KIU
Journal of Science, Engineering and Technology

KJSET Research Article

AI-advanced MPPT for optimized hybrid solar-wind energy harvesting in off-grid rural electrification: Fabrication and performance modeling

Val Hyginus Udoka Eze

Department of Electrical, Telecommunication and Computer Engineering, School of Engineering and Applied Sciences, Kampala International University, Western Campus, Kampala, Uganda (ORCID: 0000-0002-6764-1721)
udoka.eze@kiu.ac.ug

Corresponding Author: Val Hyginus Udoka Eze, ezehyginusudoka@gmail.com, udoka.eze@kiu.ac.ug

Paper history:
Received 24 March 2025
Accepted in revised form 29 May 2025

Keywords
Hybrid Renewable Energy Systems (HRES); Maximum Power Point Tracking (MPPT); Artificial Intelligence; Solar-Wind Energy Integration; Reinforcement Learning;

Abstract

Hybrid Renewable Energy Systems (HRES), which integrate solar and wind power, offer an effective solution for addressing energy demands in rural, off-grid areas. Despite the abundant availability of solar energy during the day and continuous wind energy, the intermittent nature of these resources presents challenges to system efficiency. Maximum Power Point Tracking (MPPT) techniques are crucial for optimizing energy extraction from photovoltaic (PV) panels and wind turbines, but fluctuating environmental conditions complicate their performance. This study adopted a narrative review approach and 127 related articles on the integration of Artificial Intelligence (AI) in MPPT, focusing on AI-driven algorithms like Artificial Neural Networks (ANNs), Fuzzy Logic Control (FLC), and Reinforcement Learning (RL), which enhance system performance by providing adaptive, predictive, and self-learning capabilities were successfully reviewed. ANNs offer high accuracy by predicting optimal operating points based on historical data, but require extensive datasets and computational resources. FLC manages uncertainty and nonlinearity using fuzzy rules but demands significant computational power and expert knowledge. RL autonomously learns optimal strategies and adapts in real time, though it requires substantial training data and computational resources. The incorporation of these AI techniques into HRES facilitates real-time optimization, improving energy efficiency and ensuring a reliable power supply despite dynamic environmental conditions. Additionally, the practical fabrication of AI-enhanced hybrid systems involves careful selection of solar panels, wind turbines, energy storage solutions, and power electronics, along with the implementation of AI-based MPPT controllers on microcontrollers or embedded processors. Simulation and experimental validation confirm the efficacy of these approaches, showcasing their potential to optimize power extraction and enhance energy reliability in remote applications, paving the way for efficient renewable energy systems in rural and off-grid areas.

1.0 Introduction

Over the last few decades, there has been a dramatic change in the global energy landscape, with a greater focus on sustainability and a reduction in the environmental impact of fossil fuels [1]. The world's electricity supply was primarily generated by fossil fuels in the middle of the 20th century, but worries about resource depletion and greenhouse gas emissions prompted research into renewable energy sources [2,3]. The oil crises of the 1970s further accelerated research into alternative energy sources, prompting significant investments in solar, wind, and hydropower technologies. By the late 20th century, advancements in photovoltaic (PV) technology and wind turbine efficiency made renewable energy more viable [4]. Government policies and incentives, particularly in countries like Germany and Denmark, facilitated the deployment of large-scale renewable energy projects [5]. The early 2000s saw a rapid decline in the cost of solar panels and wind turbines, driven by technological improvements and mass production, making these energy sources increasingly competitive with conventional fossil fuels. Figure 1 illustrates the current global energy mix and projects its anticipated distribution by 2032.

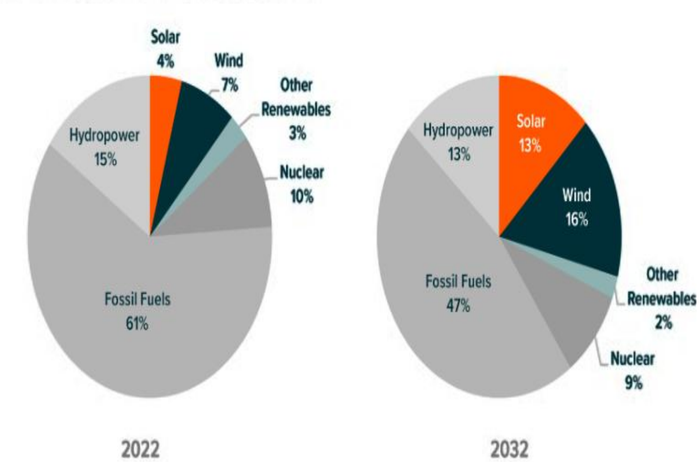

Figure 1: Non-hydro renewable energy shares of global electricity [4,5]

In rural off-grid areas, Hybrid Renewable Energy Systems (HRES) have emerged as a practical and sustainable solution to electrification challenges. These systems particularly those that integrate solar and wind power take advantage of the complementary characteristics of the two sources: solar energy is most abundant during daylight hours, while wind energy is often available both day and night. Early implementations of HRES frequently relied on diesel generators for backup power. However, significant advancements in battery storage technologies during the 2010s enabled a shift toward more self-sufficient renewable hybrid systems, reducing dependence on fossil fuels [5,6].

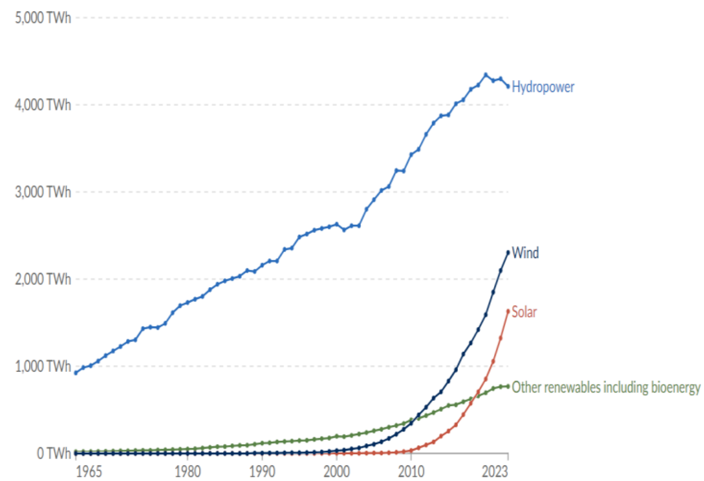

Figure 2: Statistical Review of World Energy (2024) [7]

Global electricity generation from major renewable sources, such as hydropower, wind, solar, and other renewables, including biofuels, has changed significantly between 1965 and 2023, as shown in Figure 2. Hydropower has traditionally dominated, steadily increasing to over 4,000 TWh by 2020 before stabilizing. Meanwhile, wind and solar energy began to show notable growth around 2000 and 2010, respectively [7]. Their expansion has been especially rapid in recent years, with solar power now approaching wind in total output. Other renewables, including bioenergy, have seen gradual growth but remain the smallest contributors. This trend reflects a clear global shift toward a more diversified renewable energy mix, with wind and solar emerging as major contributors. The inherent intermittency of solar irradiance and the fluctuating nature of wind speed continue to pose substantial limitations to the reliability and operational efficiency of HRES [8]. Maximum Power Point Tracking (MPPT) techniques have long been used by researchers to optimise energy capture from wind energy converters and photovoltaic arrays in order to lessen these limitations. In this field, traditional MPPT algorithms like Perturb and Observe (P&O) and Incremental Conductance (IC), which became popular in the 1990s and early 2000s, have been fundamental methods [9,10]. Nonetheless, these classical approaches often exhibit degraded performance under rapidly varying environmental conditions, resulting in suboptimal power extraction and decreased system efficiency [11].

In response to these limitations, the advent of AI and ML technologies, particularly since the late 2010s, has ushered in a new generation of intelligent MPPT controllers [12,13]. These advanced methods capitalize on adaptive learning, predictive modeling, and real-time decision-making capabilities to dynamically adjust to environmental fluctuations, thereby enhancing the overall performance of energy harvesting systems [14]. AI-based MPPT schemes, such as those utilizing artificial neural networks, fuzzy inference systems, and reinforcement learning frameworks, have consistently outperformed traditional techniques, delivering more stable and efficient energy conversion within hybrid systems [15,16].

Given the increasing importance of renewable energy in achieving global sustainability goals, the development and integration of intelligent MPPT methodologies are crucial for the advancement of HRES technologies. This review, therefore, investigates the role of AI-driven MPPT algorithms in solar-wind hybrid systems, with a focus on improving energy yield, addressing intermittency challenges, and enhancing system reliability in off-grid and remote applications [17]. The primary contributions of this review are outlined as follows:

- A thorough examination of AI-based MPPT methods in HRES An extensive examination of AI-driven MPPT methods, such as Reinforcement Learning (RL), Fuzzy Logic Control (FLC), and Artificial Neural Networks (ANNs), is given in this article. It addresses the difficulties brought on by shifting environmental circumstances and emphasises their benefits, drawbacks, and useful applications in maximising power extraction from solar and wind energy systems.
- Evaluation of AI-Enhanced Hybrid Renewable Energy System Design and Implementation: The study examines the practical aspects of integrating AI-based MPPT controllers into hybrid renewable energy systems. It discusses the selection of key system components, including solar panels, wind turbines, energy storage solutions, and power electronics, as well as the implementation of AI controllers on microcontrollers or embedded processors for real-time optimization.
- Validation of AI-Driven MPPT Approaches through Simulation and Experimental Studies: The paper reviews simulation models and experimental results that demonstrate the effectiveness of AI-based MPPT techniques in improving energy efficiency and ensuring a stable power supply. This validation supports the feasibility of deploying AI-enhanced hybrid systems for rural and off-grid electrification, contributing to the advancement of sustainable energy solutions.

2.0 Methodology

A narrative review methodology was utilized to critically synthesize and evaluate the existing body of research related to the optimization of HRES through Artificial Intelligence (AI). The review specifically focused on AI-based MPPT techniques in hybrid solar-wind systems. By analyzing 127 studies, this review aimed to provide a comprehensive understanding of the current advancements, emerging trends, and persistent challenges in applying AI to renewable energy systems. The narrative approach allowed for a broad and descriptive synthesis of the findings, highlighting the role of AI in improving the efficiency and reliability of renewable energy systems.

2.1 Search Strategy

The literature review was carried out through a systematic search of various reputable academic databases, including Google Scholar, IEEE Xplore, ScienceDirect, SpringerLink, and Scopus. The search strategy incorporated a range of keywords and phrases such as "AI-based MPPT," "Hybrid Renewable Energy Systems," "solar-wind hybrid systems," "Artificial Neural Networks in MPPT," "Fuzzy Logic Control in renewable energy," and "Reinforcement Learning in MPPT," The focus was on papers published between 2010 and 2025 to capture the most up-to-date research. The search aimed to identify both theoretical and practical applications of AI in optimizing hybrid solar-wind systems, ensuring a well-rounded review of the literature.

2.2 Inclusion Criteria

To ensure the relevance and quality of the selected studies, several inclusion criteria were established. Only studies published in English were considered, with a particular emphasis on peer-reviewed journal articles, conference papers, and technical reports. The selected studies needed to focus on AI-based optimization techniques for MPPT in hybrid solar-wind systems, specifically employing ANNs, FLC, and RL. Research that explored the application of these techniques in rural, off-grid, or low-resource areas was prioritized. The studies also needed to demonstrate clear methodology, robust data analysis, and reliable results, including those utilizing simulation models, experimental setups, or case studies. Additionally, the studies had to provide insights into the efficiency and optimization of MPPT techniques within HRES.

2.3 Exclusion Criteria

The selection process was further refined by applying specific exclusion criteria to eliminate irrelevant or low-quality studies. Non-peer-reviewed sources such as books, editorials, opinion papers, and unpublished materials were excluded to ensure the credibility of the review. Studies that were not directly related to AI-based MPPT techniques, or those that focused solely on solar or wind systems without involving hybrid configurations or AI optimization, were also excluded. Furthermore, studies with poor methodological quality, lacking clear analysis or sufficient data, were disregarded. Non-English publications were excluded due to language barriers, and duplicate studies with overlapping content were removed to avoid redundancy.

3.0 Literature Review

AI-based MPPT techniques have emerged as advanced solutions to address the limitations of traditional methods in renewable energy systems [17]. These AI-driven approaches leverage machine learning and optimization techniques to adapt to environmental changes more effectively than conventional methods [18,19]. One of the key AI-driven methods is ANNs, which utilize historical data to predict optimal operating points for PV panels and wind turbines [20]. ANNs offer high accuracy in tracking rapid fluctuations in irradiance and wind speed, making them particularly effective for dynamic conditions where traditional MPPT methods struggle [21]. Another prominent technique is FLC, which provides robust decision-making capabilities under uncertainty [22]. FLC is especially well-suited for hybrid renewable energy systems with multiple inputs and nonlinearities, where precise control is challenging. Additionally, RL has gained attention in MPPT applications due to its ability to autonomously learn and improve tracking strategies [23,24]. By continuously interacting with the system and optimizing control actions, RL-based MPPT adapts in real-time to changing environmental conditions, enhancing performance and efficiency. Comparative studies have shown that AI-based MPPT techniques generally outperform traditional methods, offering superior convergence speed, higher energy efficiency, and greater adaptability to varying environmental conditions, making them increasingly indispensable for modern renewable energy systems [25].

3.1 Artificial Neural Networks

In renewable energy systems, artificial neural networks have emerged as a potent AI-driven method for MPPT [26]. Because ANNs are built to learn from past data, they can forecast when PV panels and wind turbines will operate at their best. ANNs can swiftly adjust to changes in environmental variables, such as variations in wind speed and solar irradiation, thanks to their capacity to learn from and generalise from historical data. The primary benefit of employing ANNs in MPPT is their high precision, especially when it comes to tracking abrupt changes in wind speed and irradiance, which present difficulties for more conventional techniques like P&O and IC. The ability of ANNs to manage intricate, non-linear interactions between the system's inputs (temperature, wind speed, and solar irradiance) and output (electricity) is one of its main benefits [27]. ANNs are very useful for real-time modifications in hybrid solar-wind systems because they can predict the system's behaviour based on data-driven learning, in contrast to traditional methods that frequently rely on basic mathematical models and assumptions [28, 29]. Large datasets can also be used to train ANNs, which enables them to adjust to a wide range of environmental circumstances and increase tracking efficiency even in difficult situations.

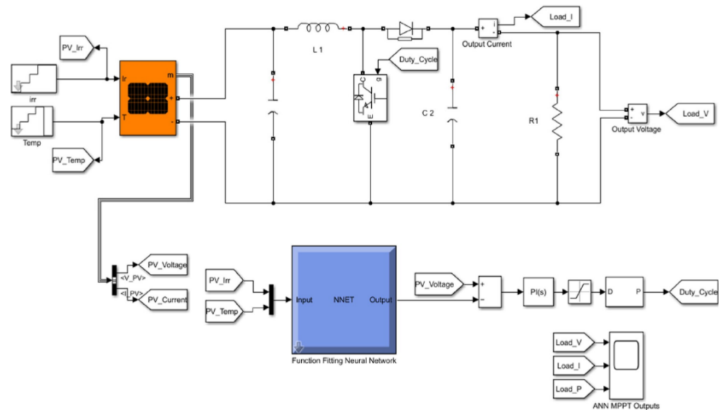

Figure 3: MATLAB Simulink model of ANN-based MPPT system [26]

As depicted in Figure 3, the trained ANN model takes ambient temperature and solar irradiance as input parameters, both calibrated to reflect real-world environmental conditions (ECs) relevant to PV system operation [26]. Based on these inputs, the ANN predicts the optimal output voltage of the PV panel, which is then compared against the actual voltage measured from the system. To enhance the precision, stability, and dynamic response of the ANN-based MPPT algorithm, a Proportional-Integral (PI) controller is employed in conjunction with the neural model [27,28].

While ANNs provide powerful nonlinear modeling capabilities and adaptability to varying environmental dynamics, their application in MPPT control is not without limitations. One of the primary challenges is the requirement for large volumes of high-fidelity training data to achieve accurate predictions. This data demand is particularly problematic in remote or resource-constrained regions where environmental sensing infrastructure may be inadequate or absent [29,30]. Additionally, the training phase of ANNs is computationally intensive, often necessitating prolonged processing time and substantial computational resources. Another critical concern is the issue of overfitting, where the model performs exceptionally well on training data but fails to generalize to novel or fluctuating operating conditions, thereby limiting its real-world applicability [31,32]. Moreover, the opaque nature of ANN decision-making processes limits interpretability, an important drawback in energy systems that require transparency, auditability, and trust, especially in critical or regulated applications [26].

An input layer, one or more hidden layers, and an output layer make up the mathematical structure of an ANN in MPPT, which can be characterised as a multi-layer network [33]. The output layer supplies the ideal voltage and current values for the PV panel or wind turbine, while the input layer receives the environmental factors (temperature, wind speed, and irradiance) [34]. Neurones that use activation functions like the sigmoid, hyperbolic tangent, or ReLU (Rectified Linear Unit) are found in the hidden layers. Backpropagation is used to modify the weights assigned to each neurone during the training phase in order to reduce the discrepancy between the actual power generated and the projected output [33, 34]. The mathematical model for an ANN-based MPPT can be formulated as follows:

Input Layer: Let $x = [x_1, x_2, ..., x_n]$ represent the input features (solar irradiance, wind speed, temperature).

Hidden Layers: The output from the ith neuron in the jth hidden layer can be expressed in equation (1)

$$hj = f\left(\sum_{i=1}^{n} wijxi + bj\right) \quad (1)$$

Where: w_{ij} are the weights, x_i are the inputs, b_j is the bias term, and f is the activation function.

Output Layer: The optimal operating point, such as voltage (V_{mppt}) and current (I_{mppt}) is determined by the output of the network as shown in inequation (2)

$$yk = f\left(\sum_{j=1}^{m} wjkhj + bk\right) \quad (2)$$

Where; m is the number of hidden neurons and y_k represents the output of the network (optimal power point).

A loss function, usually the Mean Squared Error (MSE), is used in the ANN's training phase to measure the difference between the PV system's actual and forecast output power. To reduce prediction error and enhance model performance, an optimisation approach like gradient descent is used to iteratively adjust the model's internal weights based on this error measure [35]. While ANN-based MPPT techniques offer substantial benefits in terms of nonlinear modeling and adaptive control, their practical implementation is often constrained by high computational demands and the risk of overfitting, particularly when training data are limited or unrepresentative of diverse environmental conditions. Nevertheless, when integrated with robust data acquisition and preprocessing methods, ANN-based controllers have demonstrated considerable success in maximizing energy harvesting efficiency in renewable energy systems [36].

3.1.1 Fuzzy Logic Control (FLC)

FLC is an advanced control method that has gained widespread use in MPPT applications for renewable energy systems, particularly in hybrid solar-wind configurations [37]. FLC is well-suited for situations involving uncertainty, vagueness, and nonlinearity, which are common in real-world systems [38]. Unlike traditional control methods that rely on precise, linear models, FLC uses linguistic variables and fuzzy sets to represent and process information [39.40]. This makes it particularly effective in hybrid systems, where multiple inputs, such as solar irradiance, wind speed, temperature, and load demands, interact in complex, nonlinear ways.

One of the key advantages of FLC in MPPT is its ability to make robust decisions under uncertain and fluctuating environmental conditions. Rather than relying on exact measurements or predictions, FLC uses fuzzy rules based on human-like reasoning to determine the optimal operating points [41]. For instance, instead of needing an exact value for solar irradiance, the system can make decisions based on fuzzy terms such as "high," "medium," or "low." This flexibility allows FLC to adapt effectively to varying environmental conditions, such as rapid changes in wind speed or cloud cover, which are often problematic for traditional MPPT methods [42]. The structural components of fuzzy are depicted in Figure 4 and mathematically expressed in equation (2).

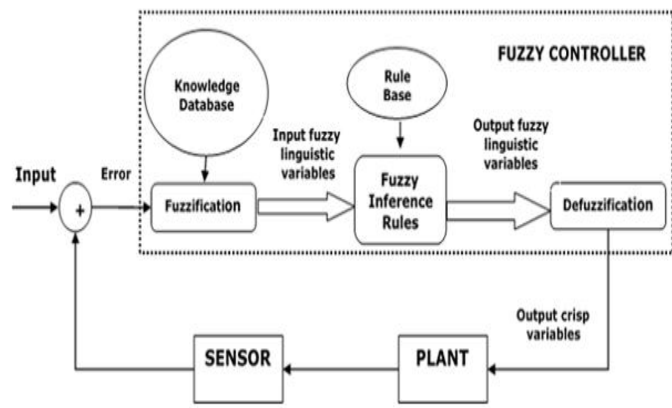

Figure 4: The structure and components of a fuzzy logic system [40]

FLC is particularly advantageous for hybrid renewable systems because it can integrate multiple inputs seamlessly. In a hybrid solar-wind system, FLC can combine data from both energy sources, accounting for their intermittent nature and non-linear interactions. This makes it more adaptable and resilient in optimizing the performance of the system. Additionally, FLC does not require precise mathematical models of the system, making it a more flexible solution when the system's characteristics are difficult to model accurately [43].

However, FLC also has some disadvantages. The primary challenge is that the design of the fuzzy rules and membership functions can be complex and requires expert knowledge. The effectiveness of the FLC heavily depends on the quality of the rules and the membership functions used, and poor rule design can lead to suboptimal performance. Additionally, FLC is computationally more intensive than simpler MPPT methods such as P&O, and the tuning of the fuzzy logic system can be time-consuming [44]. While it does not require precise mathematical models, an inadequate understanding of system behavior can hinder the FLC's effectiveness in certain scenarios.

Mathematically, FLC operates by transforming crisp inputs into fuzzy values and then applying fuzzy rules to make decisions. The process can be broken down into the following steps [44,43]:

- Fuzzification: The crisp input values (e.g., solar irradiance, and wind speed) are mapped to fuzzy sets using membership functions. For example, the solar irradiance could be mapped to fuzzy sets such as "low," "medium," and "high."

μ irradiance(x) = membership function for solar irradiance

- Rule Evaluation: Fuzzy rules are defined based on expert knowledge or empirical data. A typical fuzzy rule might be: If solar irradiance is high and wind speed is low, then increase the operating voltage. The fuzzy rule set is evaluated using logical operators (AND, OR) to determine the output fuzzy set.
- Defuzzification: Once the fuzzy outputs are computed, they need to be converted back to crisp values (e.g., optimal voltage and current). This is done through a process called defuzzification. One common method is the centroid method, which calculates the center of gravity of the output fuzzy set to determine the optimal control value is computed as shown in equation (3)

$$\text{Uopt} = \frac{\sum_{i=1}^{n} \mathbf{\mu xi}}{\sum_{i=1}^{n} \mathbf{\mu i}} \qquad (3)$$

Where: uopt is the defuzzified output (optimal voltage or current), μi is the degree of membership of each fuzzy set, and xi is the corresponding crisp value.

The fuzzy logic control system adapts to the variations in environmental conditions by continuously adjusting the operating point of the system based on the fuzzy outputs [45]. This ability to process multiple inputs and deal with uncertainties makes FLC particularly useful in optimizing the performance of hybrid renewable energy systems, even in challenging conditions.

3.1.2 Reinforcement Learning (RL)

RL has emerged as an innovative and effective approach for MPPT in renewable energy systems [46]. Unlike traditional methods, which follow predefined algorithms or rules, RL-based MPPT autonomously learns optimal power tracking strategies by continuously interacting with the system. RL models are designed to make decisions through trial and error, gradually improving their performance over time based on feedback from the environment [47]. This capability makes RL particularly well-suited for dynamic and unpredictable environments, such as those encountered in hybrid solar-wind systems, where both solar irradiance and wind speed fluctuate rapidly and unpredictably [48].

The key advantage of RL in MPPT is its ability to optimize control actions in real-time without requiring explicit mathematical models of the system [49]. Traditional MPPT methods like P&O or IC rely on predefined rules or equations, whereas RL learns the optimal strategy through interaction with the system, adjusting its behavior to maximize energy harvesting efficiency [50]. This adaptability is particularly valuable in hybrid systems where the combination of solar and wind power sources must be efficiently managed in the presence of varying environmental conditions. Another notable advantage of RL is its self-improving nature. Once an RL model is trained, it can continue to learn and adapt from new data, making it capable of fine-tuning its control strategies over time [51]. This continuous improvement allows RL-based MPPT systems to enhance performance as they experience more operational scenarios, which is a key feature in environments with highly variable conditions. Moreover, RL can effectively handle complex, multi-input, and nonlinear systems, making it ideal for hybrid renewable energy setups, where solar and wind sources interact in intricate ways [52]. Figure 5 shows the controller of the Wind Energy Conversion System (WECS), which utilizes a typical block diagram of a RL-based, model-free Q-learning MPPT algorithm. This algorithm learns an optimal policy by mapping system states to control actions in real time, updating action values based on the rewards received.

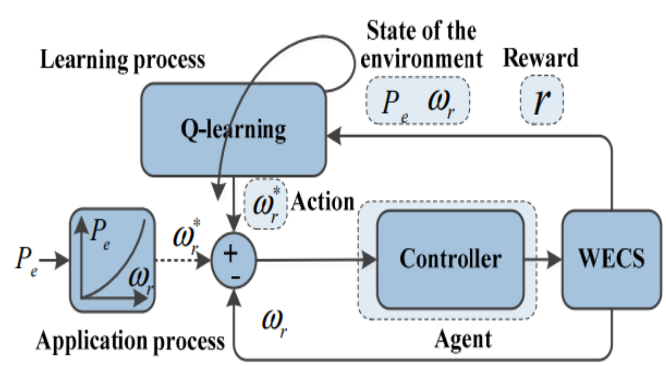

Figure 5: Block diagram of RL-based MPPT algorithm [46]

However, RL-based MPPT also comes with certain challenges and disadvantages. One major limitation is the need for large amounts of training data and computational resources [53]. The process of training an RL agent involves extensive simulation or real-world interaction, which can be computationally intensive and time-consuming. Additionally, RL models require a well-designed reward function that accurately reflects the desired outcomes, such as maximizing power output. Designing an effective reward function can be challenging, as it must balance various factors such as system stability, energy efficiency, and responsiveness to environmental changes. Furthermore, RL models may suffer from issues such as overfitting to specific conditions or insufficient exploration during the training phase, which can result in suboptimal performance when faced with new, unseen environmental conditions [54].

RL-based MPPT is grounded in the formalism of agent-environment interaction, where the agent learns to optimize control decisions through trial-and-error exploration. The framework comprises four key components: states, actions, rewards, and the policy. In the context of hybrid renewable energy systems, the agent represents the intelligent controller, the state s_t encapsulates system parameters such as solar irradiance and wind speed at time step t, and the action corresponds to control operations such as adjusting the duty cycle or reference voltage. Upon executing an action, the system transitions to a new state s_{t+1} and yields a reward rt, which reflects the instantaneous utility, typically associated with the power output or tracking accuracy [55,46].

The overarching objective of the RL agent is to learn an optimal policy π(s), which maps each state to an action that maximizes the expected cumulative reward over time. One of the widely adopted algorithms for implementing this decision-making process is Q-learning, a model-free RL technique that iteratively updates the state-action value function, known as the Q-value, as shown in equation (3). This formulation allows the RL agent to continuously improve its decision-making policy, even under varying environmental conditions, making it a robust solution for real-time MPPT in solar-wind hybrid energy systems.

$$Q(st, at) = Q(st + at) + \alpha[\mathrm{rt} + \boldsymbol{\gamma}\mathbf{maxQ}(\mathbf{st} + \mathbf{1}, \mathbf{a}') - \mathbf{Q}(\mathbf{st}, \mathbf{at})] \quad (3)$$

Where: $Q(s_t, a_t)$ = Q-value of taking action at state (s_t), α = learning rate, γ = discount factor, r_t is the reward received after taking action at state st, maxQ(st+1, a′) is the maximum expected future reward for the next state s_{t+1}. Over time, the RL agent learns the optimal policy π(s), mapping states to actions that maximize cumulative rewards, thereby achieving an optimal MPPT strategy for the system [46,50].While RL-based MPPT techniques show great potential in optimizing energy harvesting, their high computational cost and need for a large amount of training data present practical challenges. Nonetheless, as computing power increases and more efficient algorithms are developed, RL is becoming an increasingly viable approach for enhancing the performance and adaptability of renewable energy systems [54,51].

Table 1: Comparison of ANNs, FLC, and RL MPPT in renewable energy systems

Feature	Artificial Neural Networks (ANNs)	Fuzzy Logic Control (FLC)	Reinforcement Learning (RL)
Approach	Data-driven learning using historical data to predict optimal operating points.	Uses fuzzy rules and linguistic variables to make decisions under uncertainty.	Autonomous learning through trial and error to optimize power tracking.
Advantages	High accuracy in tracking rapid fluctuations in irradiance and wind speed.	Robust under uncertain and fluctuating environmental conditions.	Adapts and improves over time based on feedback.
	Handles complex, non-linear relationships.	Can handle multiple inputs and complex interactions.	Does not require explicit mathematical models.
	Effective for hybrid solar-wind systems.	Flexibility with rule-based control without precise models.	Continuous learning and improvement with more operational data.
Disadvantages	Requires substantial training data and computational resources.	Design of fuzzy rules and membership functions can be complex.	High computational cost and need for large amounts of training data.
	Overfitting can occur with insufficient data diversity.	Computationally more intensive than simpler methods.	Requires a well-designed reward function to balance multiple objectives.
	Limited interpretability and transparency.	Effectiveness depends on the quality of rules and membership functions.	Overfitting or insufficient exploration can lead to suboptimal performance.
Mathematical Model	Multi-layer network with input, hidden, and output layers.	Fuzzification, rule evaluation, and defuzzification of inputs.	Agent-based learning with states, actions, and rewards (Q-learning algorithm).
	Activation functions like sigmoid, ReLU,	Membership functions map crisp values to fuzzy sets.	Q-value update: Q(st, at) = Q(st, at) + α[rt + γmaxQ(st+1, a') - Q(st, at)].
Computational Cost	High due to the training phase (large datasets).	Moderate, depends on the complexity of the fuzzy rule base.	High due to large amounts of training data and simulations.
Real-time Performance	Suitable for real-time adjustments in dynamic conditions.	Performs well under real-time fluctuations with fuzzy decision-making.	Learns optimal strategies in real-time, improving over time.
Training/Data Requirements	Needs large datasets for training, especially in remote areas.	Requires expert knowledge to design fuzzy rules and membership functions.	Requires large datasets for training and fine-tuning reward functions.
Flexibility/Adaptability	Can adapt well to a variety of conditions after training.	Highly adaptable to different environmental conditions with fuzzy rules.	Learns from experience and adapts to new data over time.

These methods in Table 1 have their strengths and challenges, and the choice of method depends on the specific needs of the renewable energy system and the available resources for training, computation, and real-time adjustments.

3.1.3. Fabrication of AI-Enhanced Hybrid Solar-Wind Systems

The physical implementation of AI-based MPPT in hybrid solar-wind energy systems requires careful integration of hardware components and control strategies to optimize energy harvesting

[52]. This process involves both hardware fabrication and the development of robust control algorithms to manage system performance under dynamic environmental conditions [53]. The primary goal is to design a system that can seamlessly combine solar and wind power sources while utilizing AI-based MPPT techniques to ensure maximum efficiency. In terms of hardware, the system must include high-quality PV panels and wind turbines, each equipped with appropriate power electronic converters (e.g., DC-DC converters for PV panels and rectifiers for wind turbines) to interface with the energy storage system, typically a battery bank [54,55]. The hybrid system also requires a power management unit (PMU) to control and distribute power between the solar and wind sources. The key component in this setup is the MPPT controller, which plays a critical role in dynamically adjusting the operating points of both the PV and wind systems based on real-time environmental conditions [56,57].

The system must be able to process a broad range of inputs from sensors that track variables like solar irradiance, wind speed, temperature, and battery voltage in order to execute AI-based MPPT [58,59]. These sensors feed data into the AI algorithms (e.g., ANN, FLC, or RL), which use this information to optimize power output in real-time. The control strategies for hybrid systems are more complex compared to single-source systems due to the need to manage the interaction between both energy sources and ensure the smooth transfer of power to the load or storage system without overloading any component [60,61].

AI algorithms are typically implemented on a microcontroller or a digital signal processor (DSP) to ensure fast and reliable decision-making [62,63]. The algorithms receive real-time data inputs, process them using machine learning models, and output control signals to adjust the operating points of the converters [64,65]. For instance, in the case of ANNs, the system uses a pre-trained model to predict the optimal operating points (voltage and current) for both PV and wind systems [17,18]. The system then adjusts the converters to ensure that the maximum power is extracted from both sources. Similarly, FLC uses rule-based reasoning to make decisions about power optimization based on fuzzy input values. Additionally, communication protocols such as Modbus, I2C, or CAN (Controller Area Network) are often used to allow different components (sensors, controllers, converters, and storage units) to exchange data. The integration of these components into a coherent, coordinated system is essential to ensure that the energy generation and storage processes are optimized [52,53]. A real-time monitoring system is also critical for evaluating the system's performance and diagnosing potential issues such as hardware failures or environmental changes that may impact energy production.

In the fabrication of renewable energy systems, several key hardware components are integral to their functionality and performance. PV panels serve as the primary solar energy harvesters, converting incident sunlight into electrical power through the photovoltaic effect [66]. Complementing this, wind turbines capture the kinetic energy of wind and transform it into electrical energy via electromechanical conversion processes [67]. Efficient management of the generated electrical power between these sources and the load is facilitated by power electronic devices such as DC-DC converters, inverters, and rectifiers, which ensure optimal voltage and current regulation for maximum energy utilization. Energy storage units, predominantly batteries and supercapacitors, are incorporated to buffer excess energy and provide a stable power supply during periods of insufficient generation, thereby enhancing system reliability. The real-time optimization of energy extraction is achieved through AI-enabled control units, typically microcontrollers or DSPs, which implement MPPT algorithms to dynamically adjust operational parameters. Environmental sensors, including those measuring solar irradiance, wind speed, and ambient temperature, supply critical data inputs that inform the control logic, enabling adaptive system response to fluctuating conditions [66,55,67]. Finally, communication and interface modules integrate all subsystems, facilitating coordinated operation and data exchange to maintain seamless and efficient system performance.

Fabricating such a system requires careful consideration of system efficiency, component reliability, and the integration of AI algorithms into the control architecture [88,69]. The hardware components must be robust enough to withstand harsh environmental conditions, especially in off-grid rural areas where solar and wind energy systems are most commonly deployed [70]. Furthermore, the AI-based MPPT controller must be capable of processing data in real time to make rapid adjustments to the system, ensuring that the power output remains close to its maximum potential despite fluctuating environmental conditions [71,72]. The control strategy is at the heart of the system's efficiency. Hybrid solar-wind systems often require a dual-level control approach: one for managing the individual energy sources (solar and wind) and another for managing the interaction between them [73]. This dual-level strategy ensures that each source operates at its maximum potential while preventing the overloading of either system. Additionally, AI-based algorithms provide flexibility in adapting to sudden changes in environmental conditions, allowing the system to respond quickly to variations in solar irradiance or wind speed.

3.2 Solar Photovoltaic Panels and Wind Turbines

The selection of PV panels and wind turbines constitutes a critical phase in the design of hybrid renewable energy systems, as these components directly impact the overall system efficiency and reliability. Optimal component choice must be grounded in a detailed assessment of the site-specific resource availability, given that the power output from solar and wind installations is highly sensitive to local environmental parameters such as solar irradiance and wind velocity [74]. Comprehensive characterization of these factors is indispensable to achieving consistent year-round performance, maximizing energy yield, and minimizing capital and operational expenditures. Figure 6 depicts the configuration of a Hybrid Photovoltaic-Wind Microgrid System, illustrating the synergistic integration of solar and wind resources to improve both energy reliability and sustainability [75]. By capitalizing on the complementary generation profiles, solar panels predominantly produce electricity during daylight hours, and wind turbines generate power during night or overcast conditions; this hybrid system ensures a stable and continuous energy supply. This feature is particularly advantageous in off-grid or rural settings where grid access is limited or unavailable [74]. The schematic further details key system components, including solar PV arrays, wind turbines, charge controllers, battery storage units, and inverters, highlighting their interconnections within the hybrid microgrid architecture.

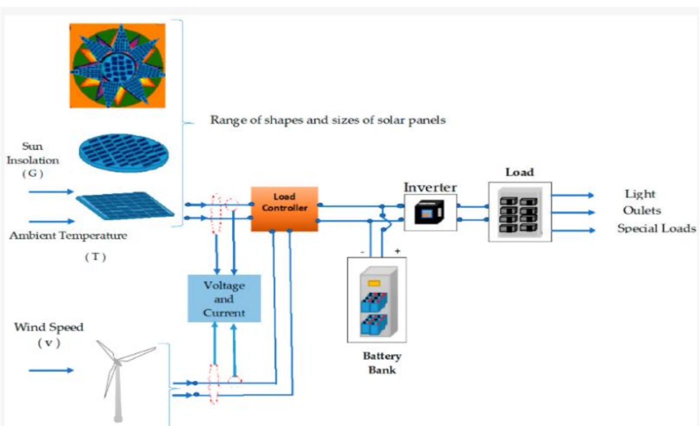

Figure 6: Hybrid Photovoltaic-Wind Microgrid System [74]

3.2.1 Solar PV Panels

Solar energy remains one of the most widely utilized renewable energy sources due to its inexhaustible nature and environmental sustainability [76]. Nevertheless, the conversion efficiency of PV panels is intrinsically linked to the magnitude and consistency of local solar irradiance, which fluctuates according to geographic location, seasonal variations, and prevailing atmospheric conditions [77]. Accurate assessment of the solar resource at a given site, typically obtained through satellite remote sensing or ground-based meteorological stations, is therefore essential to optimize the energy output from PV installations. PV panels are manufactured in several types, monocrystalline, polycrystalline, and thin-film, each exhibiting distinct efficiency profiles and operational characteristics under varying environmental contexts [78,79]. Monocrystalline panels, characterized by their high-purity silicon cells, generally offer superior conversion efficiency and are particularly suited for installations where limited space or suboptimal irradiance levels are constraints [80]. Polycrystalline panels present a more cost-effective alternative, with moderately reduced efficiency, making them appropriate for regions with moderate solar resource availability. Thin-film panels, noted for their lightweight, flexible form factors and aesthetic adaptability, cater to niche applications but typically exhibit lower efficiencies compared to their crystalline counterparts [81].

The selection of PV panels should also account for factors like temperature performance, as high temperatures can reduce the efficiency of the panels [82]. In regions with high temperatures, it may be beneficial to select PV panels that are specifically designed to perform better under such conditions. The angle of inclination and orientation of the panels also play a significant role in maximizing energy capture, and these factors should be optimized based on the specific latitude and seasonal variations of the location [83].

3.2.2 Wind Turbines

Particularly in areas with consistent and dependable wind patterns, wind energy is an essential part of hybrid renewable energy systems. By first transforming wind energy into mechanical rotational energy, wind turbines use kinetic energy from the wind to generate electrical energy via a linked generator [84]. The local wind speed profile has a significant impact on a wind turbine's power production; therefore careful evaluation and analysis of site-specific wind resource data are necessary to guarantee the best possible system design and performance. Wind resource data is typically obtained from anemometers installed at various heights to measure average wind speeds, variability, and direction [85,86]. Wind turbines are available in a range of sizes and configurations, with the two primary types being horizontal-axis wind turbines (HAWT) and vertical-axis wind turbines (VAWT), each offering distinct operational characteristics and suitability depending on the application and site conditions [87]. HAWTs are typically more efficient and are preferred for large-scale installations where higher wind speeds are available. VAWTs, on the other hand, are often used in urban or smaller-scale applications due to their ability to capture wind from any direction and their suitability for areas with more turbulent wind patterns [88].

Operational factors like the cut-out wind speed, the point at which the turbine stops producing power to avoid mechanical damage, and the cut-in wind speed, the minimum wind velocity necessary for the turbine to start producing power, must also be taken into consideration when choosing a suitable wind turbine. Furthermore, a crucial indicator for assessing turbine performance and utilisation is the capacity factor, which is the ratio of actual energy produced to the maximum energy output feasible for a specific period [85]. To maximise energy capture, ensure operating efficiency, and prolong the turbine's service life, it is crucial to choose a wind turbine that complements the local wind profile and environmental factors.

3.3 Hybrid System Considerations

The secret to optimising energy production in hybrid solar-wind systems is choosing the right mix of PV panels and wind turbines that work well together [89]. In many places, solar and wind energy availability are not synchronised; solar energy is most prevalent during the day, whereas wind energy may be more powerful at night or in certain seasons. The system may deliver more dependable and constant power all day and all year long by carefully integrating these two resources [90]. In areas with high solar irradiance but limited wind resources, the system may rely more heavily on PV panels, with wind turbines providing supplementary power during specific seasons or periods of high wind activity. Conversely, in regions with moderate or seasonal solar irradiance and higher, more consistent wind speeds, the hybrid system may use wind turbines as the primary energy source, with PV panels contributing during peak sunlight hours [91]. A typical hybrid renewable energy system is illustrated in Figure 7.

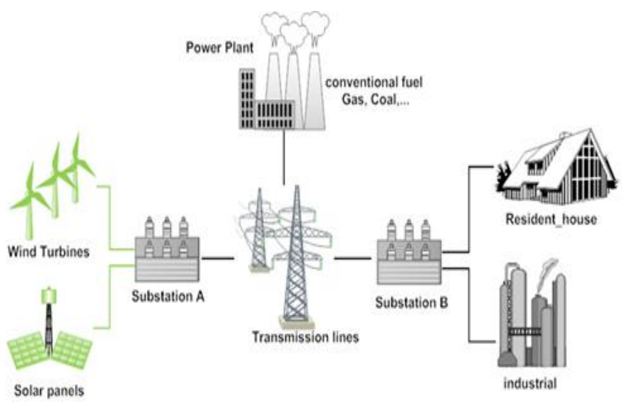

Figure 7: Hybridized Renewable Energy Dynamic Interaction System [90,91]

To ensure optimal energy production, careful site assessment and resource mapping are essential. Solar and wind resource data should be analyzed together to determine the most effective sizing and configuration of both PV panels and wind turbines [89]. This analysis helps in selecting components that not only match the expected resource availability but also ensure cost-effectiveness and system reliability over the long term.

3.3.1 AI-Embedded MPPT Controllers

AI-embedded MPPT controllers are at the heart of modern hybrid solar-wind systems, enabling efficient energy harvesting through real-time, adaptive decision-making [92,93]. These controllers integrate AI-based algorithms with microcontrollers or embedded AI processors to dynamically adjust the system's operating parameters, such as voltage and current, ensuring that both solar and wind energy sources are consistently operating at their maximum power points. The use of microcontrollers such as Arduino or Raspberry Pi, or more specialized embedded AI processors, allows for the processing of complex algorithms in real-time, which enhances system responsiveness and energy efficiency [94].

3.3.2 Microcontrollers for AI-Based MPPT Control

Microcontrollers like Arduino and Raspberry Pi are commonly used in hybrid renewable energy systems due to their cost-effectiveness, ease of use, and versatility [95]. These microcontrollers can be programmed to run AI-based MPPT algorithms such as ANNs, FLC, or RL, enabling intelligent power management in real-time [96]

1. Arduino, an open-source platform, is widely adopted for MPPT applications due to its simplicity, wide availability of libraries, and extensive community support [97]. It is particularly suitable for small-scale hybrid systems where real-time energy optimization is required. Arduino-based controllers can easily interface with sensors for measuring environmental parameters (e.g., solar irradiance, wind speed, battery voltage) and adjust the operation of DC-DC converters or inverters accordingly to track the maximum power points of both solar panels and wind turbines [98].

2. Raspberry Pi, on the other hand, is a more powerful single-board computer, often used in more sophisticated MPPT applications. It provides greater processing power, more memory, and advanced communication capabilities compared to Arduino [99]. Raspberry Pi can be programmed with Python or other high-level languages to run AI models for MPPT, enabling faster data processing and decision-making. It can also handle more complex algorithms, including deep learning models for predictive analysis, and supports integration with cloud-based systems for real-time monitoring and control [100]. While both platforms are effective, the choice between Arduino and Raspberry Pi depends on the complexity of the system and the computational requirements of the AI algorithms. Arduino is generally sufficient for simpler systems with basic MPPT algorithms, while Raspberry Pi is ideal for more computationally intensive tasks such as the integration of machine learning models or the management of multi-source hybrid systems [101].

3.3.3 Embedded AI Processors for Advanced MPPT Control

For more advanced applications, embedded AI processors offer enhanced computational power and real-time performance. These processors, such as NVIDIA Jetson, Google Coral, or Intel Movidius, are designed specifically to run machine learning algorithms efficiently in embedded systems [101. These processors can handle more complex AI tasks, such as image processing, speech recognition, and advanced control algorithms, all of which can be applied to MPPT in hybrid solar-wind systems

[102]. Embedded AI processors are often chosen when there is a need for faster processing speeds, lower latency, and more sophisticated control strategies. For example, NVIDIA Jetson boards are popular in edge computing applications, where real-time data analysis and decision-making are critical. They can run deep learning models that predict energy availability and optimize the MPPT controller's response based on the real-time analysis of sensor data, improving the system's efficiency and adaptability [103]. One of the key advantages of using embedded AI processors is their ability to perform parallel processing. This allows for the simultaneous execution of multiple tasks, such as real-time data acquisition, environmental condition prediction, and control signal generation for the power electronics. As a result, these processors can manage the hybrid system more effectively, especially in systems that require dynamic adjustments based on fluctuating energy inputs from solar and wind sources [104].

3.3.4 Integration of Sensors and AI-Based MPPT Controllers

AI-embedded MPPT controllers rely heavily on the integration of sensors to monitor the environmental conditions that affect solar and wind energy generation. For solar systems, irradiance sensors measure the amount of sunlight reaching the PV panels, while temperature sensors track the panel's temperature to adjust for efficiency loss at high temperatures [104]. Wind systems rely on anemometers to measure wind speed and wind direction sensors to determine the optimal orientation of the turbine for maximum power output [105]. Data from these sensors is fed into the AI-based MPPT controller, which uses machine learning or rule-based algorithms to predict the system's optimal performance points. The controller then adjusts the operation of power converters (such as DC-DC converters) to match these points, thereby maximizing energy production [106]. The communication between sensors, microcontrollers, and power electronics is typically achieved through communication protocols like I2C, SPI, or Modbus.

1. Advantages of AI-Embedded MPPT Controllers

1. Real-time adaptability: AI-based controllers can adapt to changing environmental conditions and predict future trends in solar and wind energy availability, leading to more efficient energy harvesting.
2. Improved accuracy and efficiency: AI algorithms can more accurately track the maximum power point compared to traditional methods, such as Perturb and P&O or IC.
3. Energy prediction: Machine learning models can predict future energy production based on historical data, allowing for better system management and storage optimization.
4. Fault detection and diagnosis: AI-based systems can detect and diagnose issues with the system (e.g., faulty sensors or power conversion inefficiencies), leading to quicker maintenance and improved reliability.

2. Disadvantages and Challenges

1. Computational complexity: Advanced AI algorithms, particularly those based on deep learning, require significant computational power and memory, which can be a limiting factor in resource-constrained environments.
2. Training data requirements: AI models require extensive training data to function optimally. This data must represent a wide range of environmental conditions, which may not always be available.
3. Cost: AI processors and the hardware required for their operation (e.g., sensors and power converters) can increase the overall cost of the system, which may be a concern for some applications.

3.3.5 DC-DC Converters and Inverters Optimized for AI-Driven Controller

Power conditioning units (PCUs) are essential components in hybrid solar-wind systems, as they ensure the smooth conversion, regulation, and distribution of electrical energy. These units typically consist of DC-DC converters and inverters, which play key roles in managing energy flows between the energy generation sources (solar and wind) and the storage or grid system [108]. In AI-embedded systems, these power conditioning units are optimized for enhanced performance through intelligent control strategies powered by AI algorithms.

3.3.5.1 DC-DC Converters

By controlling the output voltage from sources like solar PV panels and wind turbines to levels appropriate for energy storage devices or load requirements, DC-DC converters are essential components of hybrid renewable energy systems [109]. To maintain ideal operating conditions in spite of variations in the input power from the renewable sources, these converters work by either stepping up (boosting) or stepping down (bucking) the voltage [109]. In AI-enhanced MPPT systems, DC-DC converters are interfaced with intelligent control units that dynamically adjust operational parameters, such as duty cycle and switching frequency, in real time to effectively track the maximum power point of the PV arrays or wind turbines [110]. Optimization of these converters is frequently achieved through advanced AI techniques, including RL and FLC, which enable adaptive responses to varying environmental conditions like changes in solar irradiance or wind speed. By continuously tuning converter settings, these AI-driven approaches reduce energy losses and ensure the system consistently operates near its peak efficiency [111].

AI-based DC-DC converter control offers numerous advantages that enhance the overall performance of renewable energy systems [109]. One key benefit is adaptive voltage regulation, where the AI system can dynamically adjust the converter's parameters in response to fluctuations in environmental conditions. This adaptability helps optimize energy efficiency by ensuring the converter operates at peak performance under varying circumstances [111]. Additionally, AI significantly improves MPPT, allowing the converter to more accurately track the maximum power point, even in fluctuating environmental conditions such as changing solar irradiance or wind speed [96]. This leads to more effective energy extraction from both solar and wind energy sources. Furthermore, AI-based algorithms help reduce power losses by optimizing the converter's operation, minimizing inefficiencies typically associated with power conversion. As a result, overall system efficiency is enhanced. However, the use of AI in DC-DC converter control also presents challenges. The complexity of real-time control and the need for rapid response times in converters can demand substantial computational power from the control unit. AI models capable of handling high-frequency updates may require specialized embedded processors, which could increase the system's hardware requirements [100]. Ensuring that the control unit can process data and adjust converter parameters in real time is crucial for maintaining optimal system performance.

3.3.5.2 Inverters

The DC power produced by wind turbines and solar panels must be converted into AC power by inverters so that it can be used locally or added to the electrical grid [112]. To preserve grid synchronisation, voltage regulation, and current management, the conversion process needs to be closely monitored. Intelligent control systems that continuously analyse and modify their operating settings to maintain ideal power quality are a feature of AI-enhanced inverters. AI-driven inverters, such as those with FLCs or ANNs incorporated, can modify the AC output's phase, frequency, and amplitude to preserve grid stability and boost system efficiency. By using machine learning algorithms to identify irregularities and anticipate possible breakdowns before they happen, these inverters may also carry out predictive maintenance [113].

AI-based DC-DC converter control offers numerous advantages that enhance the overall performance of renewable energy systems. One key benefit is adaptive voltage regulation, where the AI system can dynamically adjust the converter's parameters in response to fluctuations in environmental conditions [114]. This adaptability helps optimize energy efficiency by ensuring the converter operates at peak performance under varying circumstances. Additionally, AI significantly improves Maximum MPPT, allowing the converter to more accurately track the maximum power point, even in fluctuating environmental conditions such as changing solar irradiance or wind speed. This leads to more effective energy extraction from both solar and wind energy sources. Furthermore, AI-based algorithms help reduce power losses by optimizing the converter's operation, minimizing inefficiencies typically associated with power conversion. As a result, overall system efficiency is enhanced [115].

However, the use of AI in DC-DC converter control also presents challenges. The complexity of real-time control and the need for rapid response times in converters can demand substantial computational power from the control unit. AI models capable of handling high-frequency updates may require specialized embedded processors, which could increase the system's hardware requirements [114,115]. Ensuring that the control unit can process data and adjust converter parameters in real-time is crucial for maintaining optimal system performance.

3.3.5.3 Integration of Power Conditioning Units with AI-Driven Control

The integration of DC-DC converters and inverters within AI-embedded hybrid solar-wind systems allows for enhanced energy management. By incorporating AI-based controllers into the power conditioning units, the system can optimize power flow in real-time, ensuring that the hybrid energy system efficiently harvests, converts, and distributes energy with minimal losses [116]. This integration allows the system to respond dynamically to changes in environmental conditions, user demand, or grid requirements, resulting in more reliable and cost-effective energy production. The AI algorithms employed in these power conditioning units are able to process data from various sensors, such as solar irradiance sensors, wind speed sensors, and battery charge sensors, to make real-time decisions about power conversion and distribution [117]. Additionally, these algorithms can predict energy availability based on historical data, enabling the system to forecast and manage energy storage, grid integration, or direct consumption more effectively.

1. Advantages of AI-Optimized Power Conditioning Units

1. Enhanced performance: AI optimization allows for real-time adjustments, improving the overall energy conversion efficiency of DC-DC converters and inverters.
2. Improved system responsiveness: AI-driven power conditioning units can adapt to fluctuating environmental conditions and user energy demands, ensuring that the system operates at peak efficiency.
3. Reduced system maintenance: Predictive maintenance capabilities built into AI controllers can detect faults early, minimizing downtime and reducing the cost of repairs.

4. Better grid integration: AI-driven inverters ensure seamless integration with the electrical grid, optimizing power quality and system stability.

2. Disadvantages of AI-Optimized Power Conditioning Units

1. Computational power demands: Real-time AI control of power conditioning units requires advanced embedded processors with sufficient computational resources, which can increase system costs and complexity.
2. Data dependency: AI algorithms require extensive data from sensors and historical performance data to make accurate decisions. Insufficient data can lead to suboptimal system performance.
3. Cost: The implementation of AI-driven power conditioning units can increase the upfront cost of hybrid solar-wind systems, though these costs are often offset by long-term improvements in energy efficiency and system reliability.

Table 2: A comparison based on fabrication materials used in AI-based MPPT hybrid solar-wind energy systems

Component	Material Used	Purpose
Photovoltaic Panels	Monocrystalline Silicon, Polycrystalline Silicon, Thin-Film (CdTe, CIGS)	Converts solar energy into electrical power. Monocrystalline silicon offers higher efficiency and longevity.
Wind Turbine Blades	Fiberglass Reinforced Plastic (FRP), Carbon Fiber Composites, Aluminum Alloys	Converts wind energy into mechanical power. FRP is lightweight and durable, while carbon fiber increases efficiency.
Turbine Generator	Copper (for windings), Aluminum (for housing), Permanent Magnets (NdFeB)	Converts mechanical energy from wind into electrical energy. Neodymium magnets improve efficiency.
DC-DC Converters & Rectifiers	Silicon-based Power MOSFETs, Gallium Nitride (GaN) or Silicon Carbide (SiC) Transistors, Aluminum Heat Sinks	Regulates voltage levels for power conversion. GaN and SiC transistors offer high efficiency and fast switching.
Inverters	Silicon IGBTs (Insulated, Gate Bipolar Transistors), Copper Wires, Aluminum Heat Sinks	Converts DC power into AC power for grid or load compatibility. Silicon IGBTs improve power handling and efficiency.
Energy Storage (Battery Bank)	Lithium-Ion (Li-ion), Lead-Acid, Sodium-Ion or Flow Batteries	Stores excess power for later use. Li-ion batteries offer high energy density and longevity.
Microcontroller / DSP	Silicon-based Processors, Printed Circuit Board (PCB) (FR4, Polyimide)	Executes AI algorithms for MPPT control. PCBs provide electrical connectivity.
Sensors	Silicon-based Photodetectors (for irradiance), MEMS (Microelectromechanical Systems) (for wind speed), Thermistors (for temperature)	Measures environmental parameters (solar irradiance, wind speed, temperature) for AI-based decision-making.
Communication Modules	Copper Traces (for wired interfaces), RF Components (for wireless communication), Fiber Optic Cables (for high-speed data transfer)	Ensures data exchange between components for efficient system operation.
Power Management Unit (PMU)	Silicon MOSFETs, Supercapacitors, Aluminum Heat Sinks	Controls energy distribution and prevents overloading of system components.
Structural Frame / Mounts	Aluminum, Galvanized Steel, Composite Materials	Provides structural support for PV panels and wind turbines, ensuring durability under harsh weather conditions.

Table 2 provides a clear comparison of fabrication materials based on their function and benefits in the system.

3.6. Performance Modeling and Evaluation

Performance modeling of AI-enhanced MPPT systems involves both simulation-based analysis and experimental validation to quantify improvements in energy harvesting efficiency, response time, and system stability [118]. By leveraging advanced computational techniques, researchers can assess the effectiveness of AI-driven MPPT methods compared to conventional algorithms.

3.6.1 Simulation-Based Performance Evaluation

Simulation is a crucial step in evaluating AI-based MPPT techniques before hardware implementation. Software environments such as MATLAB/Simulink, PSCAD, and PSpice are commonly used to model hybrid solar wind energy systems and assess the effectiveness of AI-driven control strategies [119]. The simulation of key components in the hybrid solar-wind energy system includes several critical elements to ensure optimal energy generation and transfer. PV panels and wind turbines are modelled based on empirical equations that govern variations in solar irradiance and wind speed. These models help predict how the system will behave under different environmental conditions. DC-DC converters and inverters are simulated to optimize voltage regulation and facilitate efficient energy transfer between the energy sources and storage units. The MPPT controllers play a crucial role in optimizing power extraction from both the solar and wind systems. These controllers are implemented using advanced AI techniques such as ANNs, FLC, and RL, which are designed to enhance the system's ability to adapt to fluctuating environmental factors and maximize energy output [120]. To assess the performance of these AI-driven MPPT controllers, simulation results are often compared with traditional tracking methods like P&O) and IC. This comparison helps highlight the improvements in tracking efficiency and dynamic response under varying environmental conditions, showcasing the superior performance of AI-based methods in real-time power optimization.

3.6.2 Experimental Validation

To validate the simulation results, prototype AI-embedded hybrid solar-wind systems are constructed and tested under real-world conditions. The setup includes PV panels and wind turbines, sized based on the specific energy potential of the location, ensuring optimal energy capture [121]. AI-embedded MPPT controllers, implemented on platforms such as Arduino, Raspberry Pi, or FPGA-based systems, are used to optimize power extraction from both energy sources in real-time. Sensors play a crucial role in measuring key parameters such as solar irradiance, wind speed, voltage, and current, feeding this data into the AI controllers for dynamic adjustments. A data acquisition system is employed to log and analyze the system's performance, providing critical insights into its operation. Experimental validation confirms that AI-based MPPT controllers effectively adapt to changing environmental conditions, optimizing power output while ensuring system stability under varying solar and wind conditions [122].

3.6.3 Performance Metrics

The effectiveness of AI-driven MPPT algorithms is evaluated using the following key performance indicators (KPIs) as shown below:

1. Tracking Efficiency (ηMPPT)

Tracking efficiency is an essential parameter used to evaluate how well an MPPT algorithm captures the MPP from renewable sources like solar and wind energy. It is defined as the proportion of the power obtained to the total available power, as represented in Equation (4) [123].

$$\eta\text{MPPT}\ (\%) = \frac{\mathbf{P_{extracted}}}{\mathbf{P_{available}}}\ x\ 100 \qquad (4)$$

Where: $P_{extracted}$ is the actual power harvested from the energy sources, and $P_{available}$ is the theoretical MP that can be extracted from the solar or wind energy sources.

AI-driven MPPT techniques have demonstrated improvements in tracking efficiency of up to 25% over conventional methods like P&O and IC. This enhancement arises from the AI algorithms' capacity to adapt dynamically to fluctuating environmental conditions, enabling more precise and continuous identification of the MPP.

2. Response Time (T_r)

Response time refers to the duration taken by the MPPT controller to converge to the Maximum Power Point (MPP) following a sudden change in environmental conditions, such as a shift in solar irradiance or wind speed [124]. A quicker response time minimizes power loss during transient conditions, leading to better overall energy harvesting efficiency. AI-based MPPT methods, particularly those utilizing RL and ANNs, can significantly reduce response time compared to conventional techniques. These AI algorithms rapidly adjust their control parameters to track the MPP, even under fluctuating environmental conditions. As a result, AI-based MPPT systems are able to achieve faster convergence to the MPP, improving overall system performance during dynamic conditions [125].

3. System Stability

In a hybrid renewable energy system, stability refers to the ability of the system to maintain consistent voltage and current output despite fluctuating environmental conditions [126]. AI-enhanced MPPT controllers significantly improve stability compared to traditional methods by smoothing out fluctuations, reducing voltage spikes, and mitigating current oscillations. This enhanced stability is crucial for several reasons [127]:

1. Preventing Overvoltage or Undervoltage Conditions: AI-based MPPT systems effectively prevent voltage fluctuations that could damage electrical components or shorten the lifespan of batteries and other system parts.
2. Ensuring Efficient Integration with Batteries or the Electrical Grid: Stable voltage and current outputs facilitate smoother integration with energy storage systems and the electrical grid. This not only enhances the overall reliability of the system but also reduces the likelihood of system failures. AI algorithms continuously monitor and adapt to environmental changes, ensuring that the system operates within optimal voltage and current ranges. This capability is essential for maintaining the long-term health and efficiency of the hybrid renewable energy system.

3.7 Comparative Analysis of AI vs. Conventional MPPT Methods

Experimental studies comparing AI-driven MPPT controllers to traditional techniques typically yield the following results, as shown in Table 3. From Table 3, it was observed that AI-based MPPT techniques outperform traditional methods in terms of efficiency, speed, and stability.

Table 3: Comparison of traditional and AI-based MPPT

Metric	P&O	Incremental Conductanc	AI-Based MPPT (ANN/FLC/RL)
Tracking Efficiency	85% - 90%	88% - 92%	**95% - 98%**
Response Time (s)	1 - 3 s	0.8 - 2 s	**< 0.5 s**
Voltage Fluctuations	High	Medium	**Low (Stable Output)**
Adaptability to Rapid Changes	Low	Moderate	**High**

4.0 Research Findings

HRES, particularly those integrating solar and wind energy, have emerged as promising solutions to address rising global electricity demands and reduce environmental impacts, especially in rural and off-grid regions. These systems leverage the complementary availability of solar irradiance during the day and wind resources throughout varying conditions to enhance reliability and reduce dependence on fossil fuels. However, the intermittency of renewable sources poses significant operational challenges, necessitating the adoption of advanced MPPT techniques to optimize energy harvesting. AI-driven MPPT algorithms such as ANNs, FLC, and RL demonstrate superior adaptability to dynamic environmental conditions through predictive and self-learning capabilities, enabling real-time optimization and improved fault tolerance. Despite these technical advantages, practical implementation in resource-limited settings faces constraints related to cost, scalability, and infrastructure. High initial capital investment in quality components and computational platforms, coupled with the need for large datasets and technical expertise, can hinder widespread adoption. Moreover, scalability is constrained by limited access to modular, open-source solutions and the absence of robust local supply chains. Effective deployment in rural contexts requires not only low-power, embedded AI implementations but also community-centric training, user-friendly interfaces, and maintenance strategies. Nevertheless, with appropriate policy support, pilot demonstrations, and public-private collaboration, AI-enhanced HRES can offer a transformative, scalable, and sustainable pathway to universal energy access, particularly in underserved and remote regions.

5.0 Conclusion and Recommendations

The integration of AI in HRES, particularly in the optimization of MPPT algorithms, offers a promising solution to address the challenges posed by the intermittent nature of solar and wind resources. AI-based MPPT techniques, including ANNs, FLC, RL, significantly improve system performance by enabling adaptive, real-time optimization. These methods enhance energy efficiency, reduce the impact of environmental fluctuations, and ensure more reliable power generation, especially in rural and off-grid areas where energy access is crucial. The application of AI in HRES allows for the dynamic adjustment of operational parameters, thus improving the adaptability and responsiveness of the system to changes in solar irradiance, wind speed, and other environmental variables. This leads to enhanced energy extraction and fault detection, ensuring a sustainable and efficient power supply. Despite the challenges associated with high computational requirements, large data sets, and the complexity of system design, the potential benefits of AI-driven optimization far outweigh these limitations. Fabrication of AI-enhanced hybrid systems requires careful consideration of hardware components such as solar panels, wind turbines, energy storage systems, and power electronics. The use of microcontrollers and embedded processors to implement AI-based MPPT algorithms further contributes to real-time decision-making, ensuring the optimal functioning of the system. As the demand for clean and reliable energy continues to grow, particularly in remote regions, the role of AI in improving the efficiency and scalability of hybrid solar-wind systems will be indispensable. Future research should focus on refining AI techniques, developing more efficient hardware solutions, and integrating IoT-based monitoring systems to further enhance the performance and sustainability of HRES. This approach will be instrumental in achieving the global energy transition and addressing the challenges of energy access in underserved areas.

5.1 Actionable Recommendations

1. **Promote Low-Cost, AI-Embedded MPPT Solutions for Rural Areas**: Focus on developing and deploying affordable AI-based MPPT algorithms that can operate on low-cost microcontrollers. These solutions should be optimized for resource-constrained environments, offering real-time energy optimization without requiring extensive computational resources, which is essential for rural electrification projects.
2. **Invest in Capacity Building and Local Technical Training**: Establish comprehensive training programs for local technicians and community members to enhance their skills in the installation, maintenance, and troubleshooting of AI-enhanced hybrid solar-wind systems. This will ensure long-term sustainability and reduce reliance on external expertise, empowering local communities to manage their renewable energy systems effectively.
3. **Support Modular and Scalable Hybrid Systems:** Encourage the design and deployment of modular, scalable hybrid solar-wind systems that can be easily expanded and adapted to varying energy demands. This approach will ensure that rural and off-grid regions can gradually scale their energy infrastructure as their needs grow, while also enabling ease of maintenance and upgrades.

Acknowledgements
Kampala International University is acknowledged by the authors for providing a favourable research environment and for supplying pertinent data that aided in this study.

Competing Interests
The Author states that they have no conflicting interests.

References

1. Dincer, I. (2000). Renewable energy and sustainable development: a crucial review. *Renewable and sustainable energy reviews*, *4*(2), 157-175.
2. Abbasi, T., & Abbasi, S. A. (2011). *Renewable energy sources: their impact on global warming and pollution*. PHI Learning Pvt. Ltd.
3. Papadopoulos, I. (2010). *Comparative analysis of electricity generating technologies with regards to environmental burdens* (Doctoral dissertation, University of Bath).

4. Dunlap, R. A. (2022). *Renewable Energy: Volumes 1–3*. Springer Nature.
5. Gomes, J. F. R. F. (2022). *Clean Energy ETFS: a new sustainable trend* (Doctoral dissertation).
6. Darwish, A. S., & Al-Dabbagh, R. (2020). Wind energy state of the art: present and future technology advancements. *Renewable Energy and Environmental Sustainability*, *5*, 7.
7. https://pages.owid.io/renewable-energy?utm_source
8. Ahmed, M. M. R., Mirsaeidi, S., Koondhar, M. A., Karami, N., Tag-Eldin, E. M., Ghamry, N. A., ... & Sharaf, A. M. (2024). Mitigating uncertainty problems of renewable energy resources through efficient integration of hybrid solar PV/wind systems into power networks. *IEEe Access*, *12*, 30311-30328.
9. Tajuddin, M. F. N., Arif, M. S., Ayob, S. M., & Salam, Z. (2015). Perturbative methods for maximum power point tracking (MPPT) of photovoltaic (PV) systems: a review. *International Journal of Energy Research*, *39*(9), 1153-1178.
10. Teklehaimanot, Y. K., Akingbade, F. K., Ubochi, B. C., & Ale, T. O. (2024). A review and comparative analysis of maximum power point tracking control algorithms for wind energy conversion systems. *International Journal of Dynamics and Control*, *12*(9), 3494-3516.
11. Eze, V. H. U., Eze, M. C., Ugwu, S. A., Enyi, V. S., Okafor, W. O., Ogbonna, C. C., & Oparaku, O. U. (2025). Development of maximum power point tracking algorithm based on Improved Optimized Adaptive Differential Conductance Technique for renewable energy generation. *Heliyon*, *11*(1).
12. Jathar, L. D., Nikam, K., Awasarmol, U. V., Gurav, R., Patil, J. D., Shahapurkar, K., ... & Ağbulut, Ü. (2024). A comprehensive analysis of the emerging modern trends in research on photovoltaic systems and desalination in the era of artificial intelligence and machine learning. *Heliyon*, *10*(3).
13. Ghoshal, N., & Tripathy, B. K. (2024). Artificial Intelligence Applied to the Management and Operation of Solar Systems. *Biomass and Solar-Powered Sustainable Digital Cities*, 317-338.
14. Akintuyi, O. B. (2024). Adaptive AI in precision agriculture: a review: investigating the use of self-learning algorithms in optimizing farm operations based on real-time data. *Research Journal of Multidisciplinary Studies*, *7*(02), 016-030.
15. Yap, K. Y., Sarimuthu, C. R., & Lim, J. M. Y. (2020). Artificial intelligence based MPPT techniques for solar power system: A review. *Journal of Modern Power Systems and Clean Energy*, *8*(6), 1043-1059.
16. Raj, S. A., & Samuel, G. G. (2022, January). Survey of AI based MPPT algorithms in PV systems. In *2022 4th international conference on smart systems and inventive technology (ICSSIT)* (pp. 597-604). IEEE.
17. Eze, V.H.U.; Bubu, P.E.; Mbonu, C.I.; C, O.F.; Nneoma, U.C. AI-Driven Optimization of Maximum Power Point Tracking (MPPT) for Enhanced Efficiency in Solar Photovoltaic Systems: A Comparative Analysis of Conventional and Advanced Techniques. INOSR Exp. Sci. 2025, 15, 63–81, https://doi.org/10.59298/inosres/2025/151.6381.
18. Hamdan, A., Ibekwe, K. I., Etukudoh, E. A., Umoh, A. A., & Ilojianya, V. I. (2024). AI and machine learning in climate change research: A review of predictive models and environmental impact. *World Journal of Advanced Research and Reviews*, *21*(1), 1999-2008.
19. Selvarajan, G. (2021). Leveraging AI-Enhanced Analytics for Industry-Specific Optimization: A Strategic Approach to Transforming Data-Driven Decision-Making. *International Journal of Enhanced Research In Science Technology & Engineering*, *10*, 78-84.
20. Ohalete, N. C., Aderibigbe, A. O., Ani, E. C., Ohenhen, P. E., Daraojimba, D. O., & Odulaja, B. A. (2023). AI-driven solutions in renewable energy: A review of data science applications in solar and wind energy optimization. *World Journal of Advanced Research and Reviews*, *20*(3), 401-417.
21. Hussain, M. T., Sarwar, A., Tariq, M., Urooj, S., BaQais, A., & Hossain, M. A. (2023). An evaluation of ANN algorithm performance for MPPT energy harvesting in solar PV systems. *Sustainability*, *15*(14), 11144.
22. Lamamra, K., Batat, F., & Mokhtari, F. (2020). A new technique with improved control quality of nonlinear systems using an optimized fuzzy logic controller. *Expert Systems with Applications*, *145*, 113148.
23. Kofinas, P., Doltsinis, S., Dounis, A. I., & Vouros, G. A. (2017). A reinforcement learning approach for MPPT control method of photovoltaic sources. *Renewable Energy*, *108*, 461-473.
24. Phan, B. C., Lai, Y. C., & Lin, C. E. (2020). A deep reinforcement learning-based MPPT control for PV systems under partial shading condition. *Sensors*, *20*(11), 3039.
25. Yap, K. Y., Sarimuthu, C. R., & Lim, J. M. Y. (2020). Artificial intelligence based MPPT techniques for solar power system: A review. *Journal of Modern Power Systems and Clean Energy*, *8*(6), 1043-1059.
26. Khan, M., Raza, M. A., Faheem, M., Sarang, S. A., Panhwar, M., & Jumani, T. A. (2024). Conventional and artificial intelligence based maximum power point tracking techniques for efficient solar power generation. *Engineering Reports*, *6*(12), e12963.

27. Wen, X., Shen, Q., Zheng, W., & Zhang, H. (2024). AI-driven solar energy generation and smart grid integration: A holistic approach to enhancing renewable energy efficiency. *Academia Nexus Journal*, *3*(2).
28. Lin, Y., Tang, J., Guo, J., Wu, S., & Li, Z. (2025). Advancing AI-Enabled Techniques in Energy System Modeling: A Review of Data-Driven, Mechanism-Driven, and Hybrid Modeling Approaches. *Energies*, *18*(4), 845.
29. Eze, V. H. U., Oparaku, U. O., Ugwu, A. S., & Ogbonna, C. C. (2021). A comprehensive review on recent maximum power point tracking of a solar photovoltaic systems using intelligent, non-intelligent and hybrid based techniques. *International Journal of Innovative Science and Research Technology*, *6*(5), 456-474.
30. Eze, V. H. U., Iloanusi, O. N., Eze, M. C., & Osuagwu, C. C. (2017). Maximum power point tracking technique based on optimized adaptive differential conductance. *Cogent Engineering*, *4*(1), 1339336.
31. Eze, V. H. U., Mwenyi, J. M., & Ukagwu, K. J. (2024). Analyzing the Design and Implementation of Sustainable Energy Systems in Island Communities. *International Journal of Education, Science, Technology, and Engineering (IJESTE)*, *7*(1), 29-42.
32. Mbonu, C. I., Alaekwe, B. C., & Innocent, E. E. (2025). Advancing Solar PV Efficiency and Policy Integration: A Novel MPPT-Optimized Fabrication Approach for Sustainable Energy Transition. *IAA Journal of Scientific Research*, *12*(1), 1-8.
33. Hussain, M. T., Sarwar, A., Tariq, M., Urooj, S., BaQais, A., & Hossain, M. A. (2023). An evaluation of ANN algorithm performance for MPPT energy harvesting in solar PV systems. *Sustainability*, *15*(14), 11144.
34. Haseeb, I., Armghan, A., Khan, W., Alenezi, F., Alnaim, N., Ali, F., ... & Ullah, N. (2021). Solar power system assessments using ann and hybrid boost converter based mppt algorithm. *Applied Sciences*, *11*(23), 11332.
35. Haji, S. H., & Abdulazeez, A. M. (2021). Comparison of optimization techniques based on gradient descent algorithm: A review. *PalArch's Journal of Archaeology of Egypt/Egyptology*, *18*(4), 2715-2743.
36. Yang, J., & Yang, G. (2018). Modified convolutional neural network based on dropout and the stochastic gradient descent optimizer. *Algorithms*, *11*(3), 28.
37. Khan, M. J., Mathew, L., Alotaibi, M. A., Malik, H., & Nassar, M. E. (2022). Fuzzy-logic-based comparative analysis of different maximum power point tracking controllers for hybrid renewal energy systems. *Mathematics*, *10*(3), 529.
38. Ali, M., Ahmad, M., Koondhar, M. A., Akram, M. S., Verma, A., & Khan, B. (2023). Maximum power point tracking for grid-connected photovoltaic system using Adaptive Fuzzy Logic Controller. *Computers and Electrical Engineering*, *110*, 108879.
39. Khan, M. J., & Mathew, L. (2019). Fuzzy logic controller-based MPPT for hybrid photo-voltaic/wind/fuel cell power system. *Neural Computing and Applications*, *31*(10), 6331-6344.
40. Lüy, M., Metin, N. A., & Civelek, Z. (2023). Maximum power point tracking with incremental conductance and fuzzy logic controller in solar energy systems. *El-Cezeri*, *11*(1), 120-130.
41. Li, Y., Samad, S., Ahmed, F. W., Abdulkareem, S. S., Hao, S., & Rezvani, A. (2020). Analysis and enhancement of PV efficiency with hybrid MSFLA–FLC MPPT method under different environmental conditions. *Journal of Cleaner Production*, *271*, 122195.
42. Aihua, G., Yihan, X., & Suzuki, K. (2023). A new MPPT design using ISFLA algorithm and FLC to tune the member functions under different environmental conditions. *Soft Computing*, *27*(3), 1511-1531.
43. Belghiti, H., Kandoussi, K., Harrison, A., Moustaine, F. Z., Otmani, R. E., Sadek, E. M., ... & Dost Mohammadi, S. A. (2024). A novel adaptive FOCV algorithm with robust IMRAC control for sustainable and high-efficiency MPPT in standalone PV systems: experimental validation and performance assessment. *Scientific Reports*, *14*(1), 31962.
44. Kaur, D. A., & Kaur, K. (2009, November). Fuzzy expert systems based on membership functions and fuzzy rules. In *2009 international conference on artificial intelligence and computational intelligence* (Vol. 3, pp. 513-517). IEEE.
45. Herrera, F., & Lozano, M. (1996). Adaptation of genetic algorithm parameters based on fuzzy logic controllers. *Genetic Algorithms and Soft Computing*, *8*(1996), 95-125.
46. Wei, C., Zhang, Z., Qiao, W., & Qu, L. (2015). Reinforcement-learning-based intelligent maximum power point tracking control for wind energy conversion systems. *IEEE Transactions on Industrial Electronics*, *62*(10), 6360-6370.
47. Chou, K. Y., Yang, S. T., & Chen, Y. P. (2019). Maximum power point tracking of photovoltaic system based on reinforcement learning. *Sensors*, *19*(22), 5054.
48. Kofinas, P., Doltsinis, S., Dounis, A. I., & Vouros, G. A. (2017). A reinforcement learning approach for MPPT control method of photovoltaic sources. *Renewable Energy*, *108*, 461-473.
49. Phan, B. C., & Lai, Y. C. (2019). Control strategy of a hybrid renewable energy system based on reinforcement

learning approach for an isolated microgrid. *Applied Sciences*, *9*(19), 4001.

50. Giraldo, L. F., Gaviria, J. F., Torres, M. I., Alonso, C., & Bressan, M. (2024). Deep reinforcement learning using deep-Q-network for Global Maximum Power Point tracking: Design and experiments in real photovoltaic systems. *Heliyon*, *10*(21).
51. Artetxe, E., Uralde, J., Barambones, O., Calvo, I., & Martin, I. (2023). Maximum power point tracker controller for solar photovoltaic based on reinforcement learning agent with a digital twin. *Mathematics*, *11*(9), 2166.
52. Leelavathi, M., & Suresh, K. V. (2024). Enhancing MPPT in partially shaded PV modules: a novel approach using adaptive reinforcement learning with neural network architecture. *Bulletin of the Polish Academy of Sciences. Technical Sciences*, *72*(4).
53. Wadehra, A., Bhalla, S., Jaiswal, V., Rana, K. P. S., & Kumar, V. (2024). A deep recurrent reinforcement learning approach for enhanced MPPT in PV systems. *Applied Soft Computing*, *162*, 111728.
54. Phan, B. C., Lai, Y. C., & Lin, C. E. (2020). A deep reinforcement learning-based MPPT control for PV systems under partial shading condition. *Sensors*, *20*(11), 3039.
55. Singh, Y., & Pal, N. (2021). Reinforcement learning with fuzzified reward approach for MPPT control of PV systems. *Sustainable Energy Technologies and Assessments*, *48*, 101665.
56. Taylor, A. R. (2023). Performance analysis of hybrid AI-based technique for maximum power point tracking in solar energy system applications.
57. Bale, A. S., William, P., Kondekar, V. H., Sanamdikar, S., Joshi, P., Nigam, P., & Savadatti, M. B. (2024). Harnessing AI and IoT for Optimized Renewable Energy Integration and Resource Conservation. *Library of Progress-Library Science, Information Technology & Computer*, *44*(3).
58. Bale, A. S., William, P., Kondekar, V. H., Sanamdikar, S., Joshi, P., Nigam, P., & Savadatti, M. B. (2024). Harnessing AI and IoT for Optimized Renewable Energy Integration and Resource Conservation. *Library of Progress-Library Science, Information Technology & Computer*, *44*(3).
59. Singh, R., Memon, S. A., Shaikh, R., & Upadhyay, D. S. (2022). A review of artificial intelligence applied for the solution of issues in the extensive adaption of solar and wind energy. *International Journal of Ambient Energy*, *43*(1), 7419-7436.
60. Hazra, S., Sultana, S., & Roy, P. K. (Eds.). (2024). *Optimization Techniques for Hybrid Power Systems: Renewable Energy, Electric Vehicles, and Smart Grid: Renewable Energy, Electric Vehicles, and Smart Grid*. IGI Global.
61. Eze, M. C., Ugwuanyi, G., Li, M., Eze, H. U., Rodriguez, G. M., Evans, A., ... & Min, G. (2021). Optimum silver contact sputtering parameters for efficient perovskite solar cell fabrication. *Solar Energy Materials and Solar Cells*, *230*, 111185.
62. Eze, V. H. U., Oparaku, U. O., Ugwu, A. S., & Ogbonna, C. C. (2021). A comprehensive review on recent maximum power point tracking of a solar photovoltaic systems using intelligent, non-intelligent and hybrid based techniques. *International Journal of Innovative Science and Research Technology*, *6*(5), 456-474.
63. Eze, V. H. U., Mwenyi, J. S., Ukagwu, K. J., Eze, M. C., Eze, C. E., & Okafor, W. O. (2024). Design analysis of a sustainable techno-economic hybrid renewable energy system: Application of solar and wind in Sigulu Island, Uganda. *Scientific African*, *26*, e02454.
64. Eze, M. C., Eze, H. U., Ugwuanyi, G. N., Alnajideen, M., Atia, A., Olisa, S. C., ... & Min, G. (2022). Improving the efficiency and stability of in-air fabricated perovskite solar cells using the mixed antisolvent of methyl acetate and chloroform. *Organic Electronics*, *107*, 106552.
65. Pazhani, A. A. J., & Vinodh, K. A. (2025). AI-Based ULP Microprocessors and Microcontrollers. In *Self-Powered AIoT Systems* (pp. 219-238). Apple Academic Press.
66. Singh, G. K. (2013). Solar power generation by PV (photovoltaic) technology: A review. *Energy*, *53*, 1-13.
67. Belu, R. (2013). Wind energy conversion and analysis. *Encyclopedia of Energy Engineering and Technology, Taylor and Francis*.
68. Rane, N., Choudhary, S., & Rane, J. (2023). Artificial Intelligence (Ai) and Internet of Things (Iot)–based sensors for monitoring and controlling in architecture, engineering, and construction: Applications, challenges, and opportunities. *Engineering, and Construction: Applications, Challenges, and Opportunities (November 20, 2023)*.
69. Fred, O., Ukagwu, K. J., Abdulkarim1&2, A., & Eze, V. H. U. (2024). Reliability and maintainability analysis of Solar Photovoltaic Systems in rural regions: A narrative review of challenges, strategies, and policy implications for sustainable electrification.
70. Aberilla, J. M., Gallego-Schmid, A., Stamford, L., & Azapagic, A. (2020). Design and environmental sustainability assessment of small-scale off-grid energy systems for remote rural communities. *Applied Energy*, *258*, 114004.
71. Mohammed, Y. S., Mustafa, M. W., & Bashir, N. (2014). Hybrid renewable energy systems for off-grid electric

power: Review of substantial issues. *Renewable and Sustainable Energy Reviews*, *35*, 527-539.

72. Agajie, E. F., Agajie, T. F., Amoussou, I., Fopah-Lele, A., Nsanyuy, W. B., Khan, B., ... & Tanyi, E. (2024). Optimization of off-grid hybrid renewable energy systems for cost-effective and reliable power supply in Gaita Selassie Ethiopia. *Scientific Reports*, *14*(1), 10929.
73. Yap, K. Y., Sarimuthu, C. R., & Lim, J. M. Y. (2020). Artificial intelligence based MPPT techniques for solar power system: A review. *Journal of Modern Power Systems and Clean Energy*, *8*(6), 1043-1059.
74. Icaza, D., Borge-Diez, D., Pulla Galindo, S., & Flores-Vázquez, C. (2020). Modeling and simulation of a hybrid system of solar panels and wind turbines for the supply of autonomous electrical energy to organic architectures. *Energies*, *13*(18), 4649.
75. Badwawi, R. A., Abusara, M., & Mallick, T. (2015). A review of hybrid solar PV and wind energy system. *Smart Science*, *3*(3), 127-138.
76. Maka, A. O., & Alabid, J. M. (2022). Solar energy technology and its roles in sustainable development. *Clean Energy*, *6*(3), 476-483.
77. Lewis, N. S. (2016). Research opportunities to advance solar energy utilization. *Science*, *351*(6271), aad1920.
78. Ayadi, O., Shadid, R., Bani-Abdullah, A., Alrbai, M., Abu-Mualla, M., & Balah, N. (2022). Experimental comparison between Monocrystalline, Polycrystalline, and Thin-film solar systems under sunny climatic conditions. *Energy Reports*, *8*, 218-230.
79. Genc, A. K. A. K. N. (2022). Effects of temperature and solar irradiation on performance of monocrystalline, polycrystalline and thin-film PV panels. *International Journal on Technical and Physical Problems of Engineering (IJTPE)*, *51*, 254-260.
80. Vodapally, S. N., & Ali, M. H. (2022). A comprehensive review of solar photovoltaic (PV) technologies, architecture, and its applications to improved efficiency. *Energies*, *16*(1), 319.
81. Vodapally, S. N., & Ali, M. H. (2022). A comprehensive review of solar photovoltaic (PV) technologies, architecture, and its applications to improved efficiency. *Energies*, *16*(1), 319.
82. Fouad, M. M., Shihata, L. A., & Morgan, E. I. (2017). An integrated review of factors influencing the perfomance of photovoltaic panels. *Renewable and Sustainable Energy Reviews*, *80*, 1499-1511.
83. Hasan, K., Yousuf, S. B., Tushar, M. S. H. K., Das, B. K., Das, P., & Islam, M. S. (2022). Effects of different environmental and operational factors on the PV performance: A comprehensive review. *Energy Science & Engineering*, *10*(2), 656-675.
84. Badwawi, R. A., Abusara, M., & Mallick, T. (2015). A review of hybrid solar PV and wind energy system. *Smart Science*, *3*(3), 127-138.
85. Probst, O., & Cárdenas, D. (2010). State of the art and trends in wind resource assessment. *Energies*, *3*(6), 1087-1141.
86. Brower, M. (2012). *Wind resource assessment: a practical guide to developing a wind project*. John Wiley & Sons.
87. Das, A., Chimonyo, K. B., Kumar, T. R., Gourishankar, S., & Rani, C. (2017, August). Vertical axis and horizontal axis wind turbine-A comprehensive review. In *2017 international conference on energy, communication, data analytics and soft computing (ICECDS)* (pp. 2660-2669). IEEE.
88. Bhutta, M. M. A., Hayat, N., Farooq, A. U., Ali, Z., Jamil, S. R., & Hussain, Z. (2012). Vertical axis wind turbine–A review of various configurations and design techniques. *Renewable and Sustainable Energy Reviews*, *16*(4), 1926-1939.
89. Chen, H. H., Kang, H. Y., & Lee, A. H. (2010). Strategic selection of suitable projects for hybrid solar-wind power generation systems. *Renewable and Sustainable Energy Reviews*, *14*(1), 413-421.
90. Xu, Y., & Singh, C. (2013). Power system reliability impact of energy storage integration with intelligent operation strategy. *IEEE Transactions on smart grid*, *5*(2), 1129-1137.
91. Sinha, S., & Chandel, S. S. (2015). Review of recent trends in optimization techniques for solar photovoltaic–wind based hybrid energy systems. *Renewable and sustainable energy reviews*, *50*, 755-769.
92. Balle, M., Xu, W., Darras, K. F., & Wanger, T. C. (2024). A Power Management and Control System for Portable Ecosystem Monitoring Devices. *arXiv preprint arXiv:2404.05322*.
93. Talaat, M., Mohamed, A. R., Sedhom, B. E., Wahba, A., Elkholy, M. H., Elbehairy, N. M., ... & Senjyu, T. (2024). Monolithic design of self-adaptive CMOS converter and robust event-triggered consensus control for integration of multi-renewable energy sources with battery storage system. *Journal of Energy Storage*, *88*, 111498.
94. Oliveira, F., Costa, D. G., Assis, F., & Silva, I. (2024). Internet of Intelligent Things: A convergence of embedded systems, edge computing and machine learning. *Internet of Things*, 101153.
95. Kaneva, T., Valova, I., & Halacheva, T. (2024, November). An Overview of Monitoring Systems, Methods, and Technologies for Hybrid Renewable Energy Sources. In *2024 5th International Conference on Communications, Information, Electronic and Energy Systems (CIEES)* (pp. 1-10). IEEE.

96. Priyadharsini, R., & Kanimozhi, R. (2024). A hybrid solar photovoltaic and wind turbine power generation for stand-alone system with Iot-based monitoring and MPPT control. *Electric Power Components and Systems*, *52*(10), 1763-1781.
97. González, I., & Calderón, A. J. (2019). Integration of open source hardware Arduino platform in automation systems applied to Smart Grids/Micro-Grids. *Sustainable Energy Technologies and Assessments*, *36*, 100557.
98. Khalid, W., Jamil, M., Khan, A. A., & Awais, Q. (2024). Open-source internet of things-based supervisory control and data acquisition system for photovoltaic monitoring and control using HTTP and TCP/IP protocols. *Energies*, *17*(16), 4083.
99. Alghaythi, M. L., Fathy, A., Allehyani, A., Alshammari, M. S., Atitallah, A. B., Rezk, H., & Gaafar, T. S. (2024). Highly Efficient DC–DC Boost Converter Achieved With Improved MPPT-Based Raspberry Pi for Enhancing Photovoltaic System Generation. *International Journal of Energy Research*, *2024*(1), 8834986.
100. Paredes-Parra, J. M., Mateo-Aroca, A., Silvente-Niñirola, G., Bueso, M. C., & Molina-García, Á. (2018). PV module monitoring system based on low-cost solutions: Wireless raspberry application and assessment. *Energies*, *11*(11), 3051.
101. Mellit, A., & Kalogirou, S. A. (2014). MPPT-based artificial intelligence techniques for photovoltaic systems and its implementation into field programmable gate array chips: Review of current status and future perspectives. *Energy*, *70*, 1-21.
102. Mazumdar, D., Sain, C., Biswas, P. K., Sanjeevikumar, P., & Khan, B. (2024). Overview of solar photovoltaic MPPT methods: a state of the art on conventional and artificial intelligence control techniques. *International Transactions on Electrical Energy Systems*, *2024*(1), 8363342.
103. Verhelst, M., & Moons, B. (2017). Embedded deep neural network processing: Algorithmic and processor techniques bring deep learning to iot and edge devices. *IEEE Solid-State Circuits Magazine*, *9*(4), 55-65.
104. Tomsovic, K., Bakken, D. E., Venkatasubramanian, V., & Bose, A. (2005). Designing the next generation of real-time control, communication, and computations for large power systems. *Proceedings of the IEEE*, *93*(5), 965-979.
105. Govindasamy, M., Cyril Mathew, O., Kumar Boopathi, M., & Chandran, G. (2023). Iot and AI-Based MPPT Techniques for Hybrid Solar and Fuel Cell. *Electric Power Components and Systems*, 1-21.
106. Sharma, V., Gupta, A. K., Raj, A., & Verma, S. K. (2024, December). AI-Driven MPPT: A Paradigm Shift in Solar PV Systems for Achieving maximum Efficiency. In *2024 International Conference of Adisutjipto on Aerospace Electrical Engineering and Informatics (ICAAEEI)* (pp. 1-5). IEEE.
107. Hollweg, G. V., Singh Chawda, G., Chaturvedi, S., Bui, V. H., & Su, W. (2025). Optimization Techniques for Low-Level Control of DC–AC Converters in Renewable-Integrated Microgrids: A Brief Review. *Energies*, *18*(6), 1429.
108. Zhang, N., Sutanto, D., & Muttaqi, K. M. (2016). A review of topologies of three-port DC–DC converters for the integration of renewable energy and energy storage system. *Renewable and Sustainable Energy Reviews*, *56*, 388-401.
109. Mumtaz, F., Yahaya, N. Z., Meraj, S. T., Singh, B., Kannan, R., & Ibrahim, O. (2021). Review on non-isolated DC-DC converters and their control techniques for renewable energy applications. *Ain Shams Engineering Journal*, *12*(4), 3747-3763.
110. Sharma, V., Gupta, A. K., Raj, A., & Verma, S. K. (2024, December). AI-Driven MPPT: A Paradigm Shift in Solar PV Systems for Achieving maximum Efficiency. In *2024 International Conference of Adisutjipto on Aerospace Electrical Engineering and Informatics (ICAAEEI)* (pp. 1-5). IEEE.
111. Gao, Y., Wang, S., Dragicevic, T., Wheeler, P., & Zanchetta, P. (2023). Artificial intelligence techniques for enhancing the performance of controllers in power converter-based systems—an overview. *IEEE Open Journal of Industry Applications*, *4*, 366-375.
112. Rabbani, M. A. (2020). Solar power systems and dc to ac inverters. *Acta Technica Corviniensis-Bulletin of Engineering*, *13*(2), 19-28.
113. Dogga, R., & Pathak, M. K. (2019). Recent trends in solar PV inverter topologies. *Solar Energy*, *183*, 57-73.
114. Gao, Y., Wang, S., Dragicevic, T., Wheeler, P., & Zanchetta, P. (2023). Artificial intelligence techniques for enhancing the performance of controllers in power converter-based systems—an overview. *IEEE Open Journal of Industry Applications*, *4*, 366-375.
115. Sarath, S., & Vijayakumar, K. (2024, September). A Comprehensive Review of Different DC-DC Converters and Intelligent Controlling Algorithms for Solar PV Systems. In *2024 International Conference on Integration of Emerging Technologies for the Digital World (ICIETDW)* (pp. 1-6). IEEE.
116. Badruddaza, M. (2024). *Modeling and Performance Evaluation of Traditional and AI-Based MPPT Techniques for Photovoltaic Systems* (Master's thesis, Northern Illinois University).

117. Mouaad, B. O. U. G. O. F. F. A., Samir, B. E. N. M. O. U. S. S. A., & Mohand, D. J. E. Z. I. R. I. (2024, January). Dynamic Modeling for Fault Diagnosis in PV Systems Utilizing AI Techniques Based on Multilayer Perceptron (MLP). In *2024 ASU International Conference in Emerging Technologies for Sustainability and Intelligent Systems (ICETSIS)* (pp. 1032-1036). IEEE.
118. Badruddaza, M. (2024). *Modeling and Performance Evaluation of Traditional and AI-Based MPPT Techniques for Photovoltaic Systems* (Master's thesis, Northern Illinois University).
119. Elkholy, M. H., Elymany, M., Ueda, S., Halidou, I. T., Fedayi, H., & Senjyu, T. (2024). Maximizing microgrid resilience: A two-stage AI-Enhanced system with an integrated backup system using a novel hybrid optimization algorithm. *Journal of Cleaner Production*, *446*, 141281.
120. Kazem, H. A., Chaichan, M. T., Al-Waeli, A. H., & Sopian, K. (2024). Dual axis solar photovoltaic trackers: An in-depth review. *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, *46*(1), 15331-15356.
121. Elkholy, M. H., Senjyu, T., Elymany, M., Gamil, M. M., Talaat, M., Masrur, H., ... & Lotfy, M. E. (2024). Optimal resilient operation and sustainable power management within an autonomous residential microgrid using African vultures optimization algorithm. *Renewable Energy*, *224*, 120247.
122. Talaat, M., Mohamed, A. R., Sedhom, B. E., Wahba, A., Elkholy, M. H., Elbehairy, N. M., ... & Senjyu, T. (2024). Monolithic design of self-adaptive CMOS converter and robust event-triggered consensus control for integration of multi-renewable energy sources with battery storage system. *Journal of Energy Storage*, *88*, 111498.
123. Marańda, W., & Piotrowicz, M. (2014). Efficiency of maximum power point tracking in photovoltaic system under variable solar irradiance. *Bulletin of the Polish Academy of Sciences: Technical Sciences*, (4).
124. Asoh, D. A., Noumsi, B. D., & Mbinkar, E. N. (2022). Maximum power point tracking using the incremental conductance algorithm for PV systems operating in rapidly changing environmental conditions. *Smart Grid and Renewable Energy*, *13*(5), 89-108.
125. Rico-Camacho, R. I., Ricalde, L. J., Bassam, A., Flota-Bañuelos, M. I., & Alanis, A. Y. (2022). Transient differentiation maximum power point tracker (Td-MPPT) for optimized tracking under very fast-changing irradiance: A theoretical approach for mobile PV applications. *Applied Sciences*, *12*(5), 2671.
126. Krishan, O., & Suhag, S. (2019). An updated review of energy storage systems: Classification and applications in distributed generation power systems incorporating renewable energy resources. *International Journal of Energy Research*, *43*(12), 6171-6210.
127. Ahmed, S., Rashid, H., Qadir, Z., Tayyab, Q., Senjyu, T., & Elkholy, M. H. (2025). Deep Learning-Based Recognition and Classification of Soiled Photovoltaic Modules Using HALCON Software for Solar Cleaning Robots. *Sensors*, *25*(5), 1295.