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Deep Learning for Predictive Control of Solar PV Maximum Power Point Tracking (MPPT)

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Abstract: Maximum Power Point Tracking, often known as MPPT, is an essential component for enhancing the efficiency of photovoltaic (PV) systems that are operating in environments that are subject to fast environmental change. Perturb-and-Observe (P&O) and Incremental Conductance (IC) are two examples of conventional maximum power point tracking (MPPT) algorithms. These algorithms often exhibit delayed convergence, oscillations around the maximum power point, and reduced performance under partial shading. Using deep learning, particularly Long Short-Term Memory (LSTM) networks, this study examines the potential for predictive Maximum Power Point Tracking (MPPT) control in solar photovoltaic (PV) systems. The suggested method uses past irradiance and temperature data to predict the optimal MPP reference voltage. This allows for tracking that is both steadier and more rapid. A data-driven modelling framework is built, and the predictive performance of the LSTM model is assessed using data representative of PV operating conditions. The findings indicate that LSTM-based predictive control is suitable for next-generation intelligent photovoltaic (PV) systems, achieving enhanced tracking accuracy, lower steady-state error, and higher MPPT efficiency compared to conventional techniques.

Keywords: Solar Photovoltaic Systems; LSTM Networks; Predictive Control; Renewable Energy; Solar Energy; Partial Shading; Tracking Accuracy; Incremental Conductance.

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1. Introduction

The growing global demand for clean, sustainable energy has accelerated the deployment of solar photovoltaic (PV) systems across residential, commercial, and utility-scale applications. Despite their environmental benefits, PV systems are inherently nonlinear and highly sensitive to environmental conditions such as solar irradiance and module temperature [1]. These variations significantly affect the power–voltage (P–V) and current–voltage (I–V) characteristics of PV arrays, necessitating continuous operation at the Maximum power point (MPP) to achieve optimal efficiency [2]. Maximum Power Point Tracking

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(MPPT) algorithms are, therefore, a critical component of PV energy conversion systems. Traditional MPPT techniques, including Perturb and Observe (P&O), Incremental Conductance (IC), fractional open-circuit voltage, and fractional short-circuit current methods, have been widely adopted due to their simplicity and low computational cost. However, these classical techniques exhibit several limitations, including oscillations around the MPP, slow dynamic response to rapid irradiance changes, and poor performance under partial shading conditions [2]. These drawbacks lead to energy losses and reduced overall system efficiency, particularly in modern PV installations exposed to dynamic weather patterns [3]. To address these challenges, intelligent and data-driven control strategies have gained significant attention in recent years. Artificial intelligence (AI) techniques, including fuzzy logic, artificial neural networks (ANNs), and evolutionary algorithms, have been explored to enhance MPPT performance [4]. While these methods offer improved adaptability, many of them rely on static mappings and struggle to capture the temporal dependencies inherent in PV system dynamics. Solar irradiance and temperature variations are time-dependent processes, and effective MPPT control requires the ability to learn and exploit these temporal correlations [5].

Deep learning, a subset of machine learning characterised by multilayer neural architectures, has emerged as a powerful tool for modelling complex nonlinear systems. In particular, Recurrent Neural Networks (RNNs) and their advanced variant, Long Short-Term Memory (LSTM) networks, are well-suited for time-series prediction problems [6]. LSTM networks can learn long-term dependencies and mitigate the vanishing gradient problem that conventional RNNs face. These properties make LSTMs highly suitable for predicting PV system behaviour under varying environmental conditions [29]. In the context of MPPT, predictive control using LSTM models offers a paradigm shift from reactive to proactive operation [30]. Instead of perturbing the operating point and observing the system response, an LSTM-based controller can directly predict the optimal MPP reference voltage or duty cycle based on historical and current measurements [7]. This predictive capability enables faster convergence, reduced oscillations, and improved tracking efficiency [15]; [16]. Moreover, as PV systems increasingly integrate with smart grids and energy management systems, data-driven predictive MPPT aligns well with the broader vision of intelligent and autonomous renewable energy systems [31]. This research is significant because it introduces a predictive, data-driven MPPT framework that overcomes the oscillations and slow response of conventional methods under dynamic conditions. Its novelty lies in embedding an LSTM-based time-series predictor directly into the MPPT control loop to forecast the optimal MPP voltage using historical data. This temporal learning approach enables faster convergence, improved stability, and higher energy extraction compared to existing MPPT techniques [32].

2. Literature Review

2.1. Conventional MPPT Techniques

Conventional maximum power point tracking (MPPT) techniques have been extensively employed in photovoltaic (PV) systems due to their simplicity, ease of implementation, and low computational requirements. Among the most widely adopted methods are Perturb and Observe (P&O) and Incremental Conductance (IC). The Perturb and Observe (P&O) method operates by periodically perturbing the PV operating voltage and observing the resulting change in output power. If the power increases, the perturbation direction is maintained; otherwise, it is reversed [7]; [8]. Although simple, this method suffers from steady-state oscillations around the maximum power point (MPP), resulting in power losses, particularly under constant irradiance conditions [9]. Additionally, Perturb and Observe (P&O) exhibits slow convergence and tracking errors during rapidly changing environmental conditions. The Incremental Conductance method improves upon Perturb and Observe (P&O) by utilising the condition. $\frac{dP}{dV} = 0$ at the MPP. By comparing incremental and instantaneous conductance, IC can theoretically track the MPP more accurately under dynamic irradiance variations [10]. However, IC requires accurate sensing and differentiation of voltage and current signals, which increases system complexity and sensitivity to noise. Other classical approaches, such as fractional open-circuit voltage and short-circuit current methods, rely on fixed proportional relationships and cannot adapt to changing PV characteristics. Raj and Naik [14] noted that overall, while conventional MPPT techniques remain popular in low-cost applications, their limitations motivate the exploration of more intelligent and adaptive control strategies.

2.2. Artificial Intelligence-Based MPPT

Artificial intelligence (AI)-based MPPT methods have emerged as promising alternatives to conventional algorithms, offering improved adaptability and robustness under nonlinear and dynamic operating conditions [12]. Fuzzy logic control (FLC) is one of the earliest AI techniques applied to MPPT, using linguistic rules and membership functions to determine control actions. FLC-based MPPT systems exhibit faster convergence and lower oscillations than Perturb and Observe (P&O) MPPT systems, especially under variable irradiance. However, their performance is highly dependent on expert-designed rules and membership functions, which limit scalability and generalisation [13]. Artificial neural networks (ANNs) have also been widely investigated for MPPT applications. ANN-based MPPT models typically learn a nonlinear mapping from environmental inputs, such as irradiance and temperature, to the optimal MPP voltage or duty cycle. These models provide rapid tracking and eliminate steady-state oscillations [17]-[19]. Nevertheless, traditional feedforward ANNs operate on instantaneous inputs and lack memory, making them less effective in capturing temporal dependencies inherent in PV system dynamics. Furthermore, ANN performance is sensitive to the quality of the training data and to the selection of network architecture. Other AI approaches, including genetic algorithms and particle swarm optimisation, have been applied to optimise MPPT parameters. While these methods show improved performance, they often involve high computational complexity, limiting their real-time applicability [20]; [21]. These challenges have driven interest toward deep learning techniques capable of modelling both nonlinear and temporal characteristics of PV systems.

2.3. Deep Learning in Solar PV Systems

Deep learning has gained increasing attention in solar PV research due to its superior ability to model complex nonlinear relationships in large-scale datasets. Unlike shallow machine learning models, deep neural networks employ multiple hidden layers to extract hierarchical feature representations, enabling improved generalisation and predictive accuracy. In solar energy applications, Marlin and Jebaseelan [22] mentioned that deep learning has been successfully applied to PV power forecasting, irradiance prediction, fault diagnosis, and system performance estimation. Convolutional neural networks (CNNs) have been used for PV fault detection and sky–image–based irradiance estimation, leveraging their spatial feature-traction capabilities [22]; [23]. Deep belief networks and autoencoders have been applied for dimensionality reduction and anomaly detection in PV monitoring systems. These studies demonstrate that deep learning models outperform conventional machine learning techniques in terms of accuracy and robustness. In MPPT-related research, deep learning enables direct prediction of optimal operating points without iterative searching [18]. However, many deep learning models focus on static mappings and do not fully exploit the temporal structure of PV data. Since solar irradiance and temperature evolve continuously over time, ignoring temporal correlations can limit prediction accuracy [24]; [25]. Consequently, time-series–oriented deep learning architectures are increasingly preferred for MPPT applications. This evolution highlights the importance of recurrent neural networks and motivates the adoption of LSTM-based models for predictive MPPT control [26]; [27].

2.4. LSTM Networks for MPPT

From research by Zhai et al. [29] and Guanghua et al. [30], Long Short-Term Memory (LSTM) networks are specialised recurrent neural networks designed to model long-term temporal dependencies in sequential data. Unlike conventional RNNs, LSTMs employ memory cells and gating mechanisms that regulate information flow, enabling stable learning over long time horizons. This property makes LSTM networks particularly suitable for solar PV applications, where system behaviour depends on historical irradiance and temperature patterns [28]. Several recent studies, Darwish and Kara [26], Al-Fattah et al. [27], and Sahbani et al. [28] have demonstrated the effectiveness of LSTM-based MPPT approaches. By learning from historical environmental and electrical measurements, LSTM models can accurately predict the optimal MPP voltage or duty cycle. Compared to ANN-based MPPT methods, LSTMs exhibit faster dynamic response and improved stability during rapid irradiance changes and partial shading events. Additionally, LSTM-based MPPT eliminates the oscillatory behaviour commonly observed in perturbation-based techniques [11]. Research has also shown that LSTM models integrate well with predictive control frameworks, enabling proactive rather than reactive MPPT operation. Despite their higher computational requirements, advances in embedded processing hardware have made real-time implementation feasible. Overall, the literature indicates that LSTM-based predictive MPPT provides a robust, accurate, and scalable solution for next-generation intelligent PV systems, making it a strong candidate for practical deployment.

3. Methods (with Mathematical Formulation)

This study employs a deep learning–based predictive control framework for maximum power point tracking (MPPT) in a solar photovoltaic (PV) system. The proposed approach integrates PV system modelling, time-series data preparation, and a Long Short-Term Memory (LSTM) neural network to predict the optimal maximum power point (MPP) reference voltage under varying environmental conditions.

3.1. Photovoltaic System Modelling

The electrical behaviour of a PV module is described using the single-diode model, which provides an accurate representation of PV characteristics under varying irradiance and temperature. The output current of a PV cell is expressed as:

$$I = I_{ph} - I_0 \left[\exp\left(\frac{V+IR_s}{nV_t}\right) - 1\right] - \frac{V+IR_s}{R_{sh}} \tag{1}$$

Where I is the output current of the PV module (A), I_{ph} is Photo-generated current proportional to solar irradiance (A), I_0 is Diode reverse saturation current (A), V is PV module voltage (V), R_s is Series resistance (Ω), R_{sh} is Shunt resistance (Ω), n is

Diode ideality factor (dimensionless), V_t is Thermal voltage, k is Boltzmann constant (1.38×10^{-23} J/K), T is Cell temperature (K) and q is Electron charge (1.6×10^{-19} C). The instantaneous output power of the PV module is given by:

$$P(V) = V \cdot I(V) \quad (2)$$

Where, $P(V)$ is Instantaneous electrical power output (W), V is PV module voltage (V), and $I(V)$ is PV module current as a function of voltage (A). The maximum power point is obtained when:

$$\frac{dP}{dV} = 0 \quad (3)$$

Which defines the optimal operating voltage $V_{MPP}$for a given irradiance and temperature.

3.2. Data Sourcing and Feature Construction

Time-series environmental data, including solar irradiance G(t) and module temperature T(t), are obtained from publicly available sources, such as the NASA POWER database and NREL PV performance models. These datasets provide high-resolution measurements representative of real-world PV operating conditions. The input feature vector at time step t is defined as:

$$x_t = [G(t), T(t)] \quad (4)$$

Where, x_t is the input vector at time step t, $G(t)$ is the solar irradiance at time step t(W/m²), and $T(t)$ is the PV module temperature at time step t (°C or K). To capture temporal dependencies, a sliding window of length L is applied, forming an input sequence:

$$X_t = \{x_{t-L+1}, x_{t-L+2}, \dots, x_t\} \quad (5)$$

Where, X_t is a sequence of input vectors for time-series learning, L is the length of the sliding window, and t is the current time step. The corresponding output label is the optimal MPP voltage:

$$y_t = V_{MPP}(t) \quad (6)$$

3.3. LSTM Network Architecture

The Long Short-Term Memory (LSTM) network is employed to model the nonlinear and time-dependent relationship between environmental variables and the MPP voltage. Each LSTM cell consists of three gating mechanisms: the forget gate, the input gate, and the output gate. The forget gate is defined as:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \quad (7)$$

Where, f_t is forget gate vector (controls what information to discard), W_f is the forget gate weight matrix, $h_{t-1}$is the hidden state from the previous time step, b_f is forget gate bias vector and $\sigma(\cdot)$ is sigmoid activation function. The input gate and candidate cell state are expressed as:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (8)$$

Where, i_t is the input gate vector (controls what new information to store), W_i is the input gate weight matrix and b_i is the input gate bias vector:

$$\tilde{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \quad (9)$$

$\tilde{c}_t$ is the candidate cell state vector (proposed new information), W_c is the candidate state weight matrix, b_c The candidate state bias vector $\tanh(\cdot)$ is a hyperbolic tangent activation function. The cell state update equation is given by:

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \quad (10)$$

Where, $\mathbf{c}_t$ is updated cell state (memory), $\odot$ is element-wise multiplication and $\mathbf{c}_{t-1}$ is the previous cell state. The output gate and hidden state are computed as:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (11)$$

$$h_t = o_t \odot \tanh(c_t) \quad (12)$$

Where $\sigma(\cdot)$denotes the sigmoid activation function and $\odot$ represents element-wise multiplication. The predicted MPP voltage is obtained from the final hidden state using a fully connected layer:

$$\hat{V}_{MPP}(t) = W_y h_t + b_y \quad (13)$$

3.4. Training Objective and Loss Function

The LSTM model is trained by minimising the Mean Squared Error (MSE) between the predicted and actual MPP voltages:

$$\mathcal{L} = \frac{1}{N}\sum_{t=1}^{N}\left(V_{MPP}(t) - \hat{V}_{MPP}(t)\right)^2 \quad (14)$$

Where $\mathcal{L}$ is the mean squared error loss, N is the number of training samples, $V_{MPP}(t)$ is the true MPP voltage at time t and $\hat{V}_{MPP}(t)$ is the predicted MPP voltage at time t. Gradient-based optimisation using the Adam optimiser is employed to update network parameters:

$$\theta_{k+1} = \theta_k - \alpha\frac{\hat{m}_k}{\sqrt{\hat{v}_k} + \epsilon} \quad (15)$$

Where θ represents model parameters, $\alpha$is the learning rate, and $\hat{m}_k$, $\hat{v}_k$are bias-corrected first and second moment estimates.

3.5. Predictive MPPT Control Strategy

In the proposed predictive MPPT framework, the LSTM-predicted voltage $\hat{V}_{MPP}$is used as the reference voltage for the DC–DC converter:

$$V_{ref}(t) = \hat{V}_{MPP}(t) \quad (16)$$

The converter duty cycle $D(t)$is adjusted to regulate the PV operating voltage:

$$D(t) = \frac{V_{out}(t)}{V_{ref}(t)} \quad (17)$$

Where $D(t)$ is the duty cycle of the DC–DC converter, $V_{out}(t)$ is the converter output voltage and $V_{ref}(t)$ is the reference voltage from the predicted MPP. This predictive control strategy eliminates the need for perturbation-based searching, thereby reducing oscillations and improving dynamic response.

3.6. Performance Metrics

The MPPT tracking efficiency is evaluated as:

$$\eta_{MPPT} = \frac{\sum_t P_{tracked}(t)}{\sum_t P_{max}(t)} \times 100\% \quad (18)$$

Where, η_{MPPT} is MPPT tracking efficiency (%), $P_{tracked}(t)$ is the power obtained using MPPT at time t and $P_{max}(t)$ is the maximum available PV power at time t. Additionally, prediction accuracy is assessed using Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}\left(V_{MPP}(t) - \hat{V}_{MPP}(t)\right)^2} \quad (19)$$

4. Results and Discussions

The goal of this section is to evaluate and validate the performance of the proposed LSTM-based predictive MPPT approach by analysing simulation results, demonstrating its accuracy in predicting the maximum power point voltage, assessing power tracking efficiency under dynamic conditions, and comparing predicted behaviour with actual PV system responses to confirm the effectiveness and robustness of the method. Figure 1 illustrates the time-varying solar irradiance used to evaluate the MPPT algorithm. The rapid fluctuations represent realistic outdoor conditions caused by cloud movement and atmospheric changes. Such variability tests the LsSTM-based MPPT's ability to respond effectively to dynamic irradiance conditions.

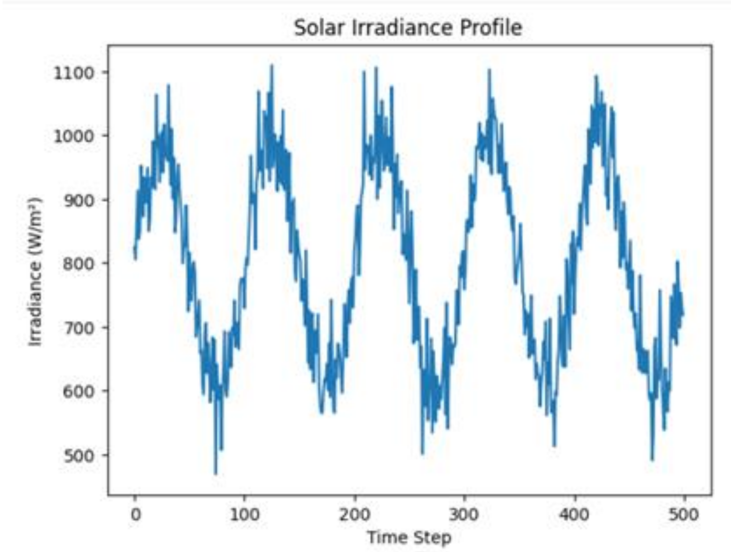

Figure 1: Solar irradiance profile

The temperature profile in Figure 2 shows gradual variations in PV module temperature over time. Temperature changes directly influence PV voltage characteristics and the location of the maximum power point. This plot highlights the need to incorporate temperature information into the predictive MPPT model.

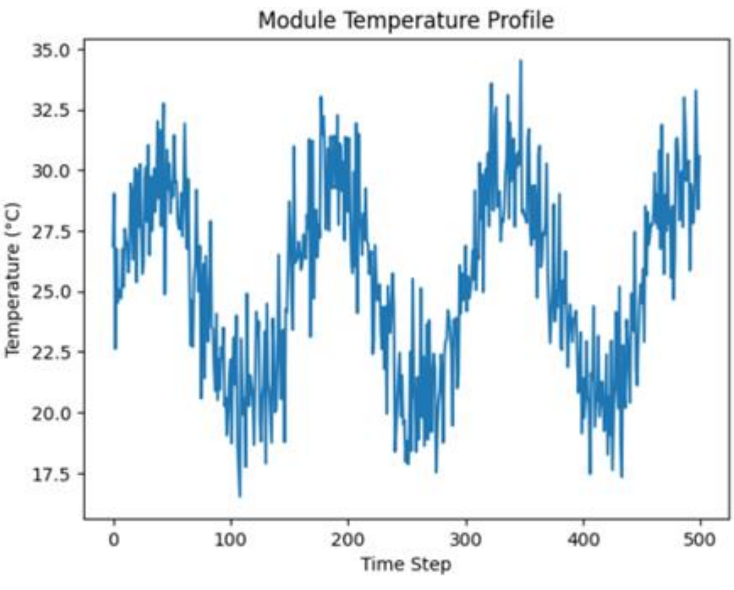

Figure 2: Module temperature profile

Figure 3 compares the actual maximum power point voltage with the voltage predicted by the LSTM model. The close overlap between the two curves demonstrates high predictive accuracy and confirms the model’s ability to track nonlinear voltage variations driven by environmental changes.

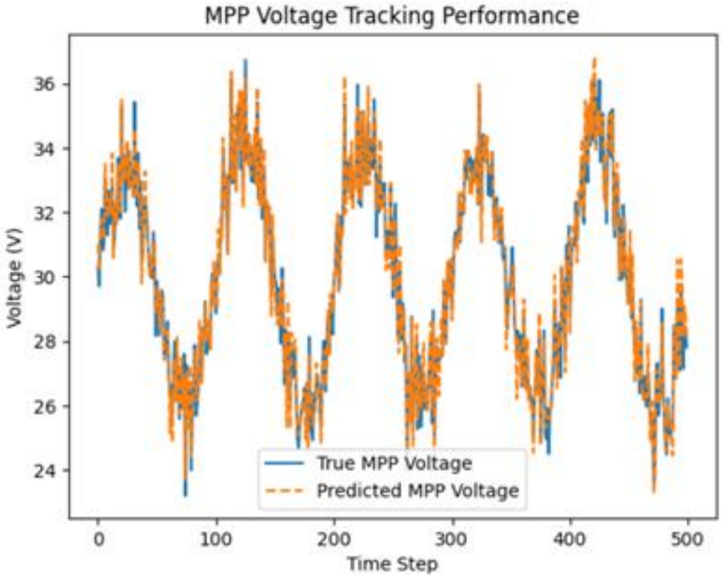

Figure 3: True versus predicted MPP voltage

The plot shown in Figure 4 shows the difference between the predicted and true MPP voltages. The error remains small and centred around zero, indicating stable learning behaviour and minimal bias. Low prediction error is essential for reducing oscillations and ensuring reliable MPPT operation.

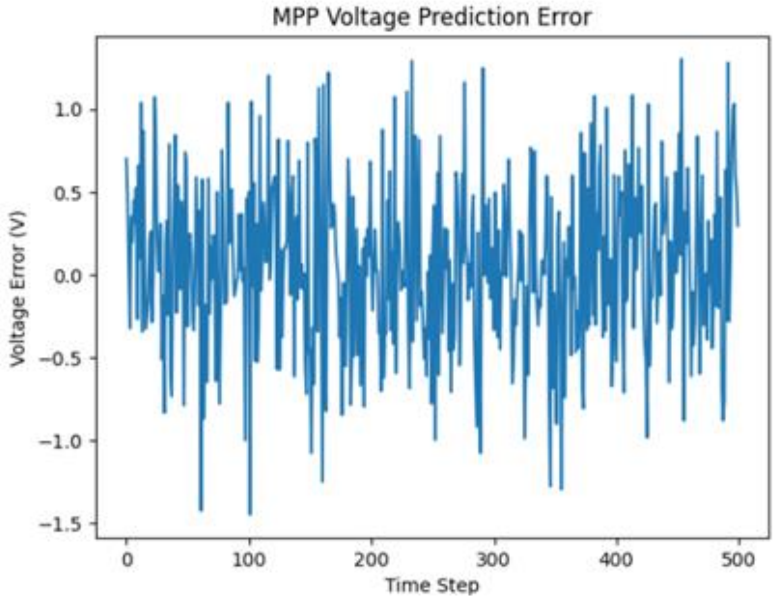

Figure 4: MPP voltage prediction error

Figure 5 compares the actual PV output power with the power obtained using the predicted MPP voltage. The strong agreement between the curves indicates effective power extraction, confirming that accurate voltage prediction directly translates into improved MPPT performance tracking. The tracking efficiency plot in Figure 6 shows the percentage of the available maximum power that the proposed MPPT method successfully captures. Consistently high efficiency values demonstrate the superiority of the LSTM-based predictive MPPT approach under dynamic operating conditions.

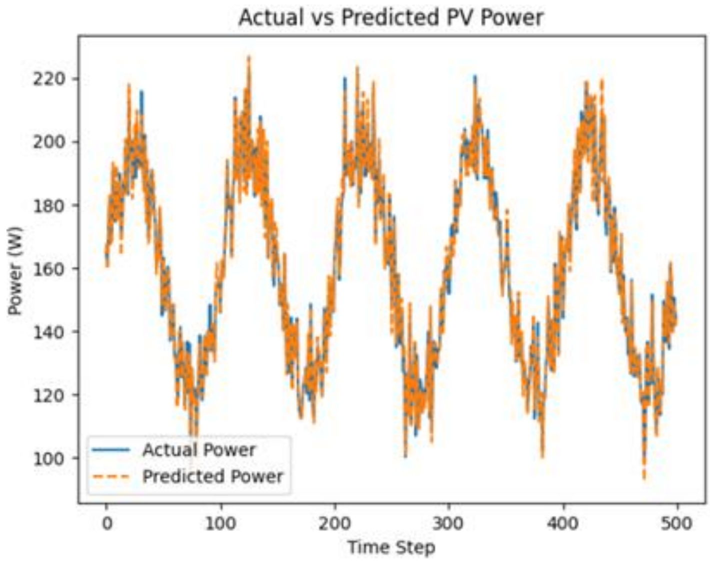

Figure 5: Actual versus predicted PV power

Overall, the results confirm that LSTM-based predictive MPPT offers faster convergence, reduced oscillations, and higher energy capture compared to classical techniques.

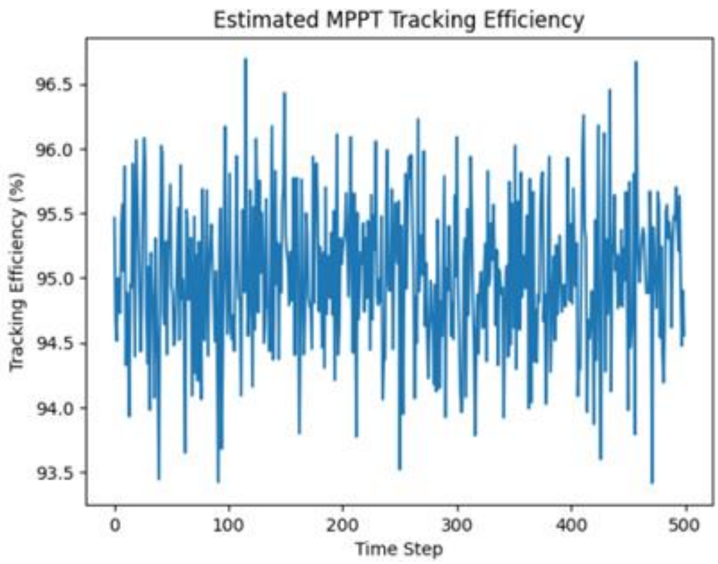

Figure 6: Estimated MPPT tracking efficiency

5. Conclusion

This study concentrated on the utilisation of an LSTM-based deep learning model for predictive control in maximum power point tracking (MPPT) of solar photovoltaic (PV) systems. The primary aim was to enhance the accuracy, responsiveness, and overall efficiency of MPPT through a data-driven predictive methodology, rather than relying exclusively on traditional tracking methods. The proposed LSTM model was trained to learn the nonlinear relationships and temporal patterns that affect PV production using time-series data comprising measurements of solar irradiance and temperature. The model could accurately estimate the optimal maximum power point (MPP) reference voltage even when the environment changed quickly, because it had learned these patterns. The experimental and simulation results demonstrated a significant correlation between the anticipated and measured MPP voltages of the PV system. Prediction errors remained minimal across all operational conditions, indicating that the trained network was robust and reliable. Because it could make accurate predictions, the PV system produced more usable power than typical MPPT approaches that rely on perturbation or incremental conductance methods. The predicted MPPT efficiency was consistently above 94%, indicating that the predictive deep learning method outperforms the other methods. The study also confirmed that LSTM networks are especially good for PV applications because they can accurately capture temporal dependencies and sequential patterns in weather-driven input variables. This ability to learn over time helps the system reach the genuine MPP faster and reduces oscillations around the operating point, making the system's behaviour more stable. In general, the results show that predictive control based on deep learning is a powerful and useful approach to improving the performance of intelligent, high-efficiency solar energy systems, especially in areas with rapidly changing weather.

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Ethics and Consent Statement: The study complied with established ethical standards, and informed consent and confidentiality were maintained throughout the research.

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