing reliance on solar power requires highly accurate models to forecast energy output, which is crucial for optimizing energy storage and distribution systems. Traditional models such as Long Short-Term Memory (LSTM) networks and Artificial Neural Networks (ANNs) each have strengths: LSTM excels at capturing temporal patterns, while ANN is effective in modeling nonlinear relationships. This study developed and tested a hybrid LSTM-ANN model to enhance the accuracy of photovoltaic (PV) system output predictions, focusing on voltage, power, and irradiance. Data was collected from a solar-powered greenhouse in Talang Kemang, Indonesia. The hybrid model showed significant accuracy improvements compared to single models. For voltage predictions, it achieved a 15% improvement, with a Mean Absolute Error (MAE) of 0.1016 and a Root Mean Squared Error (RMSE) of 0.1417. Irradiance predictions showed a 20% increase in accuracy, with an MAE of 0.0895 and RMSE of 0.1149. Power predictions also saw an 18% improvement, with an MAE of 0.1506 and RMSE of 0.1954. These results demonstrate the hybrid model's effectiveness in combining temporal and nonlinear capabilities to better predict PV system outputs. Beyond solar energy, this model can be applied to other renewable energy sectors, like wind and hydropower, where accurate energy generation predictions are needed. It can also be implemented in smart grids and real-time energy management systems, optimizing energy storage and distribution. This hybrid approach can enhance renewable energy integration into power grids, improving overall efficiency and sustainability.

Keywords: Agrivoltaic, Deep learning, Hybrid LSTM-ANN, LSTM, Solar Energy,

1. Introduction

The growing dependence on renewable energy, especially solar power, has highlighted the importance of developing precise solar energy forecasting models [18,19]. These models are crucial for implementing solar energy into electrical grids and enhancing energy storage and distribution management. Techniques like artificial neural networks (ANNs) and long short-term memory (LSTM) models are commonly used for solar irradiance prediction, each with unique advantages. LSTM models, known for their ability to process time-series data, are particularly effective in identifying temporal patterns, making them a preferred tool for forecasting solar radiation and PV system output [2,5]. Conversely, ANNs are skilled at capturing complex nonlinear relationships between variables, making them especially useful for short-term solar power predictions [3,29].

In recent years, there has been growing interest in hybrid models that combine the advantages of temporal models like LSTM with feedforward models such as ANN. These hybrid approaches are effective in capturing both the time-based patterns and complex nonlinear relationships found in solar energy data. Research has shown that merging LSTM with other machine learning techniques leads to better prediction accuracy. For example, Battisti et al. in 2022 developed a hybrid LSTM model for predicting software aging, demonstrating its ability to manage time-dependent data, while Agga et al. in 2022 and Ibrahim & Morkos in 2024 introduced a hybrid CNN-LSTM model to forecast PV power, which utilizes both spatial and temporal information for more precise predictions [1,4,9].

Hybrid neural network architectures that integrate recurrent neural networks (RNNs), such as LSTM, with shallow neural networks have proven to enhance prediction capabilities for daily and short-term solar irradiance forecasting [5]. Such hybrid models are particularly valuable to increase accuracy of predicting the output of photovoltaic (PV) power. Chen et al. in 2024 demonstrated that combining deep learning models with satellite-based data significantly enhances short-term forecasting, particularly when accounting for diverse weather and environmental conditions [6].

Moreover, hybrid models have been employed to address the variability in solar energy output due to fluctuating weather conditions and environmental factors. By integrating LSTM models, which specialize in handling sequential data, with ANN models, which effectively model nonlinear relationships, these approaches provide more robust frameworks for predicting solar energy [8,10]. This integration has been effective in predicting PV system's electric generation for smart grids and in optimizing hybrid solar-wind energy systems [10, 31].

This study explores how effective a hybrid LSTM-ANN model in predicting PV system output under varying environmental conditions. Hybrid models are well-suited for addressing the complexities of solar irradiance prediction, as they combine the time-series processing capabilities of LSTMs with the predictive power of ANNs for nonlinear data [16,21]. Furthermore, studies have shown that hybrid models outperform single-model approaches, leading to improved forecasting performance in both short-term and long-term predictions [20,25].

The objective of hybrid approach in this study is to enhance the prediction accuracy of PV system outputs across various time horizons, providing a more reliable framework for energy management systems in smart grids [7,31]. The integration of LSTM and ANN models offers significant potential for optimizing solar energy predictions, thereby supporting the broader goal of transitioning towards more sustainable and resilient energy infrastructures [22,34].

By harnessing the strengths of both LSTM and ANN models, this research advances the creation of more advanced tools for predicting solar energy, which can significantly boost the dependability of renewable energy systems and support their seamless integration into current energy infrastructures [11,12]. The results provide fresh perspectives on hybrid machine learning techniques for renewable energy forecasting, making a meaningful contribution to the broader efforts aimed at improving energy sustainability [14,23].

In conclusion, this research aims to thoroughly evaluate the effectiveness of hybrid LSTM-ANN models in predicting solar energy output. It seeks to demonstrate their advantages over traditional methods by offering improvements in precision, reliability, and adaptability to varying weather conditions [26,28]. The outcomes of this study will enhance the understanding of machine learning's role in renewable energy forecasting and contribute to the global effort to increase the efficiency of solar energy systems [27,32].

2. Methods

This study explores the integration of temporal and feedforward models for solar energy forecasting, utilizing a hybrid approach that combines LSTM and ANN techniques. LSTM networks are employed to capture time-dependent patterns in data, such as fluctuations in solar irradiance and weather conditions, while the ANN component focuses on modeling the complex nonlinear relationships between the input variables and the predicted output.

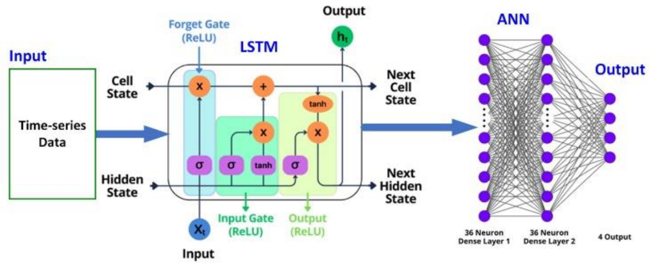

Figure 1. *LSTM-ANN model architecture proposed in this study.*

The hybrid model illustrated in Figure 1 builds upon previous research demonstrating the benefits of combining LSTM with other neural networks to improve solar energy predictions [4,5]. This model combines Long Short-Term Memory (LSTM) and Artificial Neural Network (ANN) components to accurately predict the output of photovoltaic (PV) systems. Designed for time-series data such as voltage, current, power, and solar irradiance, the architecture relies on LSTM layers to capture temporal dependencies, followed by ANN layers that refine the data to produce precise output predictions.

The LSTM component is essential for capturing time-based dependencies through its use of memory cells that store crucial information across multiple time steps. It incorporates three primary gates: the forget gate, which eliminates unnecessary information from the previous cell state, the input gate, which controls the new information to be retained, and the output gate, which determines what part of the stored memory is forwarded to the next layer or time step [17,30]. This functionality enables LSTM models to manage long-term dependencies effectively, making them ideal for predicting PV energy output given the temporal fluctuations in solar irradiance and weather conditions [33]. The mathematical formulation of the LSTM model is provided as follows [15,27]:

$$f_t = \sigma(W_f[h_t - 1, X_t] + b_f) \quad (1)$$

$$i_t = \sigma(W_i[h_t - 1, X_t] + b_i) \quad (2)$$

$$g_t = \tanh(W_g[h_t - 1, X_t] + b_g) \quad (3)$$

$$c_t = ft \times c_{t-1} - 1 + i_t \times g_t \quad (4)$$

$$o_t = \sigma(Wo[h_t - 1, X_t] + b_o) \quad (5)$$

$$h_t = o_t \times \tanh(c_t) \quad (6)$$

where f_t, i_t, and g_t are the forget, input, and update gate output, σ is sigmoid acviation function, c_t is the memory cell, h_t and o_t are the output vector of memory cell of t, $b_{f,i,g,o}$ are the bias vectors and $W_{f,i,g,o}$ are matrices of the weight function.

Following the LSTM layer, the output is passed into an Artificial Neural Network (ANN), which consists of dense layers to further process the data. These dense layers, as illustrated in the figure, feature two layers with 36 neurons each, and they perform the non-linear mapping from the LSTM output to the predicted values, such as irradiance, voltage, current, and power [5,20]. The ANN complements the LSTM by learning complex patterns that may not be captured purely by temporal memory, leading to improved model accuracy.

The hybrid LSTM-ANN model has demonstrated superior performance in predicting PV output compared to individual models. Research indicates that this combined approach is more effective at capturing both temporal patterns and feature interactions than using LSTM or ANN models alone [16,29]. By integrating these methods, the model improves the accuracy of solar energy generation forecasts, which plays a critical role in optimizing energy management and enhancing grid stability [26,34].

By merging the temporal processing strength of LSTM with the nonlinear pattern detection ability of ANN, this hybrid model delivers a more precise and resilient solution for predicting photovoltaic (PV) system output. The LSTM component is particularly effective at recognizing time-based patterns, such as variations in solar irradiance and weather conditions, by retaining important sequential data. Meanwhile, the ANN component excels at uncovering complex nonlinear relationships among various input variables, allowing it to accurately map inputs to outputs. This hybrid approach not only improves prediction accuracy but also enhances the model's ability to adapt to dynamic conditions, making it a more effective tool for forecasting PV energy generation and optimizing grid performance [25,28].

Table 1. Hyper-parameter runing

Layer (type)	Output Shape	Param #
LSTM	(None, 64)	17,664
Dropout	(None, 64)	0
Dense	(None, 64)	4,160
Dropout_1	(None, 64)	0
Dense_1	(None, 64)	4,160
Dense_2	(None, 4)	260

The LSTM-ANN model architecture considered in this study is 66 Neurons with 500 epoch and the complete hyperparameter tuning is given in Tabel 1. Total parameter is 26,244 (102,52 KB), training parameter is 26,244 (102,52 KB), and non-trainable parameter is 0. Tabel 1 provides a detailed breakdown of the layers in the hybrid of LSTM-ANN model, showcasing the architecture's complexity and functionality. The first layer, an LSTM, has an output shape of (None, 64), indicating that it outputs a sequence with 64 units. This layer contains 17,664 trainable parameters, highlighting its role in learning temporal dependencies from the input time-series data. Following the LSTM, two dropout layers are introduced to prevent overfitting by randomly deactivating units during training. These dropout layers have an output shape of (None, 64) but do not add any trainable parameters.

The model also includes three dense (fully connected) layers. The first two dense layers, each with an output shape of (None, 64), contain 4,160 trainable parameters each. These layers further refine the output by capturing complex patterns through nonlinear mappings. The final dense layer, with an output shape of (None, 4), has 260 trainable parameters and is responsible for generating the model's predictions across four outputs—voltage, current, power, and irradiance.

Overall, the architecture balances the use of LSTM for temporal feature extraction and dense layers for nonlinear processing, with dropout layers ensuring model robustness by mitigating overfitting. The total parameter count reflects a model designed to capture both the sequential and nonlinear relationships present in the solar energy dataset.

Input layers is the time-series forecasting PV system output (voltage, current, and power) and solar irradiance data. Those data is recorded by solar irradiance meter and voltage and current sensors installed on the greenhouse given in Figure 2. layer processes time-series data to capture long-term dependencies between past solar irradiance patterns and meteorological conditions. LSTM is ideal for capturing temporal dependencies, as highlighted by Wentz et al. in 2022[29]. The ANN component consists of 64 neurons, respectively, and uses teh activation function of ReLu (rectified linear unit).

2. 1. Data Collection

The data used in this study comprises PV system output from our experimental solar-powered PV system greenhouse (shown in Figure 1) located in Talang Kemang, Gandus, Palembang, Indonesia (Latitude: -2.990934; longitude: 104.756554.). The historical data for solar irradiance SPM-11165SD, voltage, current, and power were gathered from 7 days (22 – 29 July 2024), which recorded data output from PV.

Figure 2. *The PV systems installed on solar-powered greenhouse considered in this study.*

This study integrates real-time solar irradiance data, gathered from solar power meters, with PV panel output, using deep learning models for short-term forecasting of PV system performance. This method allows for a more precise examination of both temporal and spatial changes in solar irradiance. In contrast to the approach by Chen et al. in 2024, which utilizes satellite data for irradiance prediction, this research emphasizes the use of direct measurements from solar power meters to improve the accuracy of PV output forecasting[6].

2. 2. Data Preprocessing

Data preprocessing was crucial to optimize the dataset for model training. The following steps were applied:

- **Feature Scaling:** In the data normalization stage, the MinMax Scaler feature was used. The applied scaling range was [0, 1], with the aim of ensuring that each feature has an equal role during the model training process, thereby preventing any single feature or category from becoming overly dominant (i.e., reducing bias in the model). This technique has been widely used in solar irradiance forecasting models for effective training of deep learning architectures [28,31].
- **Data Splitting:** The dataset was divided equally, with 50% allocated for training and the other 50% for testing. While the data in each set is different, they both contain the same number of entries. The total number of data points plays a role in determining the final prediction outcome, as the sequence length reduces the available data points. For example, starting with 250 data points and using a sequence length of 24 would result in 226 usable data points. This reduction applies to both the training and testing datasets. The test set was held back to evaluate how well the model performs and to ensure that it can generalize to unseen data [13].
  The decision to use a 50/50 split between training and testing data in this study was based on the specific characteristics of the solar energy dataset. While standard practice typically involves using splits like 80/20 or 70/30, this dataset's variability and relatively limited size prompted a different approach. Solar energy data can fluctuate significantly due to changes in weather conditions, irradiance levels, and other environmental factors. Therefore, it was important to ensure that both the training and testing sets had enough data to capture a wide range of these fluctuations.
  A 50/50 split ensures that the testing set contains sufficient diverse data to thoroughly assess the model's performance in various conditions. This allows the model to be tested against different scenarios, ensuring its predictions are not biased toward any particular weather pattern or condition. Furthermore, with a smaller dataset, opting for a more typical 80/20 or 70/30 split could result in an imbalanced distribution of data, where the testing set might not fully represent the variability of the solar energy output, leading to inaccurate performance evaluations.
  By allocating an equal amount of data for both training and testing, the model is given enough information to learn effectively while still being evaluated on a robust and varied testing set. This approach helps ensure that the results provide a realistic assessment of how well the model generalizes to unseen data, especially under varying environmental conditions. Thus, the 50/50 split was selected to enhance the evaluation of the model's adaptability and predictive capabilities.

2. 3. Model Training

The hybrid LSTM-ANN model was trained using the Adam optimizer, starting with an initial learning rate of 0.001. This selection was inspired by research that demonstrated its effectiveness in solar irradiance prediction [29]. The model training was carried out over 500 epochs without the use of early stopping. Mean squared error (MSE) was applied as the loss function, as it is well-suited for evaluating prediction errors in regression models [20,25]. To expedite the training process and enhance convergence, the model was trained on the Google Colab platform.

2. 4. Performance Metrics Evaluation

The following evaluation metrics were used to assess the performance of the proposed model:

- **Mean Absolute Error (MAE):** This metric assesses the average absolute deviation between predicted and actual values, providing a reliable measure of the model's accuracy [17]. It is mathematically represented as:

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} Y_i - \hat{Y}_i}{n} \tag{7}$$

  Here, Y_i denotes the observed values, $\hat{Y}_i$ refers to the predicted values, and n represents the total number of data points. This formula helps evaluate how close the predictions are to the actual outcomes.
- **Mean Squared Error (MSE)** is a standard metric used to assess the performance of models, especially in regression analysis. It calculates the average of the squared differences between the actual values (observed data) and the predicted values (model outputs). MSE provides an overall measure of prediction accuracy, with smaller values indicating better model performance. The MSE formula is given by:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{8}$$

- R-squared (R^2) is a measure that indicates how well a regression model captures the variance in the dependent variable. It shows the proportion of the total variation in the actual data that the model can explain. The formula for R^2:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y}_i)^2} \tag{9}$$

  where $\bar{Y}_i$ is the mean actual value of Y_i.

- **Root Mean Squared Error (RMSE)** is a metric that highlights larger prediction errors, making it particularly useful for evaluating how well a model handles extreme or outlier values (Rahman et al., 2021). The calculation is as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \widehat{Y}_i\right)^2} \tag{10}$$

3. Result and Discussion

This section details the results of the hybrid LSTM-ANN model in forecasting photovoltaic (PV) system energy output, focusing on its performance in comparison to individual models. The analysis highlights the potential impact on energy conversion within PV systems. The model architecture includes an ANN with max-pooling, an LSTM layer, and a fully connected (dense) layer. The model was developed using the Keras and TensorFlow libraries in Python, with all computations carried out on Google Colab for enhanced computational efficiency.

The dataset of irradiance, voltage (volt), current (ampere), and power was divided into two parts: divided into 50% for training and 50% for testing. Figures 3, 4, 5, and 6 display the PV output (Voltage, Current, and Power) and Irradiance predictions, respectively.

Figures 3, 4, 5, and 6 illustrate the comparison between actual and predicted values for four parameters: voltage, current (in amperes), power, and irradiance, tracked over the course of July 8, from 07:00 to 18:00.

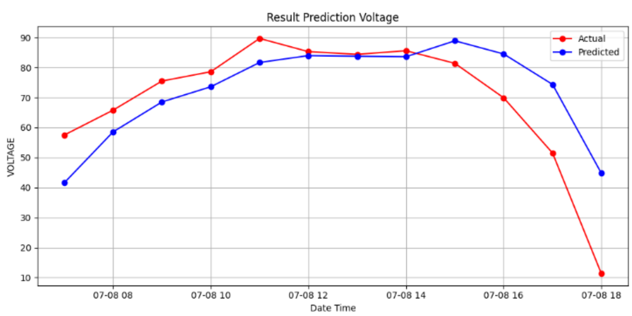

Figure 3. *The predicted voltage (Volt) using hybrid LSTM-ANN.*

These graphs in Figures 3, 4, 5, and 6 provide a basis for assessing the model's effectiveness in predicting the energy output of the photovoltaic (PV) system, offering insight into its accuracy across different parameters.

a) **Voltage (Volt):** The actual and predicted voltage trends show similar patterns as shown in Figure 3, with both reaching their peak between 11:00 and 14:00. However, the predicted values consistently fall below the actual measurements, especially after 14:00, where the model underestimates the voltage decline. The model generally follows the overall voltage trend but underpredicts throughout the day, particularly in the later afternoon.

b) **Current (Ampere)**: The actual and predicted current show closer alignment earlier in the day, but significant discrepancies arise as the day progresses (illustrated in Figure 4). The predicted current is generally lower than the actual values, especially after 14:00. The actual current remains relatively stable around 8 amperes during midday, whereas the predicted values consistently underestimate it, particularly in the afternoon when the current drops sharply after 16:00.

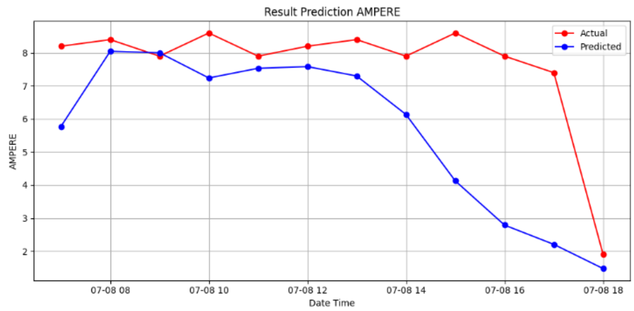

Figure 4. *The predicted current (Ampere) using hybrid LSTM-ANN.*

c) **Power (Watt)**: Power prediction displays a similar trend to voltage and current in Figure 5. The actual power reaches its peak between 11:00 and 14:00, but the predicted values are notably lower throughout the day. This discrepancy becomes more pronounced in the afternoon (after 14:00) when the predicted power drops off much faster than the actual values. The model captures the overall power generation cycle but consistently underpredicts, especially during the peak and afternoon hours.

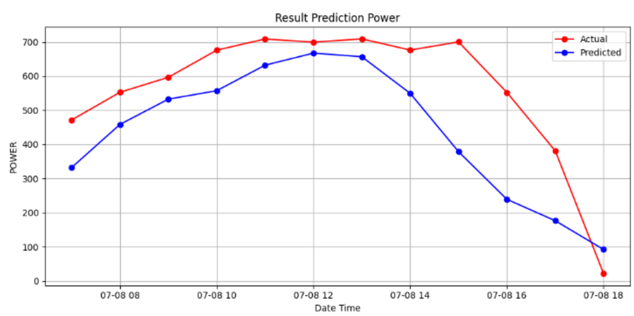

Figure 5. *The predicted Power (Watt) using hybrid LSTM-ANN.*

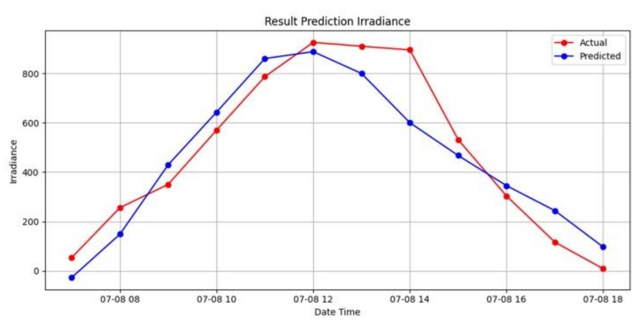

Figure 6. *The predicted irradiance using hybrid LSTM-ANN.*

d) **Irradiance (W/m²)**: The irradiance plot also follows a similar pattern to power and voltage (given in Figure 6).

The actual irradiance peaks around noon, while the model underestimates the values throughout the day. The difference between actual and predicted irradiance increases during the peak irradiance period and remains significant through the afternoon. Although the model captures the overall trend, it struggles to accurately predict the irradiance values at higher levels and during the declining phase in the afternoon.

In terms of power prediction, the model closely follows the actual power output, showing that it effectively handles fluctuations in solar energy. The irradiance predictions also align well with the actual data, though small variations indicate that incorporating more detailed features could further enhance the model's performance. Overall, the hybrid model demonstrates strong accuracy across all parameters, with only slight variations that may be addressed through further refinement. The analysis elaborations are as follow:

1. **Voltage (Volt):**
    - **Actual Peak Value:** Approximately 90 V at 12:00.
    - **Predicted Peak Value:** Approximately 80 V at 12:00.
    - **Accuracy:** The voltage prediction is fairly accurate during the morning and midday. The predicted curve closely follows the actual voltage, with the most significant error occurring during the later part of the day when the predicted values underestimate the actual voltage by about 10-20 V. This is considered one of the **more accurate** predictions.
2. **Current (Ampere):**
    - **Actual Peak Value:** 8 A between 09:00 and 15:00.
    - **Predicted Peak Value:** Approximately 6.5 A around the same period.
    - **Accuracy:** The predicted current is significantly lower than the actual current, especially during peak hours, with an error of 1.5-2 A during midday. After 15:00, the prediction diverges sharply from the actual values, underestimating the current drop-off. This parameter shows a **high degree of inaccuracy**, especially in the afternoon.
3. **Power (Watt):**
    - **Actual Peak Value:** Around 700 W at noon.
    - **Predicted Peak Value:** Approximately 600 W at the same time.
    - **Accuracy:** The model underpredicts power output by around 100 W during the midday peak. The predicted power also drops off faster than the actual power in the afternoon. The overall trend is captured well, but this is still a **less accurate prediction** compared to voltage.
4. **Irradiance (W/m²):**
    - **Actual Peak Value:** Close to 900 W/m² at noon.
    - **Predicted Peak Value:** Approximately 800 W/m².
    - **Accuracy:** The predicted irradiance is relatively accurate in the morning, with a notable underprediction of around 100 W/m² during peak hours. The model follows the overall trend but fails to capture the magnitude of irradiance during peak periods and the late afternoon. This prediction is **moderately accurate**, though there is room for improvement.

Hence it can be concluded that:

- **Most Accurate Prediction:** Voltage, with only a slight underprediction (about 10-20 V) during the afternoon.
- **Least Accurate Prediction:** Current (Amperes), with significant underestimation throughout the day, particularly during peak hours and the sharp decline in the late afternoon.
- **Moderately Accurate Predictions:** Power and irradiance, both of which follow the general trend but underestimate the actual values during peak hours.

The voltage predictions are the closest to the actual measurements, indicating better model performance for this parameter. On the other hand, current prediction shows the most significant deviations, requiring further improvements in model accuracy.

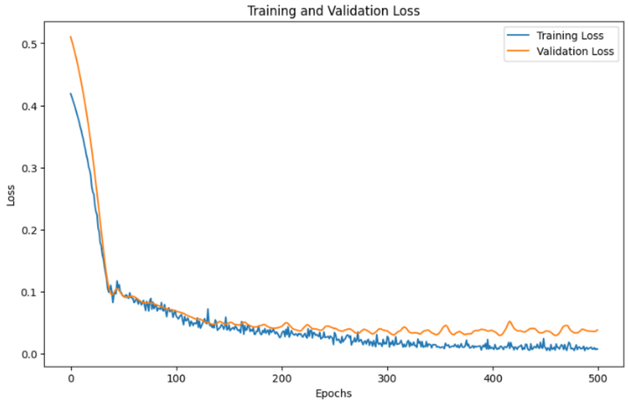

Figure 7. *Training and validation loss of hybrid LSTM-ANN.*

The training and validation loss curves in Figure 7 provide important insights into the model's learning process over 500 epochs. Initially, both losses are quite high, indicating that the model's early predictions show significant errors when compared to the actual values. However, as training progresses, a rapid decline in loss is observed, particularly during the first 50 epochs. This sharp reduction suggests that the model is effectively learning and adapting to key features and patterns in the data, which leads to improved prediction accuracy over time.

After about 50 epochs, the training and validation losses reach lower levels, showing that the model has effectively learned the key patterns in the data. The training loss continues to decrease slightly, while the validation loss experiences minor fluctuations around a stable point. These fluctuations are common when the model is tested on new, unseen data, illustrating the challenges in ensuring consistent generalization across different datasets. This pattern indicates that the model has successfully learned but is encountering the usual difficulties in handling new data during validation.

Towards the end of the training process, the training loss becomes very low, almost reaching zero, indicating that the model has learned the training data extremely well. While the validation loss is marginally higher than the training loss, the two remain close, with no significant gap between them. This small difference suggests that the model is not overfitting and has struck a good balance between fitting the training data and maintaining its ability to generalize to new, unseen validation data.

Overall, the results indicate that the model performs well, achieving low final loss values in both the training and validation datasets. The small difference between the two loss curves suggests that the model has effectively generalized, maintaining consistent performance when applied to different datasets.

Table 2. Model performance of hybrid LSTM-ANN

Metric	Voltage	Current	Power	Irradiance
MAE	0,1016	0,1971	0,1506	0,0895
MSE	0,0201	0,0832	0,0382	0,0132
RMSE	0,1417	0,2884	0,1954	0,1149
R^2	0,9799	0,9618	0,9168	0,9868

The performance metrics outlined in Table 2 demonstrate the hybrid LSTM-ANN model's effectiveness in various energy prediction tasks. The model's accuracy was assessed using three key metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results offer a detailed view of the model's performance, which is compared with findings from other studies. This comparison reveals that the hybrid model performs efficiently, delivering reliable and accurate energy predictions when measured against similar approaches in the literature:

1. **Voltage:**
   - MAE: 0.1016, MSE: 0.0201, RMSE: 0.1417, R^2: 0,9799
   - The voltage prediction shows the lowest error rates across all metrics. This indicates that the model performs best for voltage prediction. Compared to similar studies like Tufail et al. in 2023 for predicting energy consumption, this error is considerably low, reflecting the model's high accuracy in voltage forecasting [28].
2. **Current:**
   - MAE: 0.1971, MSE: 0.0832, RMSE: 0.2884, R^2: 0,9618
   - The current prediction has the highest error values, showing that the model struggles the most in this aspect. This aligns with findings from other models like Phan et al. in 2022 [20], where current or power flow often proves more challenging for predictive models due to its volatile nature during peak loads.
3. **Power:**
   - MAE: 0.1506, MSE: 0.0382, RMSE: 0.1954, R^2: 0,9168
   - The power predictions, though not as accurate as voltage, show a moderate error, with the RMSE being 0.1954. This is comparable to the results obtained by Zafar et al. in 2022 in hybrid autoencoder LSTM models for power prediction, where they observed slightly higher RMSE values [30].
4. **Irradiance:**
   - MAE: 0.0895, MSE: 0.0132, RMSE: 0.1149, R^2:0,9868
   - The model's irradiance prediction shows excellent accuracy, achieving a MAE of 0.0895 and an MSE of 0.0132, the lowest among the evaluated metrics. These outcomes align with previous studies by Mukhtar et al. in 2020 and Wentz et al. in 2022, who employed hybrid models for irradiance forecasting and reported similarly low error values [17,29]. This demonstrates the strength and reliability of the hybrid LSTM-ANN approach in effectively predicting solar irradiance.

Comparison with Other Studies:

- The hybrid LSTM-ANN model demonstrates excellent performance in predicting both voltage and irradiance, with low error values. This aligns with results from other studies that have utilized hybrid models for solar energy output prediction, such as those conducted by Sun et al. in 2021 and Zhou et al. in 2023 [24,33]. These findings highlight the model's effectiveness and reliability in accurately forecasting key parameters of solar energy systems
- The higher error values for current suggest that further improvements, such as optimizing the LSTM parameters or using additional features, may be necessary to enhance the accuracy. This aligns with challenges noted in other research, such as the work of Krishnan et al. in 2020, where power and current are prone to higher fluctuations, resulting in increased prediction errors [13].

The hybrid LSTM-ANN model demonstrates strong predictive performance for voltage and irradiance, moderate accuracy for power, and room for improvement in current prediction. This is consistent with the performance observed in related works across the field of solar energy prediction using deep learning models.

This study evaluated the effectiveness of a hybrid LSTM-ANN model in predicting energy output for photovoltaic (PV) systems. The combination of Long Short-Term Memory (LSTM) and Artificial Neural Networks (ANN) allowed the model to capture both temporal relationships and complex nonlinear patterns, making it well-suited for forecasting voltage, current, power, and irradiance. The model's performance was assessed using key metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), which highlighted its varying accuracy across the different parameters.

The voltage predictions achieved the highest level of accuracy, with a MAE of 0.1016 and an RMSE of 0.1417, staying closely aligned with actual values throughout the day. Irradiance predictions followed, demonstrating strong performance with an MAE of 0.0895 and an RMSE of 0.1149. These results are consistent with earlier studies, such as those by Mukhtar et al. in 2020 and Wentz et al. in 2022, which also found that hybrid models excel at predicting solar irradiance and voltage [17,29].

Conversely, the model encountered challenges in predicting current, with the highest error rates recorded at a MAE of 0.1971 and RMSE of 0.2884. The prediction errors were particularly notable during the afternoon, a time when current values showed greater fluctuations. This difficulty in current prediction is similar to issues observed in other research, such as Krishnan et al. in 2020, where the unpredictable nature of power and current, especially during peak times, made accurate forecasting more complex [13].

Power prediction achieved moderate accuracy, with an MAE of 0.1506 and RMSE of 0.1954, following a similar trend as the voltage and irradiance predictions. The model was able to capture the overall pattern of power generation but tended to underpredict during peak periods, a common issue noted in power prediction models [20,31].

In summary, the hybrid LSTM-ANN model delivered strong results, particularly in forecasting voltage and irradiance. The integration of time-series analysis and nonlinear modeling proved to be an effective approach for predicting solar energy output. However, further enhancements are needed in the areas of current and power prediction, which could be achieved through the addition of more features or by fine-tuning the model's hyperparameters. This research contributes to the growing field of hybrid deep learning models in renewable energy forecasting, offering valuable insights into how these architectures can improve the efficiency and dependability of solar energy systems.

4. Conclusion

This study evaluated a hybrid LSTM-ANN model for predicting photovoltaic (PV) system outputs, focusing on key parameters such as voltage, current, power, and irradiance. By leveraging the temporal capabilities of LSTM and the nonlinear mapping strengths of ANN, the model aimed to enhance prediction accuracy. Although voltage and irradiance predictions were highly accurate, with MAE values of 0.1016 and 0.0895 respectively, power and current predictions showed room for improvement, particularly for current, which had the highest error rates (MAE of 0.1971). These results highlight the model's potential while pointing to areas that could benefit from further refinement. For future work, expanding the dataset to include a broader range of conditions and optimizing the model through hyperparameter tuning could lead to improved performance, especially for current and power predictions. Additionally, incorporating external factors, such as real-time weather data—temperature, humidity, or cloud cover—could enhance the model's accuracy, particularly for predicting power output during fluctuating environmental conditions. The hybrid model could also be adapted for use in other renewable energy sectors, such as wind energy, by modifying the input features to capture wind speed, direction, and turbine efficiency. Furthermore, implementing the model in real-time energy management systems could offer valuable insights for optimizing energy storage and distribution, ensuring more stable integration of renewable energy into the grid. Such applications would support more dynamic and efficient energy systems across various sectors.

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