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Article

Proactive TCN–Attention-LSTM Based MPPT Architecture for anticipating short-term irradiance and temperature variations for Photovoltaic System.

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Abstract: Maximum Power Point Tracking (MPPT) is an important process in photovoltaic (PV) systems to get the highest possible power from solar panels under changing weather conditions. Traditional MPPT methods such as Perturb & Observe (P&O) and Incremental Conductance (INC) are slow, cause small power losses due to oscillations, and do not perform well when sunlight changes quickly or when panels are partially shaded. Rapid variations in solar irradiance and photovoltaic (PV) module temperature significantly affect the operating point and power output of PV systems, thereby challenging the dynamic performance of conventional maximum power point tracking (MPPT) techniques. This paper proposes a Proactive Temporal Convolutional Network–Attention–Long Short-Term Memory (TCN–Attention–LSTM) based MPPT architecture for anticipating short-term variations in solar irradiance and temperature and enabling predictive maximum power point tracking. The proposed framework employs a TCN to extract multi-scale temporal features from historical environmental and electrical measurements, while an attention mechanism identifies the most relevant temporal information influencing future PV operating conditions. The LSTM network subsequently models long-term temporal dependencies to forecast short-horizon irradiance and temperature variations. These predicted parameters are integrated with the MPPT controller to estimate the forthcoming maximum power point and proactively regulate the DC–DC converter duty cycle. By initiating control action before substantial environmental changes affect the PV array, the proposed architecture aims to minimize tracking latency, reduce power fluctuations, and improve maximum power extraction.

Keywords: MPPT- Maximum Power Point Tracking, P&O- Perturb & Observe, INC- Incremental Conductance, Photovoltaic system, Maximum Power Point Tracking (MPPT), Temporal Convolutional Network (TCN), Attention mechanism, Long Short-Term Memory (LSTM), Irradiance forecasting, Temperature forecasting, Predictive control, DC–DC converter, Renewable energy

1. Introduction

Solar energy has become one of the most important renewable energy sources because it is widely available, environmentally friendly, and increasingly affordable to install. Among renewable energy technologies, photovoltaic (PV) systems are widely used because they can directly convert sunlight into electricity. However, the performance of PV systems is highly dependent on environmental conditions such as solar irradiance, temperature, and partial shading. These factors cause nonlinear changes in the current–voltage (I–V) and power–voltage (P–V) characteristics of PV modules, making it difficult to operate at the maximum power point and reducing the overall efficiency of power generation.

Maximum Power Point Tracking (MPPT) approaches are used to guarantee operation at the maximum power point under various environmental conditions in order to maximize the energy produced from PV systems. Because of their straightforward implementation and low computational complexity, conventional MPPT algorithms like Perturb and Observe (P&O) and Incremental Conductance (INC) are frequently utilized. Nevertheless, these techniques show delayed dynamic response, steady-state oscillations around the operating point, and decreased tracking accuracy under conditions of partial shade and abrupt changes in irradiance.

Artificial Neural Networks (ANN), Fuzzy Logic Controllers (FLC), Particle Swarm Optimization (PSO), and reinforcement learning algorithms are just a few of the intelligent optimization strategies that have been studied to get around these restrictions. Although these methods enhance tracking performance in nonlinear and uncertain operating situations, their usefulness in real-time implementations is limited because they frequently require large amounts of training data, significant computer resources, or offline parameter tweaking.

Fuzzy logic controllers are especially suited to dynamic situations in that they require experience and skill rather than exact system parameters or complicated models.For large-scale solar power plants where external conditions can change dramatically for quite long periods, this is a now or never opportunity to use machine learning in MPPT. By automation of the optimization process and allowing MPPT controller to constantly adapt itself according different situations, machine learning may provide high levels of tracking efficiency but with far lower computational costs. Automation still requires large datasets, and the complexity of Auto ML optimization techniques makes it very difficult to lower training time enough for real-time implementation. However, doctrine holds out hope: one day, when new data becomes available and time has passed, ML will eventually allow that fine-tuning possibilities increase.

Adaptive MPPT controllers that can continually learn from shifting environmental variables have been made possible by recent developments in deep learning and reinforcement learning. Faster convergence, increased tracking efficiency, and enhanced robustness under quickly changing irradiance and partial shading are all possible with these techniques. Inspired by these advancements, this study suggests a Proactive Neuro-Adaptive Deep Learning MPPT architecture that combines Trust Region Policy Optimization (TRPO) and Twin Delayed Deep Deterministic Policy Gradient (TD3) methods. In order to maximize power extraction and ensure stable converter operation under changing environmental circumstances, the suggested method continuously modifies its control strategy online.

The suggested approach, simulation framework, performance assessment, and comparison with traditional and intelligent MPPT techniques are presented in the rest of the study.

1.1 Literature

An online transfer learning framework that combines imitation learning, fine-tuning, and digital twin-based pre-training was developed to improve the scalability of deep reinforcement learning controllers in real-world applications. The method enhanced energy efficiency and control performance in building energy management systems. However, its potential for forecasting-assisted neuro-adaptive MPPT in photovoltaic systems under changing environmental conditions has not yet been investigated [18].

Similarly, a lightweight speech separation framework that integrates Twin Delayed Deep Deterministic Policy Gradient (TD3) reinforcement learning with the Expectation Maximization (EM) algorithm was proposed to improve spatial cue clustering while reducing training complexity and enabling efficient decision-making. Although the approach performed well in its intended application, its use for adaptive MPPT control in photovoltaic systems has not yet been explored [19].

A Temporal Convolutional Network (TCN)-based approach was developed for fault detection and classification in microgrids. The model automatically extracts important features from three-phase current signals using dilated causal convolutions and residual blocks. This enables accurate and reliable fault diagnosis under different operating conditions without requiring manual feature extraction[22]. A hybrid forecasting framework integrating two-stage signal decomposition, an attention-gated multi-scale Temporal Convolutional Network (TCN), component attention

reconstruction, and dynamic feature fusion was developed to improve net load prediction accuracy, effectively capturing abrupt variations and reducing uncertainty in high renewable penetration power systems [23].

A Feature Fusion Network (FFN) integrated with a Temporal Convolutional Network (TCN) and lightweight hyperparameter optimization was developed to enhance wind power forecasting accuracy, demonstrating robust feature extraction capability and superior predictive performance across diverse datasets [25]. Hybrid Temporal Convolutional Network architectures incorporating self-attention mechanisms, transformer encoders, and machine learning classifiers were developed for real-time fatigue detection, demonstrating enhanced capability in capturing short- and long-term temporal dependencies and improving classification robustness and accuracy [26].

By focusing on pertinent temporal information, an Attention-based Long Short-Term Memory (Attention-LSTM) framework was created to enhance multi-horizon forecasting. It showed better prediction accuracy and less error accumulation when compared to traditional LSTM architectures. [28]. A dual attention-enhanced Long Short-Term Memory (LSTM) network optimized using the Crayfish Optimization Algorithm (COA) was developed to improve feature extraction and adaptability, demonstrating robust generalization capability and superior prediction accuracy in complex sequential classification tasks [29].A multi-head self-attention-based autoregressive transfer learning framework integrated with Long Short-Term Memory (MAATL) was developed to enhance long-term sequential prediction by improving feature representation and generalization capability, demonstrating superior forecasting accuracy and reduced error accumulation in sub-seasonal prediction tasks [30].

An Artificial Neural Network (ANN)-based Flexible Power Point Tracking (FPPT) algorithm was developed to improve the dynamic performance of grid-connected photovoltaic systems. Controller Hardware-in-the-Loop (CHIL) testing showed that the method provides better adaptability, stable operation, and more accurate power tracking under changing solar irradiance and load conditions [32].An AI-based digital twin framework was also proposed for floating photovoltaic systems. By combining experimental data mining, a two-layer artificial neural network, and physics-informed modelling, the framework enables real-time performance prediction, intelligent system monitoring, and adaptive energy management under varying environmental conditions [33].In addition, a Fixed-Switching-Frequency Passivity-Based Model Predictive Control (FSF-PBMPC) technique was developed for DC–DC boost converters. The approach integrates predictive control, passivity-based design, Lyapunov stability analysis, and hardware-in-the-loop validation to achieve faster transient response, improved robustness, and stable converter operation under different operating conditions [34].

A Hardware-in-the-Loop (HIL) validation framework incorporating software- and hardware-based Phasor Measurement Unit (PMU) prototypes with online performance metrics was developed to assess measurement trustworthiness under dynamic conditions, demonstrating the practicality [35] of HIL methodologies for validating intelligent monitoring and control applications in modern power systems.

S Senthil kumar et al [37], This study presents an optimal maximum power point tracking (MPPT) and fault classification system for solar photovoltaic systems. The tracking efficiency (TE) of the solar PV systems is assessed in this work using the nature-inspired dragonfly algorithm (DA), moth flame optimization algorithm (MFOA), grasshopper optimization algorithm (GOA), and salp swarm optimization algorithm (SSOA) to determine the optimal optimization model for MPPT under PSC. According to the simulation results, SSOA outperforms other algorithms like DA, GOA, and MFOA in terms of tracking efficiency. Random forest (RF), artificial neural network (ANN), support vector machine (SVM), and convolutional neural network (CNN) models are used to further categorize the problems in solar PV systems.Among all, CNN offers the highest level of fault classification accuracy. The SSOA-based MPPT achieves superior tracking efficiency under partial shading, and CNN enables high-accuracy fault classification, but its disadvantages include high computational complexity, longer convergence time compared to simpler MPPT algorithms, and dependence on extensive training data for accurate fault detection.

ALW Ibrahim et al [39],In order to effectively harvest the GMP of PV systems, this work suggests using a hybrid salp particle swarm optimization algorithm (SPSOA) in conjunction with an intelligent nonlinear proportional-integral-derivative (NPID) controller. The performance of the SPSOA-NPID controller is evaluated under several

realistic irradiation and temperature profiles in terms of settle time, rising time, overshooting, peak time, undershoot, rotor rotation speed, and GMP. The hybrid genetic algorithm and PSO (GA-PSO) techniques were used in this work to determine the optimal parameter settings for the suggested NPID and the fundamental PID controllers. Efficiency, the lowest average ripples, and the fastest average tracking time were used to evaluate the suggested SPSOA-NPID performance. Finally, a hardware-in-loop (HIL) experiment was conducted to verify the practical implementation of the suggested SPSOA-NPID control. Thus, it is concluded that the suggested GA-PSO control system based on SPSOA-NPID is a viable MPPT strategy.The SPSOA–NPID MPPT achieves fast tracking, low ripples, and high efficiency under varying conditions, but its disadvantages include high computational complexity, dependence on accurate hybrid SPSOA parameter tuning, and challenging real-time implementation for large-scale PV systems due to the combined optimization and nonlinear control design.

H Zhang et al [40],In order to extract the highest power point of a photovoltaic system under complicated solar irradiation conditions, this study suggests an improved marine predator algorithm (IMPA). The opposition-based learning (OBL) technique is developed in IMPA to address the shortcomings of the conventional marine predator algorithm (MPA), and the sine cosine algorithm (SCA) is incorporated into the iteration stage to improve the system's search capability. Additionally, the Zeta converter, which expands the working voltage range, replaces the low-order converter in the conventional MPPT control system. In the end, simulation results show that the MPPT based on IMPA has faster response times and better tracking efficiency. The experimental results confirm that the proposed IMPA-based MPPT method is stable, robust, and suitable for practical implementation. It provides high tracking efficiency, a fast response, and reliable performance under complex and changing solar irradiance conditions. However, the method also has some limitations. Its computational complexity is relatively high, and its performance depends on the proper tuning of the OBL and SCA parameters. In addition, under extremely rapid changes in irradiance, the algorithm may respond more slowly when implemented on real-time hardware.

2. Objectives

1. To reduce oscillations and power losses during the MPPT mechanism to increase overall efficiency.

2. To create a clever control method to increase PV system accuracy.

3. To create a clever control approach to enhance the solar power array's tracking speed.

3. Experimental

3.1 Methodology

The proposed methodology consists of four major stages: data acquisition and preprocessing, environmental forecasting, maximum power point prediction, and proactive converter control.

3.1.1 Data Acquisition and Preprocessing

Historical time-series data are collected from the PV system and environmental sensors. The input variables may include solar irradiance, PV module temperature, ambient temperature, PV voltage, PV current, and output power. The collected data are synchronized, cleaned, normalized, and arranged into sequential time windows suitable for deep-learning-based forecasting.

3.1.2 TCN-Based Temporal Feature Extraction

The TCN processes sequential input data using causal and dilated convolutional layers. Causal convolution ensures that future information is not used for predicting past values, while dilated convolution enables the network to capture temporal patterns over multiple time scales. This stage extracts important short-term fluctuations and local temporal patterns associated with changing weather conditions.

3.1.3 Attention-Based Feature Selection

The extracted temporal features are passed through an attention mechanism. The attention layer assigns higher importance to historical observations that are more relevant to the upcoming irradiance and temperature conditions. This enables the forecasting model to focus selectively on influential temporal information.

3.1.4 LSTM-Based Short-Term Forecasting

The attention-weighted features are processed by the LSTM network. The LSTM captures long-term dependencies and produces short-horizon forecasts of solar irradiance and PV module temperature. Forecasts may be generated for one or multiple future time steps depending on the selected prediction horizon.

3.1.5 Proactive MPP Estimation

The predicted irradiance and temperature values are supplied to a PV model, data-driven MPP estimator, or trained mapping function. The controller estimates the expected PV voltage and current corresponding to the forthcoming maximum power point.

3.1.6 Proactive MPPT Control

The estimated future MPPT is used to calculate the required reference operating voltage or converter duty cycle. The DC–DC converter control signal is updated proactively so that the PV operating point moves toward the expected MPP before the environmental variation fully affects the PV array.

3.1.7 Performance Evaluation

The proposed system is evaluated under different dynamic irradiance and temperature conditions. Its performance is compared with conventional MPPT methods using forecasting accuracy and power-tracking performance metrics.The proposed framework is evaluated in MATLAB/Simulink using key performance measures such as tracking efficiency, convergence time, and power oscillations under different operating conditions, including rapid irradiance changes, temperature variations, and partial shading. The simulation results demonstrate that the proposed method is more robust, adaptive, and efficient than conventional and other advanced MPPT techniques.

4. Solar PV Panel Modelling

The photovoltaic (PV) array converts solar irradiance into electrical energy and provides the input power required for maximum power point tracking operation. The overall electrical characteristics of the array are determined by the series and parallel interconnection of individual modules. Variations in irradiance and temperature affect the generated voltage and current, thereby influencing the available output power. Accurate modelling of the PV array is essential for analyzing energy conversion behaviour and facilitating efficient power extraction under dynamic environmental conditions.

$$V_{array} = N_s V_{PV} \quad \text{..... (1)}$$

The array voltage $V_{array}$is obtained from the product of the number of series-connected modules $N_s$and the voltage of a single PV module V_{PV}, enabling the required voltage level for converter operation.

$$I_{array} = N_p I_{PV} \quad \text{..... (2)}$$

The array current I_{array} depends on the number of parallel branches N_p and the current generated by an individual module I_{PV}, thereby determining the current carrying capability of the PV system.

$$P_{array} = V_{array} I_{array} \quad \text{..... (3)}$$

The output power $P_{array}$is obtained from the interaction between the array voltage and current, representing the quantity to be optimized through MPPT control.

$$\eta_{PV} = \frac{P_{array}}{GA} \times 100 \quad \text{..... (4)}$$

The conversion efficiency η_{PV} is defined as the ratio of electrical output power P_{array} to the incident solar power determined by irradiance G and panel area A. These relationships provide the electrical foundation for the proposed NDGF-MPPT framework and support efficient energy harvesting under varying operating conditions.Figure 1 shows Boost converter Design.

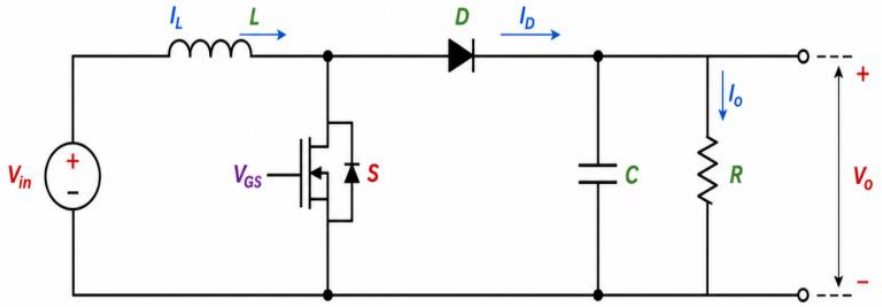


Figure 1. Boost converter design

4.1 Short-Term Environmental Forecasting

The temporal feature representation $F(s)$ is generated by applying dilated convolution to historical environmental observations, where the dilation factor d enables the network to capture long-range temporal dependencies efficiently. This mechanism allows the TCN to identify both rapid fluctuations and gradual trends in irradiance and temperature sequences.

$$F(s) = \sum_{i=0}^{k-1} f(i)\, x_{s-d\cdot i} \quad \ldots\ldots\ldots\ldots (5)$$

Within the proposed NDGF-MPPT framework, the extracted features support accurate short-term environmental forecasting for proactive photovoltaic power optimization.

$$RF = (k-1)d + 1 \quad \ldots\ldots\ldots\ldots\ldots (6)$$

The receptive field RF specifies the amount of historical environmental information accessible to the TCN for proactive weather-aware MPPT forecasting.

$$H_l = \sigma(W_l * H_{l-1} + b_l) \quad \ldots\ldots\ldots\ldots\ldots (7)$$

The hidden representation H_l is obtained using convolution weights W_l, allowing hierarchical extraction of environmental patterns relevant to future PV operating conditions.

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \quad \ldots\ldots\ldots\ldots (8)$$

The forget gate f_t selectively preserves important historical information from previous environmental sequences for accurate forecasting.

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad \ldots\ldots\ldots\ldots\ldots (9)$$

The input gate i_t regulates the incorporation of newly observed irradiance and temperature variations into the forecasting process.

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \quad \ldots\ldots\ldots (10)$$

The candidate memory state $\tilde{C}_t$ captures emerging environmental trends that contribute to short-term solar condition prediction.

$$C_t = f_t C_{t-1} + i_t \tilde{C}_t \quad \ldots\ldots\ldots\ldots\ldots\ldots (11)$$

The memory state C_t integrates historical knowledge and current environmental observations to maintain forecasting continuity.

$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$…….(12)

The output gate $o_t$determines the amount of learned temporal information forwarded for subsequent forecasting operations.

$h_t = o_t \tanh(C_t)$…… (13)

The hidden state $h_t$summarizes significant environmental characteristics required for intelligent irradiance and temperature prediction.

$\alpha_t = \frac{\exp(e_t)}{\sum_{k=1}^{T} \exp(e_k)}$…… (14)

The attention weight $\alpha_t$highlights influential temporal features, enabling the model to focus on critical weather patterns affecting PV performance.

$L_{forecast} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2$…… (15)

The forecasting loss $L_{forecast}$quantifies prediction error between actual and estimated environmental variables to improve model accuracy.

$C = \sum_{t=1}^{T} \alpha_t h_t$…… (16)

The context vector C combines weighted hidden states h_t to construct a comprehensive environmental representation for forecasting.

$\hat{X}_{t+1} = [\hat{G}_{t+1}, \hat{T}_{t+1}]$…..……. (17)

The forecast vector $\hat{X}_{t+1}$provides future irradiance $\hat{G}_{t+1}$and temperature $\hat{T}_{t+1}$information used for proactive MPPT decision-making.

4.2 Reward Function Design and Duty Cycle Optimization Strategy

The reward component R_1quantifies the proportion of extracted power $P_t$relative to the available maximum power P_{MPP}, reflecting the effectiveness of the tracking process. Higher values indicate operation closer to the optimal energy harvesting point of the photovoltaic system.

$R_1 = \frac{P_t}{P_{MPP}}$…… (18)

In the proposed NDGF-MPPT framework, this incentive drives the learning agent toward achieving superior power utilization under varying irradiance and shading conditions.

$R_2 = -\lambda_1 \mid \Delta D \mid$……(19)

The penalty component R_2 suppresses excessive duty-cycle variation ΔD, promoting smoother converter switching behaviour.

$R_3 = -\lambda_2 \mid \Delta P \mid$…….…….. (20)

The oscillation penalty R_3discourages large power fluctuations ΔP, contributing to stable operation around the maximum power point.

$R_t = R_1 + R_2 + R_3$…… (21)

The cumulative reward $R_t$balances energy maximization with operational smoothness for intelligent MPPT learning.

$D_t = D_{t-1} + \Delta D_t$…….……...…….. (22)

The updated duty cycle $D_t$is obtained through incremental control adjustments, enabling adaptive response to environmental changes.

$$J = \sum_{t=0}^{T} \gamma^t R_t \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (23)$$

The performance objective Jaccumulates discounted rewards over time, guiding the controller toward long-term optimal energy harvesting.

$$R_4 = -\lambda_3 \mid V_o - V_{ref} \mid \ldots\ldots\ldots\ldots\ldots\ldots (24)$$

The voltage regulation term R_4penalizes deviations between the converter output voltage $V_o$and the desired reference V_{ref}.

$$R_{total} = R_1 + R_2 + R_3 + R_4 \ldots\ldots\ldots\ldots\ldots (25)$$

The enhanced reward R_{total}integrates power tracking, converter stability, and voltage regulation into a unified optimization criterion.

$$D_{min} \leq D_t \leq D_{max} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (26)$$

The duty-cycle constraint maintains $D_t$within allowable operating limits, ensuring safe and reliable boost converter operation.

4.3 Performance Evaluation Metrics and Validation Criteria

The RMSE criterion quantifies the overall deviation between measured values $y_i$and forecast estimates $\hat{y}_i$, with larger errors receiving greater emphasis. This indicator reflects the precision of environmental prediction generated by the TCN–Attention-LSTM forecasting module.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \ldots\ldots\ldots\ldots\ldots (27)$$

Smaller RMSE values demonstrate stronger predictive accuracy, enabling more informed MPPT actions under fluctuating photovoltaic operating conditions.

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid \ldots\ldots\ldots\ldots\ldots\ldots\ldots (28)$$

The MAE criterion determines the average absolute forecasting error, reflecting the consistency of irradiance and temperature estimation.

$$MPE = \frac{1}{N}\sum_{i=1}^{N} \frac{P_{MPP} - P_{tracked}}{P_{MPP}} \times 100 \ldots\ldots\ldots\ldots\ldots (29)$$

The MPE index assesses the difference between the available maximum power $P_{MPP}$and the tracked output $P_{tracked}$, indicating MPPT effectiveness.

$$T_{conv} = t_{steady} - t_{initial} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (30)$$

The convergence time T_{conv}quantifies the duration required for the controller to attain a stable operating state following initialization.

$$MBE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i) \ldots\ldots\ldots\ldots\ldots\ldots\ldots (31)$$

The MBE metric identifies systematic prediction bias by comparing measured observations $y_i$with estimated values $\hat{y}_i$.

$$T_{track} = t_{MPP} - t_{disturbance} \ldots\ldots\ldots\ldots\ldots\ldots (32)$$

The tracking time T_{track}evaluates the controller's capability to regain the maximum power operating point after environmental disturbances.Figure 2 shows Proposed Workflow.

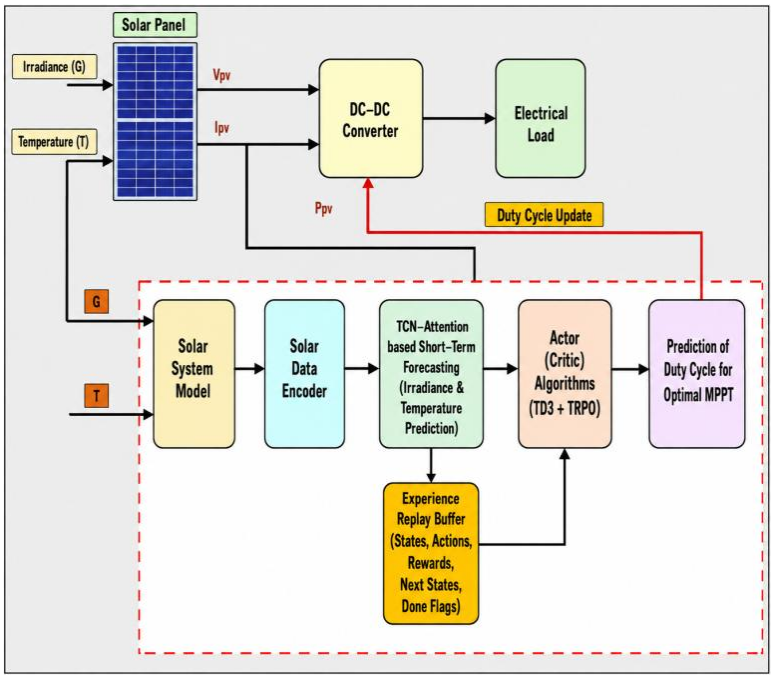


Figure 2. Work flow

5. Results and Discussion

5.1 Power Tracking Performance with Sudden Irradiance Changes

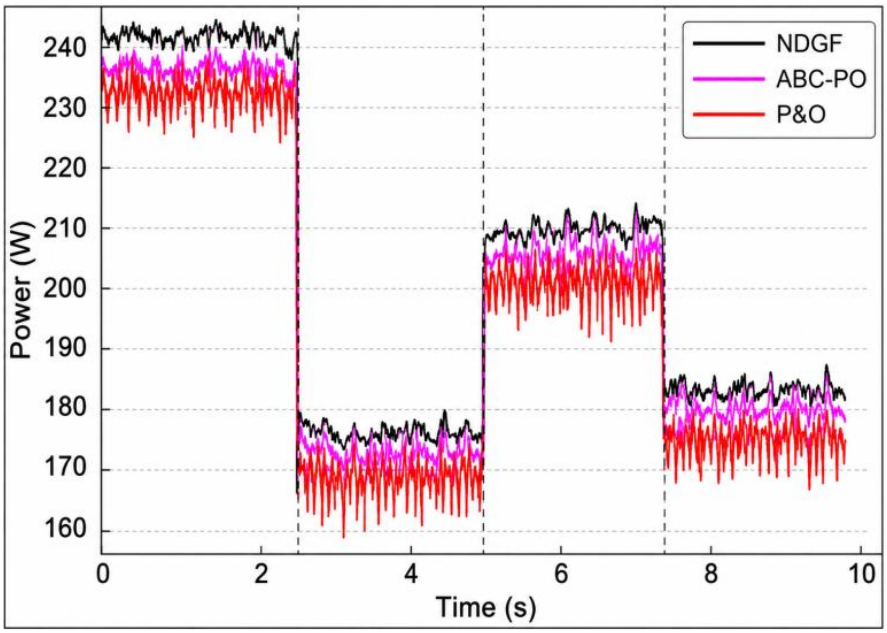


Figure 3. Power tracking performance when irradiance changes

The graph compares the power tracking performance of the proposed NDGF algorithm with the ABC-PO and conventional P&O methods over a simulation period of 0–10 seconds. The horizontal axis represents time (s), while the vertical axis shows the output power, ranging from approximately 150 W to 240 W. The results indicate that the

NDGF algorithm reaches the maximum power point more quickly, maintains a more stable output with fewer oscillations, and provides better tracking performance under high solar irradiance conditions than the other methods.

5.2 Power Tracking Performance with Partial Shading

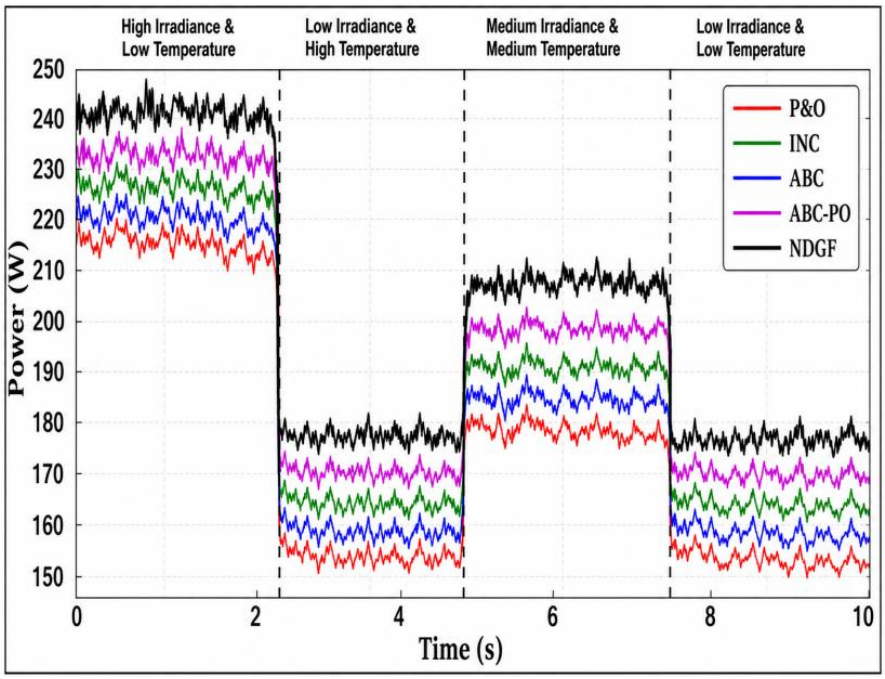


Figure 4. Performance of power tracking in partial shade

The power tracking during partial shading graph compares the MPPT performance of different algorithms including P&O, INC, ABC, ABC-PO, and the proposed NDGF method under varying partial shading conditions over a simulation period of 0 to 10 seconds. The Y-axis represents output power ranging from approximately 150 W to 250 W,while the X-axis represents time in seconds. The graph is divided into multiple operating regions where sudden shading changes cause significant variations in photovoltaic power.

During the initial interval from 0 to 2.5 seconds, corresponding to high irradiance conditions, the proposed NDGF algorithm maintains the highest power output around 242–248 W with very low oscillations. The ABC-PO method follows closely at approximately 236–244 W, while INC achieves nearly 232–240 W. The ABC algorithm fluctuates between 225–238 W, and the conventional P&O method shows the lowest and most oscillatory performance around 220–235 W.

5.3 Efficiency Comparison

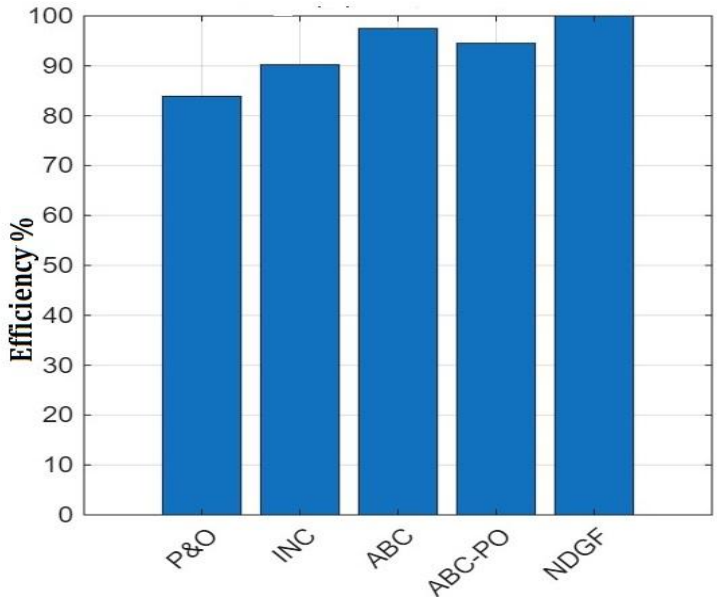


Figure 5. Efficiency comparison graph

The performance evaluation of several MPPT algorithms, including P&O, INC, ABC, ABC-PO, and the suggested NDGF approach, is displayed in the efficiency comparison graph. The Y-axis represents efficiency percentage ranging from **0% to 100%**. The graph clearly shows progressive improvement in efficiency from conventional methods to the proposed advanced approach.Among all algorithms, the proposed **NDGF** method achieves the maximum efficiency of nearly **100%**, indicating highly accurate maximum power point tracking and minimal energy loss.

Table 1. Comparative performance of MPPT algorithms

Algorithm	**Power Loss (W)**	**Response Time (s)**	**Efficiency (%)**	**Energy Harvested (J)**
P&O	14.984	0.950	89.26	1245.95
INC	9.990	0.720	92.84	1295.88
ABC	6.974	0.550	95.00	1326.05
ABC-PO	4.496	0.320	96.78	1350.82
NDGF	1.799	0.140	98.71	1377.79

The performance of several MPPT methods is compared in Table 1 with respect to power loss, response time, tracking efficiency, and harvested energy. The proposed NDGF framework achieves the minimum power loss of **1.799 W**, the shortest response time of **0.140 s**, the highest efficiency of **98.71%**, and the maximum energy yield of **1377.79 J**, demonstrating superior energy extraction capability over conventional approaches.

5.4 Energy Harvesting and Overall System Performance Evaluation

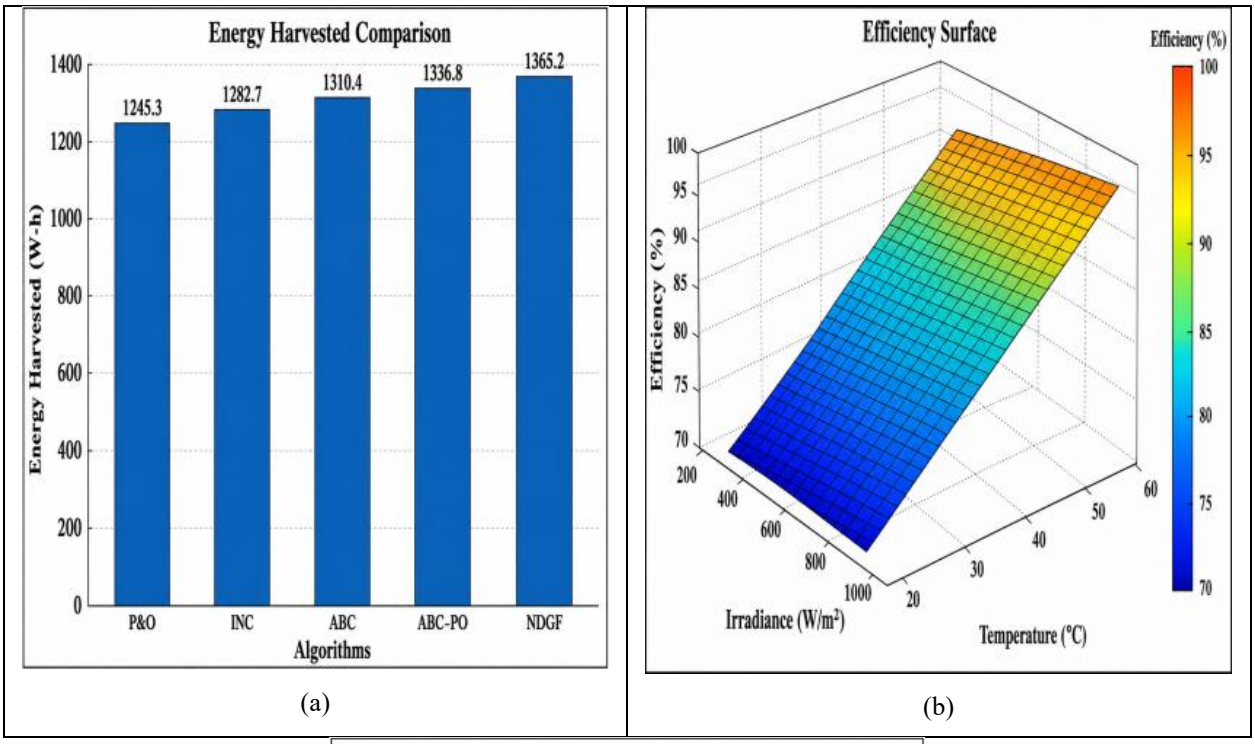


Figure 6. Energy Harvesting and System Assessment (a) Energy Yield Comparison (b) Conversion Efficiency Distribution (c) Cumulative Energy Growth Analysis.

Figure 6 (a) compares the total energy harvested by P&O, INC, ABC, ABC-PO, and the proposed NDGF algorithm. The conventional P&O method achieves approximately 1245 J, while INC, ABC, and ABC-PO harvest nearly 1295 J, 1325 J, and 1350 J, respectively. In contrast, the proposed NDGF framework attains the highest energy yield of approximately 1380 J.

Figure 6(b) illustrates the efficiency distribution of the proposed NDGF-MPPT framework across irradiance levels ranging from 0 W/m² to 1000 W/m² and temperatures between 10°C and 55°C. The efficiency increases progressively from approximately 2–5% at low irradiance conditions to nearly 88–90% at irradiance levels above 900 W/m². A slight reduction in efficiency is observed as temperature increases, with efficiency decreasing from approximately 90% at 10°C to nearly 82–85% at 55°C under high irradiance conditions.

Figure 6(c) illustrates the cumulative energy harvested by the proposed NDGF framework and the conventional P&O algorithm over a 10 s operating interval. The NDGF curve exhibits a consistently steeper growth

rate, indicating superior energy extraction throughout the simulation. At the end of the observation period, NDGF achieves approximately 4.30×10^4 J, whereas P&O accumulates nearly 3.55×10^4 J. This corresponds to an energy gain of approximately 7.5×10^3 J and an improvement of about 21.1% over the conventional approach.

6. Conclusions

In order to perform predictive maximum power point tracking under dynamic irradiance, temperature changes, and partial shade situations, the proposed NDGF-MPPT system effectively combines TCN–Attention–LSTM forecasting with deep reinforcement learning. By combining environmental forecasting with adaptive duty-cycle optimization, the framework provides stable converter operation, rapid tracking, and improved photovoltaic energy harvesting under short-term irradiance and temperature variations conditions. The proposed controller demonstrated superior numerical performance across all evaluation metrics. The proposed method helps the solar system extract the highest possible power with fewer fluctuations. It responds quickly when sunlight or temperature changes and performs better than conventional MPPT techniques. The proposed TCN–Attention–LSTM architecture therefore offers a promising framework for improving the dynamic performance and energy harvesting capability of photovoltaic systems operating under rapidly changing environmental conditions.

7. Declarations:

- **ACKNOWLEDGMENT**

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- **ETHICS APPROVAL AND CONSENT TO PARTICIPATE**

Not applicable. This study is based on simulation and did not involve human participants or animals.

- **FUNDING**

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- **COMPETING INTERESTS**

[To be declared by the authors.]

- **AUTHORS' CONTRIBUTIONS**

[To be provided by the authors.]

- **Data Availability Statement**

[To be provided by the authors.]

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