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Predictive MPPT Algorithm using Hybrid ANFIS and LSTM for Solar Photovoltaic Systems

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***Abstract*—Solar photovoltaic (PV) systems have become one of the fastest-growing renewable energy sources, contributing approximately 8% of global electricity generation [1]. However, their efficiency is significantly affected by rapidly varying environmental conditions such as solar irradiance and temperature. Maximum Power Point Tracking (MPPT) is essential for maximising power extraction under these dynamic conditions. Conventional MPPT algorithms, such as Perturb and Observe (P&O), are computationally simple but often suffer from oscillations and poor performance during rapid environmental changes. Artificial intelligence techniques, including the Adaptive Neuro-Fuzzy Inference System (ANFIS), improve tracking accuracy but remain primarily reactive. This paper proposes a hybrid ANFIS-LSTM predictive MPPT architecture in which an LSTM network forecasts future irradiance and temperature from historical environmental data. These predictions are supplied to the ANFIS controller to proactively determine the optimal operating point. By combining time-series forecasting with intelligent decision-making, the proposed framework shifts MPPT from reactive to predictive-reactive control, enabling faster adaptation to changing conditions and improving the efficiency and reliability of solar PV systems.**

***Index Terms*—Solar Photovoltaic, Maximum Power Point Tracking (MPPT), Adaptive Neuro-Fuzzy Inference System (ANFIS), Long Short-Term Memory (LSTM), Renewable Energy**

I. Introduction

A. Background

Solar photovoltaic (PV) technology has become one of the fastest-growing sources of renewable energy and currently contributes about 8% of global electricity generation [1]. Despite this rapid expansion, the performance of PV systems is strongly affected by changing environmental conditions such as solar irradiance, temperature, and shading.

Partial shading is one of the major factors that reduce the output of a PV system. Even when only a small section of a PV array is shaded, the overall power output can decrease by up to 25%. Similarly, the efficiency of PV modules decreases as temperature increases, typically by about 0.3–0.5% for every 1°C rise in operating temperature [2].

To improve energy extraction under these varying conditions, Maximum Power Point Tracking (MPPT) techniques are employed. MPPT continuously adjusts the operating point of a PV system to ensure that it operates at its maximum power point despite changes in irradiance and temperature. Although conventional MPPT algorithms perform well under stable conditions, their performance often degrades in practical environments due to sensor noise, module aging, parameter uncertainties, and partial shading. These challenges motivate the development of more intelligent and adaptive MPPT strategies.

B. Related Work

A wide range of MPPT techniques has been proposed in the literature, including conventional optimization algorithms and artificial intelligence (AI)-based approaches.

Among conventional methods, Perturb and Observe (P&O) and Particle Swarm Optimization (PSO) are widely used because of their simplicity and ease of implementation [3] [4]. However, these methods primarily rely on continuous feedback from the system, making them reactive in nature. As a result, they may exhibit slower convergence, oscillations around the maximum power point, and reduced performance under rapidly changing environmental conditions.

To address these limitations, AI-based techniques such as Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) have been introduced [5]. These methods can effectively model the nonlinear behavior of PV systems and provide more reliable MPPT performance under varying operating conditions.

Although ANFIS offers significant improvements over conventional algorithms, it still responds only after changes in operating conditions have occurred. To overcome this limitation, the proposed work incorporates a predictive layer that anticipates changes in environmental conditions, enabling faster tracking of the maximum power point and improving the dynamic response of the PV system.

II. Methodology

This work proposes a hybrid MPPT framework that combines a Long Short-Term Memory (LSTM) network with an Adaptive Neuro-Fuzzy Inference System (ANFIS) [6] [7]. The objective is to improve the tracking performance of photovoltaic (PV) systems under rapidly changing environmental conditions. Unlike conventional MPPT methods, which respond only after changes in irradiance or temperature occur, the proposed approach predicts upcoming environmental variations and uses this information to determine the optimal

operating point of the PV system. This predictive capability enables faster convergence to the maximum power point while reducing power loss during transient conditions.

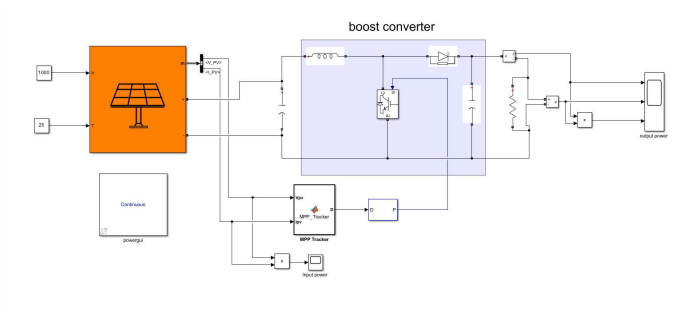


Fig. 1. MATLAB Simulation of PV array

The proposed architecture consists of two main components: an LSTM-based prediction layer and an ANFIS-based control layer. The LSTM network forecasts future environmental conditions, while the ANFIS controller uses these predictions to generate appropriate control signals for MPPT.

A. LSTM Predictive Layer

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) specifically designed to learn long-term dependencies in sequential data. Unlike conventional neural networks, which process each input independently, LSTM networks maintain an internal memory that allows them to capture temporal relationships between past and present observations. This capability makes LSTM particularly suitable for time-series forecasting problems.

Environmental parameters affecting PV systems, such as solar irradiance and module temperature, vary continuously over time and often exhibit temporal patterns. Since these variations directly influence the maximum power point of the PV array, accurately predicting future conditions can significantly improve MPPT performance.

In the proposed framework, the LSTM network is trained using historical environmental data collected from the PV system. The input sequence consists of previous irradiance and temperature measurements, enabling the network to learn both short-term fluctuations and long-term trends. Based on these learned patterns, the LSTM predicts the environmental conditions for the next time step before they occur.

The primary functions of the LSTM layer are as follows:

- Learn temporal patterns in historical solar irradiance data.
- Capture the variation of PV module temperature over time.
- Forecast future irradiance and temperature values.
- Provide predicted environmental conditions to the ANFIS controller for proactive decision-making.

By forecasting environmental changes in advance, the LSTM enables the control system to respond before significant variations in PV output occur. This predictive capability is particularly beneficial during rapidly changing weather conditions, such as passing clouds, where conventional MPPT algorithms often experience delayed responses and temporary power losses.

B. ANFIS Control Layer

The Adaptive Neuro-Fuzzy Inference System (ANFIS) combines the learning capability of Artificial Neural Networks (ANN) with the reasoning mechanism of Fuzzy Logic Systems (FLS). This hybrid structure enables ANFIS to model complex nonlinear relationships while maintaining the interpretability of fuzzy rules.

In a PV system, the relationship between environmental conditions and the maximum power point is highly nonlinear. Conventional controllers often require precise mathematical models or predefined operating conditions, which may not accurately represent real-world scenarios. ANFIS overcomes this limitation by learning the nonlinear mapping directly from training data.

The ANFIS architecture consists of multiple layers that perform fuzzification, rule evaluation, normalization, and defuzzification. During training, the parameters of the fuzzy membership functions are automatically adjusted using learning algorithms, allowing the controller to improve its decision-making accuracy over time.

In the proposed framework, the ANFIS controller receives the predicted irradiance and temperature values generated by the LSTM network instead of relying solely on instantaneous sensor measurements. Using this information, it estimates the optimal operating point of the PV system and generates the appropriate control signal, such as the duty cycle for the DC-DC converter, to ensure operation near the maximum power point.

The main functions of the ANFIS layer include:

- Receive predicted environmental parameters from the LSTM network.
- Process nonlinear relationships between environmental conditions and PV output.
- Estimate the optimal operating point corresponding to the predicted conditions.
- Generate MPPT control signals for the power converter.
- Continuously adapt its parameters to maintain high tracking accuracy under varying operating conditions.

C. Hybrid Framework

The proposed hybrid architecture combines the forecasting capability of LSTM with the adaptive control capability of ANFIS to create a predictive MPPT system. The LSTM predicts future environmental conditions based on historical observations, while the ANFIS controller uses these predictions to determine the optimal operating point before the environmental changes affect the PV array.

This approach transforms the MPPT process from a purely reactive strategy into a predictive-reactive strategy. For example, when cloud movement is expected to reduce solar irradiance, the LSTM forecasts the decrease in advance. The ANFIS controller then adjusts the converter operating point

proactively, minimizing the delay associated with conventional MPPT techniques.

The integration of these two technologies offers several advantages over traditional approaches, including:

- Faster convergence to the maximum power point.
- Reduced oscillations around the operating point.
- Improved energy harvesting during rapidly changing weather conditions.
- Better robustness against sensor noise and environmental uncertainties.
- Enhanced overall efficiency and stability of the PV system.

By combining accurate environmental forecasting with intelligent nonlinear control, the proposed ANFIS-LSTM architecture provides a more adaptive and efficient solution for maximum power point tracking in modern photovoltaic systems.

III. Results

The proposed hybrid ANFIS-LSTM MPPT framework was evaluated using a photovoltaic (PV) system modeled in MATLAB/Simulink. The simulation considered varying environmental conditions, including changes in solar irradiance and temperature, to assess the controller's performance under realistic operating scenarios. The proposed method was compared with two widely used MPPT approaches: the conventional Perturb and Observe (P&O) algorithm and a standalone Adaptive Neuro-Fuzzy Inference System (ANFIS) controller.

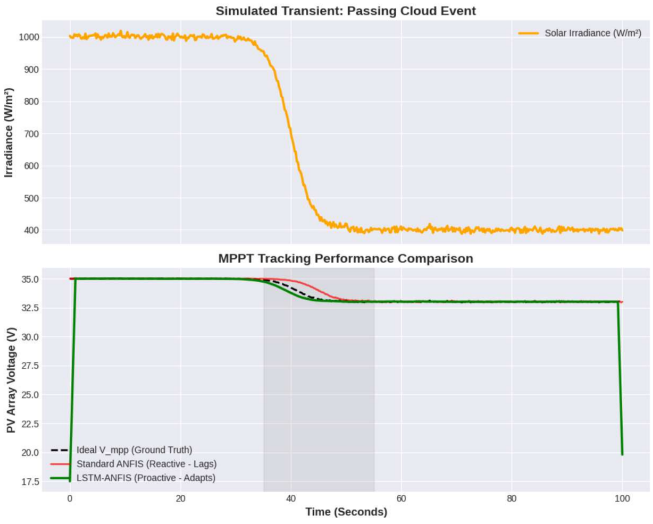


Fig. 2. Reactive v/s Proactive ANFIS on Cloud passing events

The performance of each controller was evaluated using key MPPT metrics, including energy yield, tracking accuracy, convergence speed, and response to changing environmental conditions. The results indicate that incorporating an LSTM-based prediction layer enhances the overall performance of the ANFIS controller by enabling proactive rather than purely reactive control.

Compared with the conventional P&O algorithm, the proposed ANFIS-LSTM framework achieved an approximately 10% increase in total energy yield, demonstrating its ability to extract more energy from the PV system under dynamic operating conditions. In comparison, the standalone ANFIS controller provided an improvement of approximately 5% over the P&O method. These results show that integrating environmental prediction with intelligent control offers a clear advantage over using ANFIS alone.

The predictive capability of the LSTM network allows the controller to anticipate changes in irradiance and temperature before they affect the PV array. As a result, the ANFIS controller can adjust the operating point more quickly, reducing the delay typically observed in conventional MPPT techniques. This leads to faster convergence toward the maximum power point, reduced oscillations around the operating point, and improved tracking efficiency during rapidly changing weather conditions.

Overall, the simulation results demonstrate that the proposed hybrid ANFIS-LSTM framework provides more efficient maximum power point tracking than both conventional and standalone intelligent MPPT methods. The improved energy extraction and faster dynamic response highlight the potential of the proposed approach for enhancing the performance and reliability of photovoltaic energy systems operating under real-world environmental conditions.

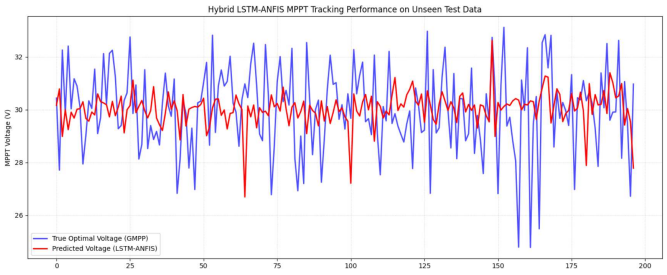


Fig. 3. Performance comparision

IV. Discussion

A. Addressing Location-Specific Variability

One of the primary challenges in applying AI-based MPPT techniques is their dependence on the data used during training. Models trained using data from a specific geographical region often perform well only under similar climatic conditions, while their accuracy may decrease when deployed in regions with different weather patterns, solar irradiance levels, or seasonal variations. This limitation, commonly referred to as location-specific bias, reduces the generalizability of AI models.

To overcome this challenge, the proposed framework incorporates transfer learning together with adaptive online retraining. Initially, the LSTM-ANFIS model is trained on a large and diverse dataset representing a wide range of environmental conditions. This enables the model to learn

general relationships between environmental variables and the optimal operating point of the PV system.

When the model is deployed in a new location, instead of training it from scratch, the previously learned parameters are fine-tuned using a relatively small amount of locally collected weather and irradiance data. This process allows the model to adapt to regional characteristics while significantly reducing the amount of training data and computational effort required [8].

Furthermore, adaptive online retraining enables the model to update its parameters periodically as new operational data become available. This allows the controller to account for seasonal weather changes, long-term variations in environmental conditions, and gradual performance degradation of PV modules due to aging. As a result, the proposed framework can maintain reliable MPPT performance across different geographical locations and varying operating conditions without requiring complete retraining.

B. Hardware Requirements and Deployment

Although training the hybrid LSTM-ANFIS model involves significant computational resources, particularly for optimizing the neural network parameters, this process is performed offline and only during the model development stage. Graphics Processing Units (GPUs) are typically used to accelerate the training process and reduce computation time.

Once the model has been trained, the deployment phase requires only inference, which is computationally much less demanding. During normal PV system operation, the controller simply processes the current and predicted environmental inputs to generate the appropriate MPPT control signal. This inference process requires relatively low computational power and can be executed in real time.

Consequently, the proposed framework can be implemented on commonly available hardware platforms used in photovoltaic systems, including inverter controllers, Digital Signal Processors (DSPs), microcontrollers, and edge-computing devices. Since no intensive model training is performed during deployment, the additional hardware requirements remain minimal.

This lightweight deployment architecture makes the proposed method suitable for both new PV installations and existing solar farms. The ability to integrate the controller with current inverter hardware without major modifications enhances its practicality and supports cost-effective large-scale adoption.

V. Conclusion

This paper presented a hybrid ANFIS-LSTM framework for Maximum Power Point Tracking (MPPT) in photovoltaic (PV) systems operating under dynamic environmental conditions. Conventional MPPT techniques primarily rely on reactive control, which can lead to delayed responses and reduced energy extraction during rapid changes in solar irradiance and temperature.

To address these limitations, the proposed approach integrates the time-series prediction capability of Long Short-Term Memory (LSTM) networks with the adaptive nonlinear control of an Adaptive Neuro-Fuzzy Inference System (ANFIS). The LSTM network forecasts upcoming environmental conditions, while the ANFIS controller uses these predictions to proactively determine the optimal operating point of the PV system. This predictive-reactive strategy enables faster tracking of the maximum power point and improves the overall efficiency of energy conversion.

Simulation results demonstrate that the proposed hybrid controller achieves approximately 10% higher energy yield compared with the conventional Perturb and Observe (P&O) algorithm and outperforms the standalone ANFIS controller under varying operating conditions. In addition to improved energy extraction, the framework provides faster dynamic response, reduced oscillations around the maximum power point, and enhanced robustness to environmental uncertainties.

Although the model requires computational resources during the training phase, deployment involves only lightweight inference, allowing it to run efficiently on existing inverter controllers, Digital Signal Processors (DSPs), and other edge-computing devices. Furthermore, the use of transfer learning enables the framework to adapt to different climatic regions with minimal retraining, making it suitable for large-scale deployment.

Overall, the proposed ANFIS-LSTM MPPT framework offers an efficient, scalable, and practical solution for improving the performance of modern photovoltaic systems. Future work may focus on validating the proposed approach using real-world PV installations and extending the framework to incorporate additional environmental parameters for further enhancing prediction accuracy and energy harvesting.

VI. Statements and Declarations

A. Funding

The authors did not receive any specific funding for this work.

B. Competing Interests

The authors declare that they have no relevant financial or non-financial interests to disclose.

C. Ethics Approval

This study did not involve human participants, human data, or animals; therefore, ethical approval was not required.

D. Consent to Participate

Not applicable.

E. Consent for Publication

Not applicable.

F. Data Availability

The datasets used in this study are publicly available from their respective data providers. ERA5 reanalysis data are available through the Copernicus Climate Data Store, while the satellite and geospatial datasets used in this study were obtained from publicly available sources as described in the manuscript.

G. Code Availability

The code used for data processing, feature engineering, and model development is available from the corresponding author upon reasonable request.

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