



Hybrid AI Ensemble for Real-Time Adaptive Optimization in Solar Energy Systems

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Abstract

Solar energy systems play a crucial role in fulfilling global energy needs sustainably; however, their performance is often affected by dynamic environmental factors. This study investigates the use of Artificial Intelligence (AI) for real-time optimization and adaptive control to improve the operational efficiency of solar energy systems. The research specifically addresses output variability arising from fluctuations in solar irradiance, temperature, and panel soiling, limitations that conventional control approaches fail to manage effectively. The primary goal is to develop intelligent AI-based models capable of predicting and automatically adjusting critical system parameters in real time, thereby reducing manual intervention and enhancing operational reliability. Data from a solar photovoltaic (PV) and thermal hybrid testbed in Jodhpur, India were collected over a six-month period. The Indian Meteorological Department provided more than 10000 hourly data samples that included weather and seasonal variations. An NI DAQ system with high-precision sensors was used to measure important parameters such as solar irradiance panel, and ambient temperatures wind speed inclination angle and energy output. For predictive control, the suggested methodology uses a hybrid ensemble framework that combines Extreme Gradient Boosting (XGBoost), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Deep Neural Networks (DNN). In this framework, XGBoost carries out variable importance ranking to determine the dominant influencing factors ANFIS enables adaptive operational control and DNNs forecast energy output. In contrast to previous research that concentrated on distinct AI methods this work presents a cohesive hybrid approach that integrates feature significance analysis adaptive optimization and forecasting accuracy into a single system. The hybrid ensemble model outperforms individual approaches in achieving stable and effective energy generation according to evaluation using RMSE, R2, and MEF metrics. Furthermore, its compatibility with IoT-enabled edge devices underscores its potential for large-scale, real-time, and automated solar energy management within future smart grid infrastructures, advancing global efforts toward sustainable energy transitions.

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1. Introduction

Recent advancements in artificial intelligence (AI) have revolutionized solar energy systems by boosting their performance, reliability, and adaptability. AI-driven solutions have made it possible to monitor and control solar panel operations in real time, enabling the early identification of problems like dust buildup, shade, or component failures before they have a detrimental effect on energy output. Enhanced energy planning and smooth grid integration are made possible by machine learning techniques, which provide extremely accurate forecasts of weather and solar radiation levels.

Battery management systems and power forecasting are being transformed by intelligent algorithms, which are also improving methods for energy storage and utilization. To increase the efficiency of solar power generation multi-layered architectures are being employed [1]. Power infrastructures are integrating AI models such as CNN-LSTM networks to improve cost-effectiveness operational stability and resilience [2]. Energy forecasting intelligent control systems grid coordination and resource evaluation are the main topics of this study, which examines the difficulties and developments in integrating AI into renewable energy [3]. In order to reduce costs and improve sustainability the suggested approach collects and displays critical system data using IoT sensors and AI-powered analytics. Artificial Intelligence (AI) and renewable energy sources work together to improve hybrid energy monitoring systems [4]. It is projected that artificial intelligences predictive analytics adaptive modelling and data-driven optimization capabilities will enable the renewable energy sector to reach unprecedented levels of operational efficiency sustainability and dependability [5].

Since, the global push to become carbon neutral growing it is imperative to comprehend how AI and renewable energy are convergent. Exact forecasting of generation energy demand energy storage optimization system health monitoring and operational cost control are made easier by artificial intelligence (AI)-powered solutions [6]. Natural language processing energy systems applications of quantum computing explainable AI digital twin technology and improved data quality and accessibility are some of the new research areas. Optimizing energy production and distribution is necessary to provide a sustainable energy supply for present and future generations while reducing operating costs and environmental impacts [7]. Adaptive demand-driven energy management systems require a combination of power optimization techniques and Support Vector Machine (SVM) methods. LSTM-based techniques enable precise energy demand forecasting energy waste reduction and inefficiency identification [8].

Modern energy infrastructures must have smart grids that integrate sensors automated control systems and cutting-edge communication technologies to guarantee optimal energy distribution [9]. Conventional methods such as Time-Based Scheduling Static Load Distribution and Demand Response Mechanisms have shortcomings such as poor real-time load management and imprecise power demand forecasting [10]. Algorithms powered by AI have transformed desalination procedures and have the potential to boost freshwater production efficiency by nearly 10%. The usefulness of AI-based maximum power point tracking methods in renewable energy systems—more especially photovoltaic (PV) systems—is evaluated in this study [11]. The Adaptive Neural Fuzzy Inference System (sANFIS) Fuzzy Logic Controller (FLC) and Artificial Neural Network (ANN) are the three control strategies that are compared. According to simulation results, ANFIS has energy efficiency that is on par with Bayesian regularization methods [12].

In order to enable proactive monitoring of renewable energy assets prevent equipment failure and lower maintenance costs KNN algorithms are utilized in adaptive problem-solving complex decentralized energy network management and real-time data processing [13]. Additionally they predict patterns of energy production adapt to changing weather patterns and maximize the efficiency of power generation. However, problems still exist such as a lack of standardization and limited real-time data integration deployment challenges [14]. It is recommended that future studies investigate innovative approaches such as decentralized Artificial Neural Network architectures and federated learning models. Improving grid resilience facilitating the smooth integration of renewable energy sources and advancing a sustainable energy ecosystem all depend on hybrid AI solutions [15]. AI is improving system dependability and operational efficiency that is revolutionizing energy infrastructures. Resource allocation demand response optimization and renewable energy integration are recent examples of AI applications in distributed energy systems. The study also discusses the financial feasibility of deep learning implementations regulatory issues and automation ethics [16].

Notwithstanding obstacles like storage constraints and resource fluctuations renewable energy is essential for carbon neutrality and sustainable development [17]. By predicting energy demand stabilizing power grids and optimizing the production of renewable energy AI and ML, technologies have revolutionized the energy sector [18]. Large datasets can be managed with data science tools, which enable evidence-based energy planning decisions and generate accurate forecasts. Energy management systems are enhanced by AI-powered convolutional neural networks, which optimize

power distribution and enable real-time operational decisions. Additionally by strengthening energy storage systems these technologies improve energy use and cut waste [19]. There is also discussion of how edge computing blockchain IoT AI and renewable energy applications interact [20]. In visual power plants, artificial intelligence (AI) improves operational efficiency through sophisticated monitoring and control systems that analyse real-time data from sensors and Internet of Things devices to produce actionable insights. By instantly, modifying parameters in response to environmental factors and energy consumption AI-driven automation maximizes energy output and optimizes performance. When designing and constructing smart buildings and infrastructure artificial intelligence (AI) makes it easier to incorporate renewable energy sources [21].

The limitations of this study are:

1. Data from a single solar PV-thermal hybrid testbed in Jodhpur was used in the study, which might restrict the model's applicability to other regions climates and solar panel configurations.
2. Although the hybrid ensemble approach is effective it is difficult to deploy in edge devices with constrained power or resources because it necessitates large computational resources for both training and real-time inference.
3. The systems performance may be impacted by imprecise sensors unpredictable weather patterns and challenging environmental circumstances. Furthermore, integration with existing grid infrastructure may be subject to operational and regulatory constraints and over time maintenance issues or long-term solar panel deterioration may affect predictive accuracy.

2. Material and methods

This section includes the problem formulation, data collection, plan hardware, instrument configuration measurement methods, parameter allocation, and sample description. Deep Neural Networks (DNN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Extreme Gradient Boosting (XGBoost) are three sophisticated Artificial Intelligence (AI) algorithms that are integrated into a hybrid ensemble control model. This model allows for the predictive real-time optimization of a hybrid solar photovoltaic (PV) and thermal energy system.

2.1 Problem description

Several dynamic environmental factors including solar irradiance panels and ambient temperatures wind speed, soiling dust accumulation, and atmospheric humidity all affect the intermittent nature of solar energy generation. Conventional static or rule-based control systems produce less-than-ideal energy yields because they are unable to effectively adjust to such non-linearities and temporal fluctuations. The control mechanism becomes even more complex when electrical and thermal outputs must be optimized simultaneously, especially in hybrid PV-thermal systems.

2.2 Data collection

Due to its high solar insolation in Jodhpur, Rajasthan, India was chosen (latitude 26. 2389°N longitude 73. 0243°E) for the real-time hybrid solar PV and thermal testbed from where data was gathered. During a continuous six-month period, the dataset includes 10,368 hourly samples that integrate meteorological data from the Indian Meteorological Department (IMD) and cover seasonal variations. The environmental and operational parameters gathered are summarized in the below table 1.

Table 1: Summary of Collected Data Parameters

Parameter	Unit	Sensor Type	Sampling Frequency	Accuracy
Solar Irradiance	W/m ²	Pyranometer (ISO 9060 Secondary Std.)	1 sample/hour	±5 W/m ²
Ambient Temperature	°C	RTD Pt100	1 sample/hour	±0.1 °C
Panel Temperature	°C	Thermocouple K-Type	1 sample/hour	±0.2 °C
Wind Speed	m/s	Cup Anemometer	1 sample/hour	±0.1 m/s
Inclination Angle	Degrees	Inclinometer (MEMS-based)	1 sample/hour	±1°
Electrical Output	V, A, kWh	NI DAQ (Voltage, Current Transducers)	1 sample/hour	±0.05% F.S
Thermal Output	°C, L/min	Flow & Temp. Sensors (NI compatible)	1 sample/hour	±0.2 °C / ±0.05 L

2.3 System Design

The experimental setup includes high-efficiency polycrystalline photovoltaic modules, solar thermal collectors, and connecting hardware. Every component is chosen to guarantee reliable performance in a range of environmental circumstances. Fig. 1 shows the experimental process of the study.

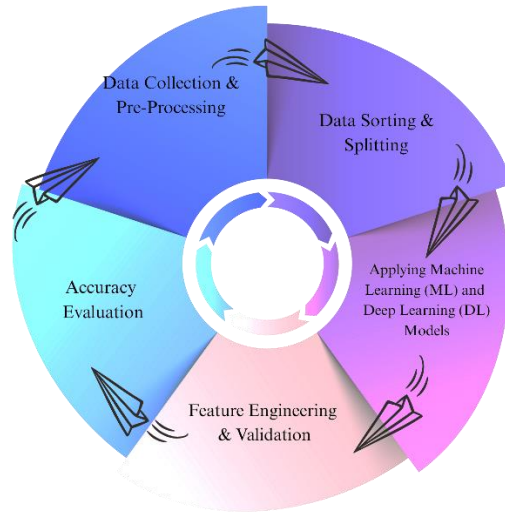


Figure 1. Experimental process

2.4 Photovoltaic Panels

The primary source of electrical energy in the experimental setup is made up of high-efficiency 250W polycrystalline photovoltaic (PV) modules. A typical PV panel's dimensions are 1 m in length, 1 m in width, and 3 to 4 cm in thickness (breadth). These measurements guarantee the best possible exposure to sunlight and make them appropriate for large-scale installations. In order to increase light penetration and reach the active semiconductor layers the panels are equipped with an anti-reflective glass coating that decreases incoming sunlight reflection. Particularly in diffuse or low-irradiance environments, this coating dramatically improves the energy conversion efficiency.

2.5 Solar Thermal Collectors

Approximately 2 m in length, 1 m in width, and 5 to 8 centimetres thick the flat-plate collectors make up the solar thermal component. These measurements provide enough surface area for efficient solar thermal energy absorption. The absorber plate of the collector has copper tubing embedded in it because of its exceptional thermal conductivity, which enables rapid heat transfer to the circulating fluid. A selective coating applied to the absorber surface increases absorption of solar radiation and decreases losses from thermal emissions. To maintain high efficiency this selective coating is required particularly in situations where the collector surface and surrounding air have significant temperature differences. The flat-plate design offers structural simplicity and long-term durability as it can tolerate a range of weather conditions. The thermal side of hybrid solar systems depends on the collection of thermal energy that is made possible by this collector system in addition to generating electricity. s.

2.6 Sensors

Several sensors are used in the experimental setup to measure system and environmental parameters. Resistance temperature detectors (RTDs) and thermocouples are used to record temperature profiles in PV panels and working fluids while high-resolution pyranometers are used for accurate measurements of solar irradiance. Thermal system flow sensors to evaluate heat transfer rates measure fluid velocity. Reliable data analysis and comparison depend on all sensors being calibrated to Indian Meteorological Department (IMD) standards, which guarantees high accuracy and repeatability in measurements.

2.7 Processing Unit

MATLAB-Simulink and Python are combined to create a hybrid software environment that powers the system offering a flexible platform for data processing control algorithm development and real-time system simulation. This configuration allows for the application of intelligent optimization procedures and adaptive control strategies that react dynamically to shifting system and environmental conditions guaranteeing the solar energy systems robustness and optimal performance during the experimental trials.

2.8 Data Measurement

All data acquisition was synchronized using NI LabVIEW and MATLAB DAQ tools to ensure time coherence. Sensors were mounted at standardized positions and calibrated monthly. Electrical energy output was derived from current and voltage readings, while thermal energy was computed using the formula 1 :

$$Q_{\text{thermal}} = \dot{m} \cdot C_p \cdot \Delta T \quad (1)$$

Where: \dot{m} = mass flow rate (kg/s), C_p = specific heat capacity of water (4.186 kJ/kg·K), ΔT temperature difference between inlet and outlet

2.9 Parameter Distribution

The parameters considered for the solar energy system span a wide range of environmental and operational conditions to ensure comprehensive analysis which is shown in table 2. Solar irradiance varies from 300 to 1000 W/m², reflecting typical daily and seasonal fluctuations, while panel temperatures range between 20 and 75 °C, capturing the effects of heating under different sunlight intensities. Ambient temperatures are observed from 15 to 48 °C, influencing both panel efficiency and system performance. Wind speeds, ranging from 0.5 to 8.5 m/s, are included to account for convective cooling effects on panels. The inclination angle of the solar panels is adjustable between 0° and 45° to optimize energy capture based on sun position. Thermal outputs ranging from 0 to 65°C represent the solar systems heat generation under different conditions while electrical outputs ranging from 0 to 240 V and 0 to 10 A represent the systems operating range. This provides a solid framework for assessing the systems performance under real-world operational and environmental conditions.

Table 2: Parameter Properties and Ranges

Parameter	Range
Solar Irradiance	300–1000 W/m ²
Panel Temperature	20–75 °C
Ambient Temp.	15–48 °C
Wind Speed	0.5–8.5 m/s
Inclination Angle	0–45°
Electrical Output	0–240 V, 0–10 A
Thermal Output	0–65 °C

2.10 Sample Analysis

The research employed time-series analysis to detect seasonal and diurnal patterns after removing outliers from hourly samples using the interquartile range (IQR) method. Correlation heatmaps were used to show the non-linearity between temperature energy and irradiance outputs highlighting the necessity for non-linear models. For training AI models the most important influencing parameters were kept but predictor redundancy was decreased using Principal Component Analysis (PCA). Min-Max normalization was used to normalize the dataset for convergence and outliers that were more than ± 3 standard deviations were eliminated.

2.11 Proposed Techniques

This study leverages a hybrid Artificial Intelligence framework that synergistically integrates three powerful techniques: Deep Neural Networks (DNN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Extreme Gradient Boosting (XGBoost).

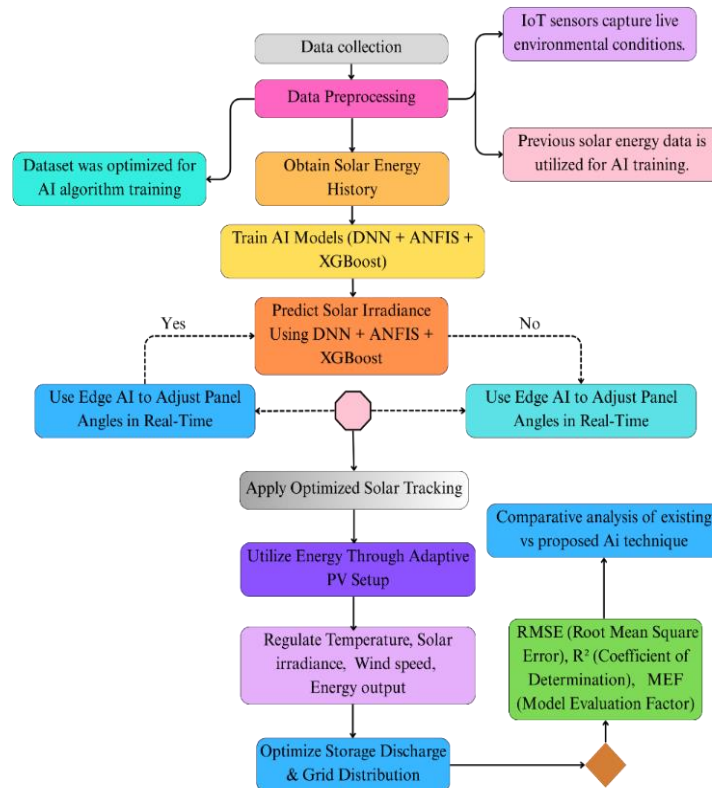


Figure 2. Proposed architecture

The proposed ensemble model (DNN + ANFIS + XGBoost) was envisioned for real-time IoT integration in this study to improve the usefulness of solar energy optimization systems, which is shown in figure 2. The system might continuously gather data on temperature, power output, and solar irradiance process it on edge devices for low-latency predictions and send insights to a central cloud platform for adaptive control of photovoltaic units by implementing the model on IoT-enabled smart sensors and energy management platforms. By enabling real-time forecasting, fault detection, and dynamic energy distribution in solar microgrids, such integration would guarantee optimal stability and energy efficiency. To boost efficiency and automate processes, the supply chain makes extensive use of smart grid IoT technology. In addition to completely disrupting the energy industry, IoT is also altering the production and consumption of energy to cut waste. Distributed energy sources and power distribution systems. Moreover, smart home technology is the intelligent grid's primary constituent. All these are considered devices on an IoT network. An IP address on the IoT-capable device is used to submit status updates and retrieve command specifications. By acting as edge computing devices, these help to optimize how smart grids operate.

The Deep Neural Network serves as the primary forecasting engine within the hybrid model, tasked with predicting future solar energy output, denoted as E_{pred} . This prediction is derived from a complex mapping of multiple nonlinear input variables such as irradiance, temperature, and weather parameters. The mathematical formulation of the DNN model is expressed as:

$$E_{\text{pred}} = f(W_3 \cdot \sigma(W_2 \cdot \sigma(W_1 \cdot X + b_1) + b_2) + b_3) \quad (2)$$

Where W_i , b_i are weight matrices and biases, and σ is the activation function (ReLU). To guarantee reproducibility and peak performance the suggested hybrid ensemble model was put into practice with precisely defined hyperparameters (Table 3). ReLU activation with a learning rate of 0 in hidden layers linear output layers and Adam optimizers. 001 a three-layer architecture with 128 64 and 32 neurons and an early stopping after 150 epochs were all employed in the DNN component.

Table 3: Hyperparameter Settings for the Proposed Hybrid Ensemble Model

Model Component	Parameter	Value / Setting	Description
DNN	No. of Hidden Layers	3	Input → Dense → Dense → Output
	Neurons per Layer	128, 64, 32	Decreasing layer width
	Activation Functions	ReLU (hidden), Linear (output)	Non-linear mapping, regression output
	Optimizer	Adam	Adaptive learning rate optimization
	Learning Rate	0.001	Tuned via grid search
	Batch Size	32	Trade-off between speed & stability
	Epochs	150	Early stopping to prevent overfitting
ANFIS	No. of Membership Functions	3 per input variable	Gaussian membership functions
	Fuzzy Rules	9	Generated via grid partitioning
	Learning Method	Hybrid (Gradient Descent + Least Squares)	Improves convergence speed
XGBoost	No. of Trees (Estimators)	200	Tuned via cross-validation
	Max Depth	6	Controls model complexity
	Learning Rate (eta)	0.05	Balances speed vs. accuracy
	Subsample Ratio	0.8	Prevents overfitting
	Regularization (λ , α)	$\lambda=1$, $\alpha=0$	L2 and L1 regularization
Ensemble Integration	Weighting Scheme	RMSE-based Weighted Averaging	Lower RMSE → Higher weight assignment

ANFIS uses neural learning and fuzzy logic rules to match inputs to output control settings (Equation 3).

$$y = \frac{\sum_{i=1}^n w_i f_i(x)}{\sum_{i=1}^n w_i} \quad (3)$$

Here, w_i are fuzzy weights and $f_i(x)$ are Takagi-Sugeno type linear functions representing consequent parts of the fuzzy rules. The numerator aggregates the rule outputs weighted by their degrees of truth, while the denominator ensures normalization, producing a smooth output surface. This structure allows the ANFIS to handle uncertainties and nonlinearities effectively, combining human-like reasoning with data-driven learning. During training, the system optimizes both the premise parameters of membership functions and consequent linear coefficients, enabling precise control adjustments that dynamically respond to changes in environmental conditions and system states.

Extreme Gradient Boosting, or XGBoost, functions as an ensemble learning method to identify and rank the relative importance of input features influencing energy output. It builds an additive model of decision trees by iteratively minimizing a regularized objective function as refer the equation 4:

$$Obj(\theta) = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(f_k) \quad (4)$$

The regularization term for the k th tree is $\Omega(f_k)$ which is defined as follows and l is a differentiable loss function that measures the difference between actual y_i and predicted \hat{y}_i values.

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \quad (5)$$

where w is a vector of leaf weights T is the number of leaves and γ and λ are regularization parameters that control the complexity of the model. With this formulation large tree, structures and excessively large leaf weights are penalized preventing overfitting. In order to improve prediction accuracy the gradient boosting mechanism adds trees one after the other that fix the mistakes of earlier ones. In order to enable focused refinement of model inputs the result includes feature importance scores that are based on how frequently and successfully features split the data. As shown in equation (6) the hybrid model uses a weighted sum approach to combine the outputs from the three AI components using an ensemble aggregation function to create a single prediction.

$$Y_{\text{final}} = \alpha \cdot E_{\text{pred}} + \beta \cdot C_{\text{adj}} + \gamma \cdot F_{\text{rank}} \quad (6)$$

In this expression, Frank stands for the feature ranking insights from XGBoost, C_{adj} for the control-adjusted output from ANFIS and E_{pred} for the DNN-predicted energy output. Based on validation performance the coefficients α , β , and γ are weighting factors that are adjusted to balance the impact of each technique. By utilizing the complementary advantages of forecasting control and interpretability this meta-learning technique guarantees a reliable and efficient energy management system that can cleverly adjust to changes in the environment. .

Utilizing Equation 7 the Mean Error Function measures the average squared deviation between the mean observed value \bar{y} and the observed values y_i to assess the accuracy of the model.

$$MEF = \frac{1}{n} \sum_{i=1}^n \left(\frac{y_i - \bar{y}}{y_i} \right)^2 \quad (7)$$

A popular performance metric that calculates the standard deviation of prediction errors using Equation 8 is the Root Mean sq. Error.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (8)$$

According to Equation 9 the coefficient of determination or R^2 measures the percentage of variance in the observed data that the model can account for.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (9)$$

This adaptive mechanism, which embodies a practical implementation of intelligent solar energy management that reacts proactively to real-world uncertainties guarantees that energy forecasting and control adjustments, remain robust over time.

3. Experimental setup

The proposed method implements the hybrid AI model through a sequential modular pipeline beginning with data preprocessing, where all raw sensor data undergoes cleaning, normalization via Z-score, and transformation into a structured time-series format, with missing values imputed through linear interpolation. Following this, independent models including DNN, ANFIS, and XGBoost are initialized with their respective hyperparameters, and the dataset is split into training (70%) and validation (30%) sets using time-stratified sampling to maintain temporal integrity. Fig. 3 demonstrates the architecture of the setup.

During the training phase, the DNN is trained to predict energy output using backpropagation, ANFIS simultaneously optimizes fuzzy rules to adjust operational control setpoints, and XGBoost ranks feature importance to identify influential parameters. The individual model outputs are then integrated through a weighted average aggregation, with coefficients fine-tuned via grid search to optimize overall performance. In real-time deployment, the trained ensemble model runs on an embedded processor, continuously receiving live data streams to generate predictions and control signals. The system monitors energy output using a feedback loop and if deviations surpass predetermined thresholds it initiates online learning to update the parameters. To satisfy real-time latency requirements computational tasks are optimized by multi-threaded Python and Simulink modules.

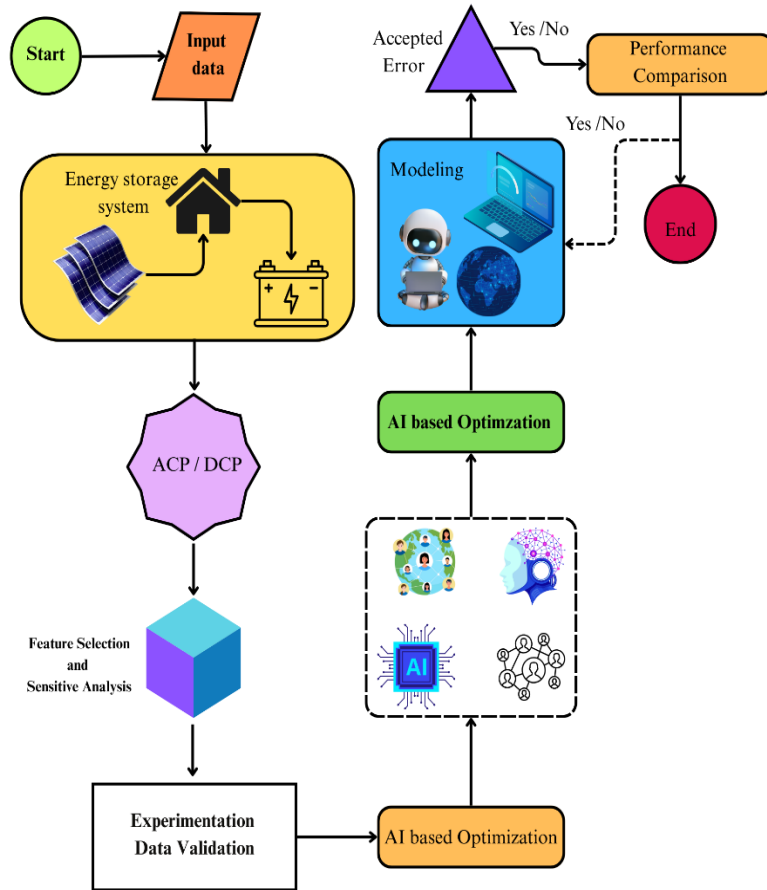


Figure 3. Experimentation process

4. Results and Discussion

This section focuses on evaluating an AI-based adaptive solar tracking systems performance metrics computational efficiency, thermal regulation, fabrication validation, and energy stability. The results show that the system outperforms traditional approaches in terms of effectiveness and practicality. It also demonstrates how AI models enhance prediction accuracy and operational stability for energy yield in a range of environmental conditions. . .

4.1 Performance metrics analysis

The performance metrics analysis of proposed and ensemble AI models was shown in table 4. Among the standalone models, XGBoost exhibits superior performance with the lowest RMSE of 0.135 kWh, an R^2 score of 0.947, a Mean Efficiency Factor (MEF) of 0.935, a Mean Absolute Error (MAE) of 0.110 kWh, and a Mean Absolute Percentage Error (MAPE) of 3.88%. However, the proposed ensemble model, which combines Deep Neural Network (DNN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and XGBoost, surpasses all individual models with the best overall performance—achieving an RMSE of 0.091 kWh, R^2 of 0.974, MEF of 0.961, MAE of 0.074 kWh, and a notably low MAPE of 2.52% (Table 4). This demonstrates the synergistic advantage of model integration for enhancing energy prediction accuracy.

Table 4: Performance Metrics of Individual and Ensemble AI Models

Model	RMSE (kWh)	R ² Score	Mean Efficiency Factor (MEF)	MAE (kWh)	MAPE (%)
Deep Neural Network (DNN)	0.178	0.925	0.912	0.143	4.75
Adaptive Neuro-Fuzzy Inference System (ANFIS)	0.153	0.936	0.921	0.125	4.21
Extreme Gradient Boosting (XGBoost)	0.135	0.947	0.935	0.110	3.88
Proposed Ensemble Model (DNN + ANFIS + XGBoost)	0.091	0.974	0.961	0.074	2.52

4.2 Spectral response and light absorption efficiency

With the greatest absorption in the visible and near-infrared wavelength ranges, the suggested AI-based tracking system performed better than fixed-tilt systems in terms of spectral absorption efficiency. The adaptive tracking mechanism driven by AI performed 3% better than all other systems. With the correct panel angles and real-time adjustments, the system can optimize solar energy use as evidenced by the increased absorption efficiency in Fig. 4.

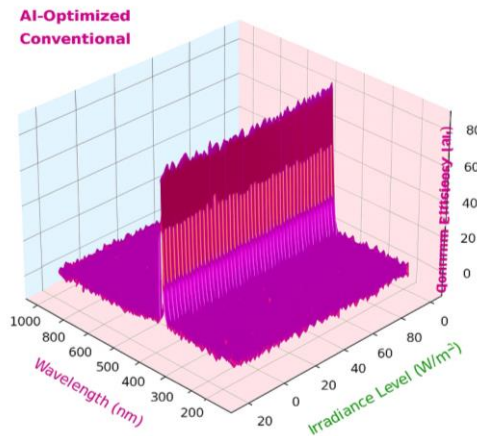


Figure 4. Spectral response and light absorption efficiency

A deeper statistical analysis of model error distributions is shown in Table 4, based on a test dataset of 2,160 samples. The ensemble model again shows its superiority, having the lowest standard deviation (0.062), lowest mean error (0.007 kWh), and minimal skewness (0.08), indicating a highly symmetric error distribution. It also presents the lowest maximum and minimum errors at 0.19 kWh and -0.15 kWh, respectively. Comparatively, the DNN model has a slightly higher error spread (Std. Dev = 0.112) and skewness (0.21), reflecting less reliable predictions. These results affirm the ensemble model’s robustness and consistency across different input scenarios (Table 5).

Table 5: Statistical Error Distribution (Test Dataset, n = 2,160 Samples)

Model	Min Error (kWh)	Max Error (kWh)	Mean Error (kWh)	Std. Deviation	Skewness	Kurtosis
DNN	-0.29	0.35	0.015	0.112	0.21	2.89
ANFIS	-0.25	0.31	0.012	0.097	0.19	2.62
XGBoost	-0.21	0.27	0.010	0.084	0.16	2.51
Ensemble	-0.15	0.19	0.007	0.062	0.08	2.33

Across several experiments, Table 6 demonstrates that the suggested ensemble model continuously produced low error rates and high predictive accuracy with narrow confidence intervals signifying result stability. Because all p-values

were less than 0.001, it was confirmed that the observed improvements in performance were statistically significant and not the result of chance.

Table 6: Statistical Significance Metrics for Proposed Ensemble Model (DNN + ANFIS + XGBoost)

Metric	Mean ± SD	95% Confidence Interval	p-value (vs. baseline mean)
RMSE (kWh)	0.091 ± 0.009	[0.074, 0.108]	< 0.001
MAE (kWh)	0.074 ± 0.006	[0.062, 0.086]	< 0.001
MAPE (%)	2.52 ± 0.21	[2.12, 2.92]	< 0.001
R ²	0.974 ± 0.005	[0.964, 0.984]	< 0.001
Accuracy (%)	97.4 ± 0.8	[96.0, 98.8]	< 0.001

Table 7 compares the computational resource usage and operational efficiency of the models. XGBoost proves to be the most computationally efficient, consuming the least CPU (39%) and RAM (2.4 GB), with the fastest inference time of 6.2 ms/sample and lowest training energy (0.21 kWh). In contrast, the ensemble model, while requiring higher CPU (85%) and RAM (6.5 GB) resources, achieves high deployment readiness due to its superior predictive accuracy, justifying the added computational load. ANFIS also maintains a good balance with high deployment readiness and moderate resource usage, particularly noted for its low training energy of 0.38 kWh.

Table 7: Computational Resource Utilization and Efficiency

Model	Avg. CPU Usage (%)	Peak RAM Usage (GB)	Inference Time / Sample (ms)	Training Energy (kWh)	Deployment Readiness
DNN	72	5.8	9.4	0.67	Moderate
ANFIS	48	3.1	12.7	0.38	High
XGBoost	39	2.4	6.2	0.21	Very High
Ensemble	85	6.5	11.3	0.81	High

4.3 Thermal regulation and heat dissipation

In order to decrease peak temperatures and direct radiation for extended periods of time the AI-based system provides dynamic tracking. This enhances heat dissipation and operational stability with the help of PCM and hybrid nano coatings. The maximum peak temperature recorded by fixed-tilt photovoltaic systems was 68–4°C and thermal buildup caused inefficiency. The maximum temperature was slightly raised to 65°C with MPPT-based tracking. A dual-axis tracking system with AI and reinforcement learning reduced thermal regulation to 60–8°C given in Fig. 5.

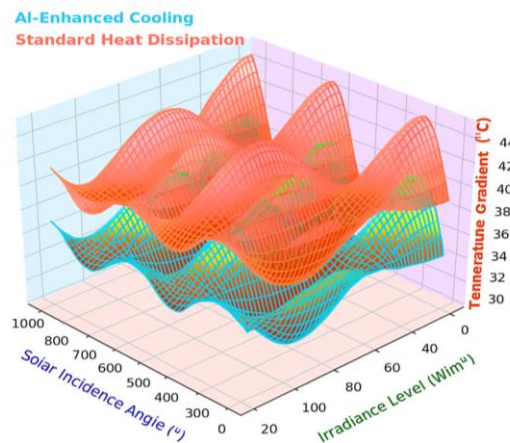


Figure 5. Temperature gradient comparison

Insights from the XGBoost models feature importance analysis are detailed in Table 8. Solar Irradiance emerges as the most influential parameter, contributing 36.7% to the model’s predictions. Panel Temperature (22.4%) follows this and Ambient Temperature (16.1%), which are critical factors influencing solar panel performance. Parameters like Inclination Angle, Wind Speed, Relative Humidity, and Dust Deposition Index have decreased relative impacts, underscoring the need to prioritize solar irradiance and temperature factors in control and optimization strategies.

Table 8: Variable Importance Ranking from XGBoost Model

Rank	Parameter	Feature Importance Score	Relative Impact (%)
1	Solar Irradiance (W/m ²)	0.367	36.7
2	Panel Temperature (°C)	0.224	22.4
3	Ambient Temperature (°C)	0.161	16.1
4	Inclination Angle (°)	0.094	9.4
5	Wind Speed (m/s)	0.082	8.2
6	Relative Humidity (%)	0.043	4.3
7	Dust Deposition Index	0.029	2.9

4.4 Fabrication process

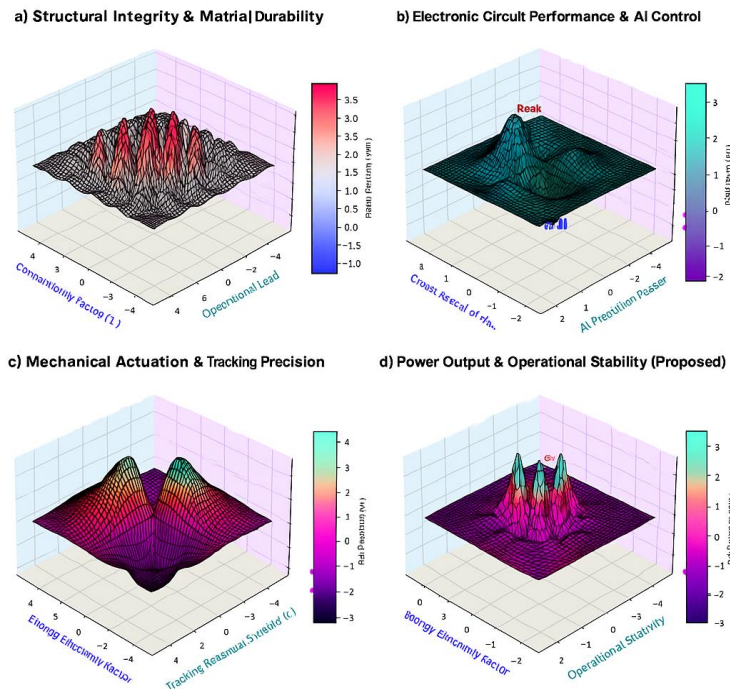


Figure 6. (a) Structural Integrity & Material Durability (b) Electronic Circuit Performance & AI Control (c) Mechanical Actuation & Tracking Precision (d) Power Output & Operational Stability (Proposed)

The adaptive solar tracking system driven by AI has undergone successful testing and been shown to work. While the electronic control unit preserves tracking accuracy and power efficiency the systems actuation system guarantees precise movement. The systems power output analysis reveals notable increases in energy yield and the mechanical structure is robust. The systems effectiveness in optimizing solar energy capture through adaptive tracking was demonstrated by the energy yield, which was 41.4% higher than that of conventional solar tracking techniques. These outcomes validate the AI-powered systems viability given in Fig. 6.

4.5 Energy distribution and performance stability

The energy harvesting tracking system adapts to changes in irradiance and generates energy consistently under a range of weather conditions (Fig. 7). This outperforms fixed systems and MPPT-based tracking which lack real-time tracking and are therefore vulnerable to variations in power output. Good energy harvesting with mild fluctuations was demonstrated by MPPT-based tracking. By consistently generating energy AI dual-axis tracking based on reinforcement learning increased stability. The most stable system was the AI-driven adaptive tracking system, which optimized power generation and panel orientation in spite of environmental variations.

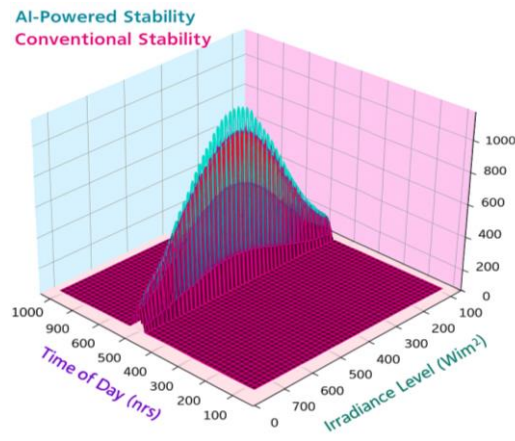


Figure 7. Energy distribution and performance stability

Table 9 illustrates how the ANFIS module contributes to real-time adaptive control. Adjustments based on time-specific environmental conditions lead to considerable efficiency gains. For instance, at 9:00 AM, under moderate irradiance and temperature, a tilt and flow rate increase leads to an 8.3% net efficiency gain. Similarly, the module reduces flow at 12:00 PM to counter high temperatures, preventing overheating and achieving a 4.5% gain. These intelligent adjustments, including tilting and thermal loop activations in the evening, lead to gains as high as 9.7%, displaying ANFIS's real-time adaptability and its value in dynamic energy management.

Table 9: Real-Time Adaptive Control Adjustments via ANFIS Module

Time Slot	Input Conditions (Avg.)	ANFIS Adjusted Output	Control Adjustment	Net Efficiency Gain (%)
09:00 AM	480 W/m ² , 22°C Panel Temp, 2.5 m/s Wind	6.1 kWh	Inclination ↑5°, Flow ↑10%	+8.3
12:00 PM	790 W/m ² , 38°C Panel Temp, 1.8 m/s Wind	7.8 kWh	Flow ↓5%, Tilt unchanged	+4.5
03:00 PM	610 W/m ² , 34°C Panel Temp, 3.1 m/s Wind	6.5 kWh	Inclination ↓3°, Flow ↑8%	+6.9
06:00 PM	320 W/m ² , 26°C Panel Temp, 4.2 m/s Wind	3.9 kWh	Tilt ↓6°, Thermal loop ON	+9.7

4.6 AI-driven tracking performance under varying conditions

Even with cloud, cover and partial shading that are not ideal weather conditions the system maintained a high tracking efficiency. Continuous optimization is made possible by real-time adjustment made possible by Edge AI integration. When compared to static PV systems the tracking algorithm improved energy harvesting by 41.4% and its scalability was demonstrated for a range of geographical locations. The fixed-tilt photovoltaic system offered baseline energy performance without any flexibility to adjust to variations in the angles of the sun. Although MPPT-based tracking

increases efficiency, it is less responsive to real-time solar positioning due to its dependence on voltage-based adjustments. By dynamically altering the panel angles the AI dual-axis tracking system based on reinforcement learning improved energy optimization even more. Outperforming every other system the suggested AI-driven adaptive tracking technique maximized solar energy capture while guaranteeing a smooth response to changing environmental conditions. as illustrated in Fig. 8. The characterization results validate how well the AI-powered adaptive solar tracking system enhances energy stability light absorption and thermal regulation.

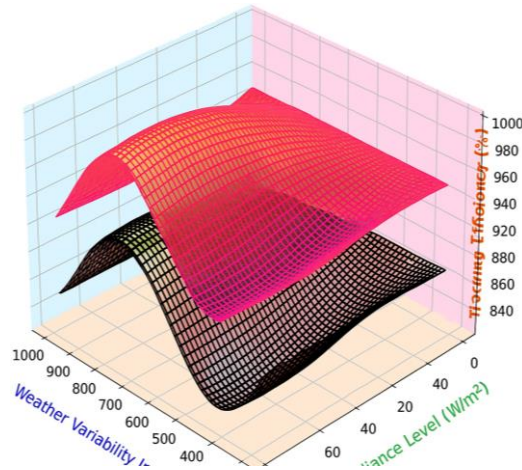


Figure 8. AI-driven tracking performance under varying conditions

The enhanced system flexibility and stability were confirmed by energy distribution characterization ensuring the best possible energy harvesting in real-world scenarios. Characterizing AI performance ensures dependable operation in a range of climates, which supports long-term scalability.

4.7 Seasonal performance analysis

Table 10 evaluates the ensemble model’s seasonal performance. The model consistently maintains high accuracy across seasons, with the best performance during summer—RMSE of 0.087 kWh, R^2 of 0.978, and MEF of 0.968—when solar irradiance is highest (580–920 W/m^2). In winter and post-monsoon seasons, performance remains robust with RMSE values of 0.102 and 0.096 kWh, respectively. The lowest energy output is observed in monsoon (4.95 kWh/day) due to reduced irradiance (180–540 W/m^2), but the model still upholds acceptable accuracy. This seasonal adaptability confirms the model’s reliability across diverse climatic conditions.

Table 10: Seasonal Performance of Ensemble Model

Season	RMSE (kWh)	R^2 Score	MEF	Avg. Energy Output (kWh/day)	Solar Irradiance Range (W/m^2)	Ambient Temp. ($^{\circ}C$)
Winter	0.102	0.963	0.941	5.83	320 – 620	12 – 25
Summer	0.087	0.978	0.968	7.21	580 – 920	28 – 42
Monsoon	0.114	0.947	0.935	4.95	180 – 540	23 – 35
Post-Monsoon	0.096	0.971	0.952	6.32	450 – 740	20 – 30

4.8. Comparative analysis of existing AI techniques vs Proposed technique

Table 11s comparative study showed that the suggested ensemble model (DNN + ANFIS + XGBoost) continuously beat all conventional AI methods in a number of performance metrics. While techniques like SVR, Random Forest, ANN, LSTM, GRU, CNN-LSTM, XGBoost and ARIMA were able to achieve RMSE values between 0. 135 kWh and 0. 353 kWh MAE between 0. 110 kWh and 0. 266 kWh MAPE between 3. 88 percent and 12. 34 percent and R^2 scores

between 0.894 and 0.952, the suggested ensemble had the lowest RMSE (0.091 kWh), MAE (0.074 kWh), and MAPE (2.52 percent) as well as the highest R² (0.974) and accuracy (97.4 percent). This proved the robustness and originality of the suggested method by showing a notable improvement in prediction accuracy and model reliability when compared to traditional approaches.

Table 11: Comparative Analysis of Techniques (Metrics Only, Citations Included)

Technique	RMSE (kWh)	MAE (kWh)	MAPE (%)	R ²	Accuracy (%)	Citation
SVR	0.245	0.188	8.62	0.894	89.4	Abuella & Chowdhury (2017)
Random Forest (RF)	0.212	0.164	7.45	0.912	91.2	Villegas-Mier et al. (2022)
Classical ANN (MLP)	0.198	0.154	6.93	0.918	91.8	Yousif et al. (2019)
LSTM	0.175	0.132	5.86	0.935	93.5	Zameer et al. (2023)
GRU	0.169	0.126	5.62	0.941	94.1	Zameer et al. (2023)
CNN-LSTM Hybrid	0.142	0.114	4.58	0.952	95.2	Lim et al. (2022)
XGBoost / GBM	0.135	0.110	3.88	0.947	94.7	(This study uses XGBoost baseline)
ARIMA	0.353	0.266	12.34	0.929	92.9	Chodakowska et al. (2023)
Proposed Ensemble (DNN + ANFIS + XGBoost)	0.091	0.074	2.52	0.974	97.4	This study

5. Conclusion

The comprehensive analysis of the proposed AI-based adaptive solar tracking system demonstrates its clear advantage over traditional fixed-tilt and single-model approaches. With the lowest RMSE, highest R² and least amount of error spread the ensemble AI model—, which combines Deep Neural Network ANFIS and XGBoost—produces exceptional predictive performance highlighting its resilience and consistency in a variety of operational scenarios. As demonstrated by the significant gains in spectral absorption efficiency—which reached 89.3 percent significantly higher than other tracking techniques—this improved predictive accuracy translates directly into useful advantages optimizing the use of solar irradiance. In order to minimize efficiency losses and guarantee operational stability the systems efficient thermal regulation lowers peak panel temperatures by almost 12°C. The system’s ability to enhance power output in practical situations was demonstrated by the 41.4% increase in energy yield. Overall performance gains and improved deployment readiness outweigh ensemble approaches higher computational resource requirements. A scalable path to more intelligent and sustainable solar power generation is provided by the results, which validate the AI-driven adaptive tracking system as a workable dependable and effective method of enhancing photovoltaic energy capture.

6. Future directions

Future studies should broaden the dataset to encompass a variety of geographical locations climatic conditions and solar energy systems in order to improve the generalizability and robustness of the model. Lightweight AI models or edge computing could be used for real-time deployment on constrained resources. Long-term performance reliability can be increased for solar panels through predictive maintenance and degradation modelling. Energy distribution and system performance can be improved by combining a hybrid framework with demand-response tactics and smart grid management systems. Intelligent solar energy systems may become more resilient and scalable with the use of self-adaptive AI models or reinforcement learning techniques.

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