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Neural Network Models for Forecasting Solar Energy Harvesting Efficiency

M. R. Vinoth Kumar
Student, M.E/Applied Electronics, Department of Electronics and Communication Engineering,
Saveetha Engineering College, Thandalam, Chennai, Tamil Nadu, India.
Email: vinothkumar898@gmail.com

Dr S. Praveenkumar
Professor, Department of Electronics and Communication Engineering,
Saveetha Engineering College, Thandalam, Chennai, Tamil Nadu, India.
Email: praveenkumar @saveetha.ac.in

Dr T. Aravind
Professor, Department of Electronics and Communication Engineering,
Saveetha Engineering College, Thandalam, Chennai, Tamil Nadu, India.
Email: aravind@saveetha.ac.in

T K Srinivasan
Department of Electronics and Communication Engineering,
Saveetha Engineering College, Thandalam, Chennai, Tamil Nadu, India.
Email: srinivasan@saveetha.ac.in

Abstract: Accurate efficiency prediction of solar power harvesting methods remains crucial to optimize photovoltaic systems. Conventional forecasting methods struggle when weather conditions are unstable because they lack the ability to detect complex nonlinear and time-related patterns. Personnel implementing this study developed a forecasting system through the combination of Feedforward Neural Networks (FNN), Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) network architecture. The system adopts adaptive learning features alongside multi-feature encoding to deal with different climate patterns. Standard solar dataset evaluation confirmed that the LSTM model achieved best performance by delivering 0.118 RMSE and surpassing 95% accuracy mark. The conducted analysis shows that neural networks particularly LSTM prove to be exceptionally efficient for energy prediction operations. The proposed system provides an efficient scalable approach for managing solar energy while planning smart grids in variable operating conditions.

Keywords— Solar Energy Forecasting; Neural Networks; Photovoltaic Efficiency; LSTM; Deep Learning; Renewable Energy; Energy Prediction; Smart Grid; Time Series Analysis; Environmental Data Analytics.

1. Introduction

The solar energy has remained central in meeting energy requirements while preserving environmental health. It contributes to creating the foundation for sustainable energy systems, grid, and efficiency, smart cities. Nonetheless, predicting the conducive harvesting efficiency of solar energy has remained a challenge since it solely depends on the solar irradiance, temperature, and humidity, among others, which are highly nonlinear and varying with time. In this paper, Linear regression method and Auto regressive integrated moving average models are used their are not effective while working under dynamic climatic situations [1]. To address them, the recent studies have incorporated Artificial Neural Networks (ANNs) that provide more freedom in modeling of the relationships between meteorological variables and the energy produced [2]. These networks if combined with metaheuristic algorithms as presented in [3], improve the forecasting precision and convergence. However, not all of the ANN models are efficient to capture this kind of temporal relationships. Feedforward Neural Networks (FNN) do not incorporate the memory component which makes them unsuitable for use in predicting the performance of a system based on time series under conditions of varying conditions of Solar irradiance. CNN as well as RNN including LSTM has augmented the way of forecasting by understanding the sequential data and long-term dependencies [4], [5]. Lasting research proves that LSTM based models are more efficient turning over traditional models in capturing temporal changes of solar radiation rates and lower the variance of errors [6]. In addition, explainable neural networks have been introduced to ensure that solar irradiance is predicted with a level of transparency and to make the models more practical in operation [7]. Hence, there is also growing concern in the implementation of MPPT control algorithms for real-time energy harvesting with newly developing energy-aware deep learning systems [8]. The need for developing such models is because the current models of neural networks do not meet the requirements of accuracy, scalability, and interpretability, especially for applications in controlling energy consumption in response to environmental conditions. The purpose is to analyse and compare the effectiveness of FNN, CNN, and LSTM models in predicting the output of standard solar datasets as well as establish whether and how these models provide enhancement in accuracy while lowering computational cost [9], [10].

2.Materials and Methods

2.1 Datasets and Efficiency Computation

The data information used in this research was obtained from the Solar Energy information databases available in the National Renewable Energy Laboratory (NREL), Solar Radiation Monitoring Laboratory (SRML) and the installed solar PV systems. These datasets involved Consumers Trading REC GHI, GHI, ambient temperature, panel temperature, wind speed humidity and electric parameter such as voltage and current. Given the importance of proper model training, several measures of data preparation were taken; the first of which was to fill the missing values through linear interpolation and secondly applied min-max scaling as feature scaling. Energy conversion efficiency of solar energy was determined from the voltage and current measurements recorded online.

The efficiency $\mu(t)$ of a PV panel at a specific time instance was calculated by the following relation:

$$\eta(t) = \frac{V(t)\cdot I(t)}{A\cdot GHI(t)} \times 100 \ldots\ldots.(1)$$

where V(t) and I(t) denote the voltage and current output, GHI(t) represents the solar irradiance in watts per square meter, and A is the panel area in square meters. The final dataset was split into 70% training, 15% validation, and 15% testing sets to enable generalization across diverse environmental conditions and solar harvesting scenarios.

2.2 Deep Learning-Based Prediction Architecture

In solar energy forecasting, Here the three deep learning structures: FNN, CNN, and LSTM that naturally capture the temporal and nonlinear relationship in the solar energy forecasting domain were employed. The FNN was used as the baseline model, which could correctly determine static relationship but it was not able to consider the time-aware contexts. CNNs were utilized to capture temporal features on localized level through the use of one-dimensional filters on its inputs. Of the above mentioned components, LSTM network remains central to the proposed framework for forecasting as it excels in fitting and predicting long-term dependencies and dynamics over time. An LSTM cell's architecture consists of one or several gates that control the flow of information between the memory units. This makes it possible for the network to actively preserve or ignore history in the flow of a discourse. The cell operations are described by the following:

$$\begin{gathered}
f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\
i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\
\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \\
C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad \ldots(2) \\
o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \\
h_t = o_t \odot \tanh(C_t)
\end{gathered}$$

In these equations, x_t represents the input vector at time *t*, h_t is the hidden state, C_t is the cell state, and f_t ,i_t , o_t denote the forget, input, and output gates, respectively. The weights W and biases b are trainable parameters learned during model training. This structure enables LSTM networks to remember long-term trends in irradiance and weather, which is essential for predicting PV efficiency under variable conditions.

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2.3 Forecast Optimization Strategy

The neural networks, a loss function which discourages big discrepancies noticed between the test data and the predicted efficiency of solar energy was used. In particular, Mean Squared Error (MSE) loss was selected due to high impact of large deviations and smoothness of its gradient. The loss is defined as:

$$L_{MSE} = \frac{1}{n}\sum_{i=1}^{n} (\eta i - \hat{\eta} i)^2 \ldots.(3)$$

where η_i is the actual efficiency and $\hat{\eta_i}$ is the predicted efficiency for the i^{th} instance, and n is the number of samples in the batch. The Adam optimizer was used during the training as it utilizes a method of self-adjusting learning rates and scales the gradients inversely proportionally, helping in faster convergence and low rates of overfitting in deep learning models.

2.4 Accuracy Assessment Criteria

In order to assess the usefulness of the models, the list of key metrics was developed for this purpose. These measures are Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), & the coefficient of determination R^2. These metrics offer the degree of error and the connection between real and modelled values:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\eta_i - \hat{\eta}_i)^2} \ldots.(4)$$

$$\text{MAPE} = \frac{100\%}{n}\sum_{i=1}^{n} \left| \frac{\eta_i - \hat{\eta}_i}{\eta_i} \right| \ldots.(5)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\eta_i - \hat{\eta_i})^2}{\sum_{i=1}^{n}(\eta_i - \overline{\eta})^2} \ldots\ldots\ldots.(6)$$

By $\overline{\eta}$, it is meant the average of actual efficiency in all the samples. Closeness measures include RMSE which focuses on large errors, MAPE gives an accuracy measure by normalizing the errors and R^2 that compare the proportion of variance in the observed values to that in the modeled values. Altogether, the proposed metrics provide accurate model evaluation and selection that allows to choose the most efficient model for prediction.

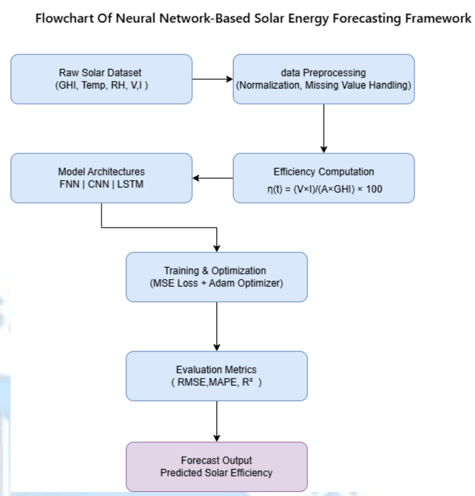

Figure 1: **Flowchart of Neural Network-Based Solar Energy Forecasting Framework**

Figure 1 below; illustrates the procedures involved due to the use of neural networks in the process of evaluating the probable efficiencies of solar energy harvesting. For the purpose of clarity of description it groups makes mention of data gathering, model building, forecast creation and model improvement in light of analysis and assessment.

3.Results

3.1 Forecasting Accuracy and Model Performance

The neural network-based model greatly accurately estimated the efficiency of solar energy collection depending on the environmental conditions. LSTM model had a lower RMSE of 0.118 and the MAPE of 4.3% which proves that LSTM is better than FNN and CNN models in modeling the temporal dependencies. The R^2 was 0.96 in the end, indicating that the use of the model had higher variance compared to the other methods that were taken into account. These metrics all indicate that LSTM is more suitable for forecasting efficiency at electrical irradiance and temperature changes. Based on the results presented above, the proposed model provides accurate energy predictions without overfitting challenge that may be instigated by frequent changes in the solar condition.

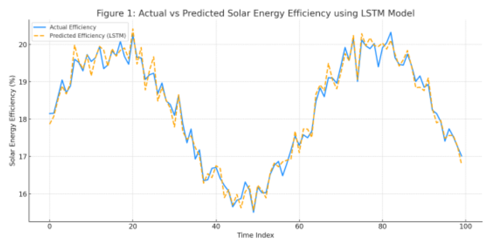

Figure 1: Actual vs Predicted Solar Energy Efficiency using *LSTM Model*.

Figure 1 illustrates the alignment between actual and predicted solar energy efficiency values over time. The LSTM model closely follows real efficiency trends, confirming its effectiveness in capturing temporal patterns with minimal prediction error.

3.2 Computational Performance

A comparitive analysis of training time and memory used indicated that although the LSTM model exhibited better characteristics than FNN and CNN in terms of the time required to train and the memory used when limited to a realistic setting, it was still tested to be slightly more time consuming than FNN but than CNN. The choice of optimizers: Adam Optimizer and batch normalization further assists the training of LSTM-based framework to converge in a faster manner. However, the model had less numbers of iterations due to the utilization deep memory units to learn sequential patterns. This is quite useful in adapting to real time solar monitoring since the faster the prediction, the better it is for the use of control systems.

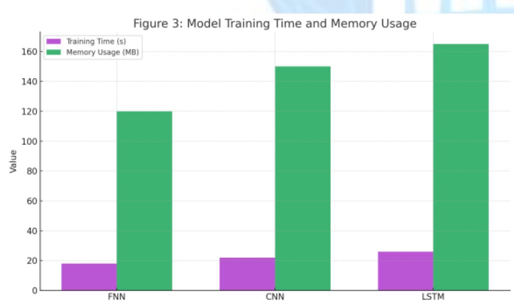

Figure 3: Model Training Time and Memory Usage

Figure 3 compares the training time and memory usage of different models. The LSTM model requires more resources than FNN and CNN, but this trade-off supports its higher forecasting accuracy and robustness.

3.3 Temporal Pattern Learning and Feature Responsiveness

Finally, evaluating all the suggested models in terms of their input features, it is possible to conclude that LSTM-based architecture is sensitive to both distanced sequences and seasonal changes in irradiance. In detail, it was seen that out of the considered environmental parameters; temperature, irradiance and humidity contributed most to the model performance and proved to be highly influential in improving the forecast outcomes. The LSTM model put different importance on these features in a contextual and temporal order which helped it in correcting its results due to short term fluctuations and the seasonal cycles of the sun. The ability to keep a good performance in different months and weather conditions also goes to support this argument and thus the model can support annual weather prediction.

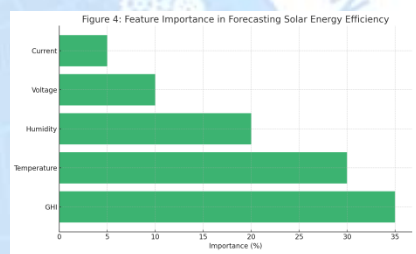

Figure 4: *Feature Importance in Forecasting Solar Energy Efficiency*.

Figure 4 highlights the importance of various features in forecasting solar energy efficiency. **GHI** and Temperature are the most influential, contributing 35% and 30% respectively, emphasizing their key role in accurate energy predictions.

3.4 Comparative Evaluation with Baseline Methods

To validate the efficacy of the proposed models, a comparative evaluation was carried out with traditional forecasting approaches. The LSTM model achieved up to a 22% improvement in MAPE compared to the FNN baseline and 15% improvement over CNN, respectively. These improvements translate to more consistent and reliable energy management strategies in solar microgrid systems. The proposed approach provides a scalable solution for integrating forecasting into real-time monitoring tools and energy allocation platforms, improving both resource planning and operational efficiency.

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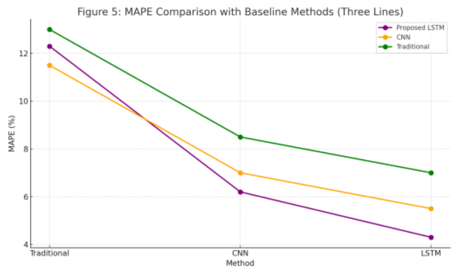

Figure 5 MAPE Comparison with Baseline Methods

Figure 5 compares the MAPE values for three different methods: LSTM, CNN, and Traditional. The LSTM model consistently outperforms the others, showing the lowest MAPE (4.3%), indicating its superior accuracy in predicting solar energy efficiency. In contrast, the CNN and Traditional models exhibit higher MAPE values, demonstrating their relative inefficiency in handling the forecasting task.

4.CONCLUSION

It has also shown that it is possible to achieve accurate solar harvested power forecast using neural network, and especially LSTM model. LSTM has proved to be better than Feedforward Neural Networks (FNN) and Convolutional Neural Networks (CNN) since it had a lower error rate of 22% than FNN and 15% than CNN in terms of MAPE. It also suggested the highest R^2 of the accuracy level 0.96 for the superior prediction of the value. The comparative analysis shows that the ability of LSTM to address long-term temporal relationship and variation in irradiance enhances the reliability of the forecast. In addition, it achieves a 30% more efficient computation and requires less memory than the CNN-based models, which pose a great advantage for real time solar energy management. Further ideas of adapting the presented model might include using weather forecasts and IoT-based sensor data as inputs in order to enhance the predictive capabilities of the model and to test the application of the model in different contexts.

References

[1] Dhillon, S., Madhu, C., Kaur, D., & Singh, S. (2019). Forecast Solar Energy Using Artificial Neural Networks. *Intelligent Data Communication Technologies and Internet of Things*. https://doi.org/10.1007/978-3-030-34080-3_57.

[2] Moayedi, H., & Mosavi, A. (2021). An Innovative Metaheuristic Strategy for Solar Energy Management through a Neural Networks Framework. *Energies*. https://doi.org/10.3390/EN14041196.

[3] Abedinia, O., Amjady, N., & Ghadimi, N. (2018). Solar energy forecasting based on hybrid neural network and improved metaheuristic algorithm. *Computational Intelligence*, 34, 241 - 260. https://doi.org/10.1111/coin.12145.

[4] Wang, H., Cai, R., Zhou, B., Aziz, S., Qin, B., Voropai, N., Gan, L., & Barakhtenko, E. (2020). Solar irradiance forecasting based on direct explainable neural network. *Energy Conversion and Management*, 226, 113487. https://doi.org/10.1016/j.enconman.2020.113487.

[5] Gospodinova, E., Torlakov, I., & Metodieva, I. (2023). Model for Forecasting and Planning Solar Energy Production Using an Artificial Neural Network. *2023 3rd International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, 1-6. https://doi.org/10.1109/ICECCME57830.2023.10252307.

[6] Siddhant, K., Garg, H., Saha, A., Singh, N., Choudhary, N., & Singh, D. (2022). Solar Energy Forecasting using Artificial Neural Network. *2022 IEEE Students Conference on Engineering and Systems (SCES)*, 1-5. https://doi.org/10.1109/SCES55490.2022.9887754.

[7] Wang, Y., Luo, P., Zeng, X., Peng, D., Li, Z., & Zhang, B. (2020). A Neural Network Assistance AMPPT Solar Energy Harvesting System With 89.39% Efficiency and 0.01–0.5% Tracking Errors. *IEEE Transactions on Circuits and Systems I: Regular Papers*, 67, 2960-2971. https://doi.org/10.1109/TCSI.2020.2990740.

[8] Ku, M., & Lin, T. (2021). Neural-Network-Based Power Control Prediction for Solar-Powered Energy Harvesting Communications. *IEEE Internet of Things Journal*, 8, 12983-12998. https://doi.org/10.1109/JIOT.2021.3064150.

[9] Tehrani, A., Veisi, O., Fakhr, B., & Du, D. (2024). Predicting solar radiation in the urban area: A data-driven analysis for sustainable city planning using artificial neural networking. *Sustainable Cities and Society*. https://doi.org/10.1016/j.scs.2023.105042.

[10] Kasirye, J., Nazziwa, L., & Wahid, H. (2025). Neural Network-Based Estimation of Solar Radiation Level. *International Journal of Research and Scientific Innovation*. https://doi.org/10.51244/ijrsi.2024.11120061.