AI-Based Maximum Energy Harvesting and Power Management of a Hybrid PV–Geothermal-Emulated System Using Thermoelectric Generation in a Closed-Loop Water Channel

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ARTICLE INFO

ABSTRACT

Here provide an AI-empowered maximum harvesting and power management system for PV–TEG hybrid integrated with geothermal heat emulation based on a closed loop water channel in a novel approach. The presented approach provides a PV module with a photovoltaic panel and a thermoelectric generator to recover waste thermal energy produced by the PV module and/or a regulated thermal generator while improving the electrical output, providing the overall power. To ensure controllable thermodynamic stability and reliable experimentation, a geothermal heat emulator is used for stable thermal conditions. Experimental and numerical results show that independent PV module produces power in the range of 100–140 W while the thermoelectric generator contributing 20–30 W in a stable temperature difference (16–20 °C). Without good control, the hybrid PV–TEG system produces a total power from 120 W to 160 W, while using AI-based power management the total output is 125–170 W. The peak value is around 168–170 W by using coordination between multiple sources of energy. This AI-based voltage regulation can significantly improve system stability, reducing a voltage deviation from ±1.5 V (22.5–25.5 V) for conventional control of this type to ±0.4 V (23.6–24.4 V). During energy-based analysis, the total harvested energy rises from around 138 Wh to 145 Wh, corresponding to an improvement of approximately 5–6% (with an aggregation of nearly 130 Wh of total stored power after 60 min use). Results for different AI classifiers indicate a comparison between Random Forest and ANFIS with the highest accuracies of both 96% and 95.2%, respectively.

1. Introduction

This growing global appetite for clean, and renewable sources of power has led to a more urgent need for research on renewable energy techniques that can enhance their efficiency, reliability and yields. Photovoltaic (PV) technologies are among these renewable technologies that are commonly used, as PV is simple, scalable and environmentally friendly. Nevertheless, the PV systems performance is intrinsically dependent on solar radiation and operating temperature, resulting in fluctuating power supply, diminished efficiency and energy wastage. Therefore, increasing the energy harvesting efficiency of PV systems is a critical challenge. A downside of traditional PV is the large amount of thermal energy produced at operating temperature that is normally dissipated to the outside world, not used. High cell temperatures not only reduce PV efficiencies, but also are a wasted type of energy. More recently, hybrid renewable energy systems are presented as promising approach to solve this problem by employing numerous types of energy conversion

mechanisms for improved system performance. Especially, linking the thermoelectric generators (TEGs) to PV modules has received more focus, as TEGs can transform the temperature gradients directly to electrical electricity, in order to partially recover the waste heat. Geothermal is a second stable and reliable renewable energy alternative; however, the deployment of this scheme can be intricate due to a complex infrastructure and costly installation. These challenges justify limiting these experimental and laboratory-scale studies to use geothermal heat emulation by means of controlled electrical heaters as a valuable alternative. Combined with a closed-loop water channel, these geothermal emulators provide a stable and controllable thermal source that is conducive to efficient thermoelectric energy production. The control of temperature distribution, flow conditions and thermal gradients can be achieved through this process, making it suitable for hybrid PV–TEG system development and performance evaluation. However, effective power management and control strategies are strongly critical for performing these hybrid PV–TEG systems. Although traditional control techniques such as Perturb and Observe (P&O) and Incremental Conductance (INC) are extensively applied in maximum power point tracking (MPPT) for PV systems, they have steady state oscillations, slow dynamic response and poorer accuracy under rapidly changing operating conditions. In addition, traditional control methods usually do not manage multiple energy sources (e.g., PV and TEG) in one system. Artificial intelligence (AI)–driven control methodologies have recently attracted significant efforts in renewable energy applications because of their potential to represent nonlinear structures, manage changes, and adopt smart choices in the course of action. Some AI algorithms, e.g., Artificial Neural Networks (ANN), Fuzzy Logic, Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Support Vector Machines (SVM), Random Forest classifiers exhibited promising performance in optimizing MPPT, system monitoring and intelligent energy control. AI-based controllers leverage data-driven learning to greatly improve power

extraction, voltage stability, and system efficiency over classical methods.

(Abualigah et al., 2022) [1] reviewed a wide range of the machine learning and deep learning techniques exploited for the wind-solar-PV systems with and without storage in accordance with optimization trends and research gaps in intelligent energy management (Agarwal & Batista, 2023) [2] integrated solar chimney project with integrated geothermal project resulting in significant improvements in the thermal performance of the buildings and stresses on hybrid renewable integration concept of the sustainable building. (Alhawsawi et al., 2024) [3] selected microgrids existing and proposed microgrids on the university campus for studying the control strategies, renewable penetration level, and smart energy management system use for universities' campus systems. (Almodfer et al., 2022) [4] Used AI-based RVFL networks, the authors derive a solar-powered thermoelectric air-conditioning system and demonstrate improved predictive accuracy (with metaheuristic optimization). (Asad & Sánchez-Fernández, 2025) [5] frequency regulation of hybrid wind–diesel systems using inertial emulation and droop control to enhance the stability of such systems under varying wind states. (Bedakhanian et al., 2024) [6] increased energy-efficiency and emission reduction, a multi-objective optimization framework for a solar-based cogeneration system providing hydrogen, cooling, and electricity is presented for the energy system production to optimize and improve the efficiency and minimize the emissions. (Boussafa et al., 2024) [7] improved the MPPT performance in PV arrays by implementing backstepping control which has been optimized for a genetic algorithm, leading to rapid convergence and high tracking accuracy. (Cavagnoli et al., 2024) [8] proposed a novel geothermal system for heritage revitalisation in the field of historic architecture, which is capable of energy conservation with historical heritage, by delivering energy saving without affecting architectural form. (Elewa, 2024) [9] detailed survey of renewable energy-assisted desalination technologies which focuses on

energy storage inclusion and the road to zero liquid discharge systems. (Elmetwaly et al., 2023) [10] derived and perform an experimentally validated AI-optimized MPPT for hybrid renewable sources paired with UPQC, which results in improved power quality and energy production. (Fatah et al., 2024) [11] performed a hardware-in-the-loop emulation of a photovoltaic pumping system, demonstrating dynamic performance and reliable implementation for green energy. (Gurgenc et al., 2024) [12] enhanced the accuracy of ANN models for predicting geothermal reservoir temperature, an optimal metaheuristic & ANN hybrid is proposed for application. (Hassanein et al., 2025) [13] Optimization based metaheuristic in sizing- and uncertainties-managing hybrid renewable energy systems has been employed to deal with demand-side variability. (Kabengele et al., 2023) [14] An ANFIS-based hybrid thermal power plant effectiveness is evaluated that shows enhanced precision prediction and control ability using nonlinear settings. (Kebbati & Baghli, 2023) [15] demonstrated the design and control of grid-connected PV–wind system that demonstrates regional adaptability (and hence increased energy availability and reliability). (Khan et al., 2023) [16] A hybrid general regression neural network model is developed for centralized thermoelectric generator systems, which deals with non-uniform temperature gradients effectively. (Mahjoub et al., 2023) [17] An intelligent energy management strategy for PV–wind–battery microgrids is proposed, using predictive algorithms to improve power balance and system efficiency. (Muna & Kuo, 2022) [18] techno-economic perspective is used to evaluate the charging of EVs via PV/wind/diesel/battery hybrid systems and assess the effect of choosing suitable battery technology. (Osei et al., 2024) [19] analyzed the feasibility of decentralized PV-based green hydrogen production to confirm its economic and environmental viability in developing regions. (Patel et al., 2022) [20] Machine learning is used to predict power generation in small off-grid PV systems, which in turn provides an improved forecast for more predictive and efficient power planning. (Posada Contreras & Rosas-Caro, 2024) [21] hardware-in-the-loop emulation of a SEPIC multiplier converter designed for PV systems and confirm real-time control, and converter performance. (Sarbu et al., 2024) [22] integrated solar forecasting and correction algorithms to lower the predictive error, practical microgrid energy management options are presented with predictive modeling. (Shezan et al., 2023) [23] reviewed is given on optimization methods and control for hybrid microgrids and the strengths and weaknesses of the existing techniques are identified. (H. Wang et al., 2024) [24] For PV systems with partial shading, a hybrid MPPT approach is presented to obtain fast and precise maximum power tracking. (Y. Wang et al., 2024) [25] presents an economic and technical analysis of wind–PV–fuel cell hybrid systems using an improved optimization algorithm to reduce overall system cost. (Waqas et al., 2024) [26] developed a hybrid power distribution system for the remote gas pipeline stations designed and modeled to improve reliability and operational resilience in this work. (Yuvaraj & Kumar, 2022) [27] Grey Wolf Optimization is utilized on solar-wind hybrid systems to increase efficacy and power dispatch.

Most existing studies on hybrid renewable energy systems primarily focus on photovoltaic energy or conventional hybrid configurations, with limited utilization of waste thermal energy and minimal coordination between multiple energy sources. In addition, AI-based control strategies are commonly applied only to PV maximum power point tracking, while the combined management of photovoltaic, thermoelectric, and thermal subsystems remains insufficiently explored. Moreover, geothermal-based hybrid systems often rely on real geothermal resources, which are costly and difficult to control experimentally, and comparative evaluations of different AI classifiers under realistic operating conditions are still scarce. To overcome these limitations, this work proposes a novel AI-assisted hybrid PV–TEG system using a geothermal heat emulator in a closed-loop water channel. The proposed approach enables controlled thermal

energy recovery, coordinated multi-source power management, and systematic comparison of multiple AI classifiers. This integrated framework demonstrates improved power output, energy harvesting, voltage stability, and overall system efficiency, providing a practical and scalable solution for intelligent hybrid renewable energy systems.

Although the work available is comprehensive on PV-based energy systems and AI-supported maximum power point tracking, there are quite a few significant research gaps being insufficiently addressed. Existing studies typically target PV-only or standalone modeling of thermoelectrics with minimal experimental integration of waste-heat recovery under controlled thermal conditions. Moreover, AI-based control strategies are applied to individual subsystems, such as PV MPPT, but without coordinated management of multiple energy sources and auxiliary components. In addition, geothermal-assisted hybrid systems are often grounded in real geothermal resources, which are expensive, location-dependent, and difficult to control experimentally, and comparisons between different AI classifiers under realistic and noisy operating conditions are rarely reported. To overcome these limitations, the current work presents an experimentally validated hybrid PV–TEG system that seamlessly integrates a geothermal heat emulator in the form of a closed-loop water channel with a common unified AI-based power management structure. The proposed approach allows control over thermal energy recovery, coordinated multi-source optimization, and comparative assessment of various AI classifiers, breaking new ground in previous works, contributing new perspectives for smart hybrid renewable energy system design.

2. Methodology

The approach applied in this study is to evaluate the application of artificial intelligence-based energy harvesting and power management in hybrid photovoltaic–thermoelectric systems with geothermal heat emulation. The overall methodological framework includes system design, experimental data acquisition, mathematical modeling, AI-based control, and performance evaluation.

2.1 System configuration and setup of the experiment

The proposed hybrid energy system comprises a photovoltaic (PV) module, thermoelectric generator (TEG), and geothermal heat emulator within a closed-loop water channel. The PV panel is used as the main electrical energy source, and the TEG is employed to convert recovered thermal energy into additional electrical energy. A heater pad is used to emulate geothermal heat by providing a controlled and stable thermal input to the circulating water inside the closed-loop channel. The flow rate is controlled with the aid of the water pump, maintaining continual heat transfer and temperature distribution among the water flowing in the channel. The TEG module is attached on the channel wall and detects the temperature difference between hot water in the channel and the outside environment or heat sink. Sensors at various channel locations have been built to record voltage, current, water temperature, and pump speed. All signals are acquired with a data acquisition system and delivered to a control unit for real-time monitoring and decision-making.
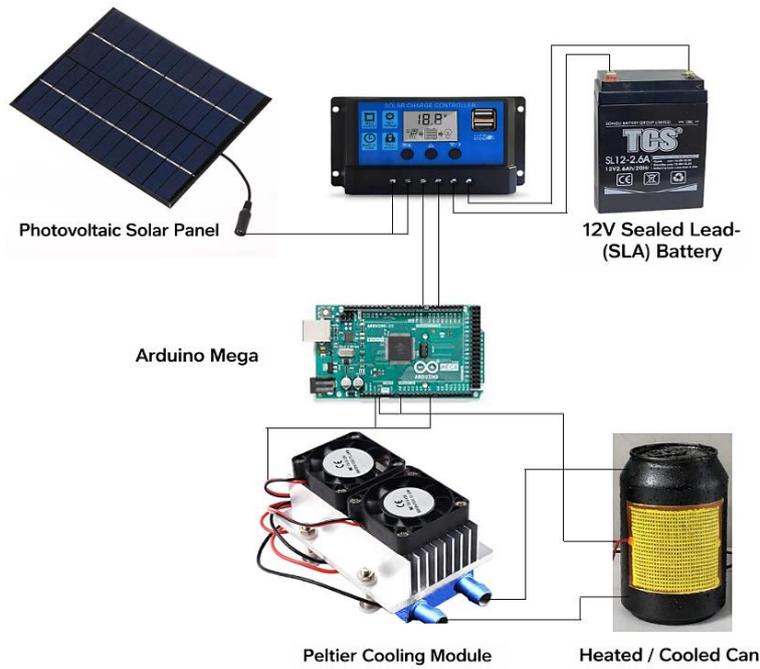
Figure 1. Schematic Diagram of the Hybrid Photovoltaic–Thermoelectric System with Battery Storage and Arduino-Based Control

Table 1: Photovoltaic (PV) Module Specifications

Parameter	Symbol	Value	Unit
PV type	—	Monocrystalline Silicon	—
Rated power	Prated	200	W
Maximum power voltage	Vmp	18–20	V
Maximum power current	Imp	9.5–10.5	A
Open-circuit voltage	Voc	21–22	V
Short-circuit current	Isc	10.5–11.2	A
PV area	Apv	1.2	m²
Efficiency	ηpv	18–20	%
Temperature coefficient	—	−0.4	%/°C

Table 2: Thermoelectric Generator (TEG) Specifications

Parameter	Symbol	Value	Unit
TEG type	—	Bi_2Te_3-based module	—
Seebeck coefficient	α	0.05–0.06	V/K
Internal resistance	Rint	3.0–3.5	Ω
Operating temperature difference	ΔT	16–20	°C
Open-circuit voltage	Voc	0.8–1.2	V
Maximum output power	Pteg	0.25–0.35	W
Hot-side temperature	Th	55–65	°C
Cold-side temperature	Tc	35–45	°C

Table 3: Geothermal Heat Emulator (Heater Pad) Specifications

Parameter	Symbol	Value	Unit
Heater type	—	Electric silicone heater pad	—
Rated thermal power	Qh	200–300	W
Operating temperature range	—	30–80	°C
Voltage supply	—	220 AC / 24 DC	V
Control method	—	PWM / PID	—
Heat transfer mode	—	Conduction–Convection	—

Table 4: Closed-Loop Water Channel Specifications

Parameter	Symbol	Value	Unit
Channel length	L	٢٠	cm
Inner diameter	D	10–15	mm
Working fluid	—	Water	—
Fluid density	P	998	kg/m³
Specific heat	Cp	4180	J/kg·K
Thermal conductivity	K	0.6	W/m·K
Flow regime	—	Laminar–Transitional	—

Table 5: Water Pump Specifications

Parameter	Symbol	Value	Unit
Pump type	—	DC centrifugal pump	—
Operating speed range	N	800–1600	rpm
Flow rate	V˙	1–3	L/min
Maximum head	H	2–3	m
Electrical power	Ppump	8–15	W
Efficiency	Hp	60–70	%

Table 6: Sensors and Measurement Devices

Device	Parameter Measured	Range	Accuracy
Voltage sensor	Voltage	0–30 V	±0.5%
Current sensor	Current	0–20 A	±1%
Temperature sensor (DS18B20 / K-type)	Water temperature	0–100 °C	±0.5 °C
Irradiance sensor	Solar irradiance	0–1200 W/m²	±5%
Flow sensor	Flow rate	0–5 L/min	±2%

2.2 Working Conditions and Control Policies

Two primary operating scenarios are considered in this research. The first approach uses conventional control methods; they are Perturb and Observe (P&O) traditional MPPT techniques and Incremental Conductance (INC) advanced techniques with fixed system parameters. The second scenario aims to implement AI-based power management, implementing intelligent algorithms for flexible power management that adapt the key variables of the system as needed for optimum energy harvesting and stability, ensuring constant energy utilization. The AI-based strategy also manages the PV operating point, TEG contribution, and pump speed in parallel with the energy of the PV processing system. This integrative control mechanism allows an optimum use of the electrical and thermal energy source under different environmental and operating conditions.

2.3 Artificial intelligence classifiers and learning models

A number of artificial intelligence classifiers are developed and compared to see at a glance how well they work for intelligent energy management. Among them, Artificial Neural Networks (ANN), Fuzzy Logic, Adaptive Neuro-Fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Random Forest classifiers. The input features of the classifiers are PV voltage and current, irradiance, water temperature, temperature difference across the TEG, and pump speed. It produces output values corresponding to optimal control decisions including MPPT reference signals and adjusting pump speed. Experimental and simulated datasets represent various operating conditions for training each classifier. The evaluation of performance is conducted based on accuracy, precision, recall, F1-score, error rate, computational cost, and robustness against measurement noise. This comparative method guarantees a fair and complete assessment of each classifier.

2.4 Mathematical modeling and performance metrics

Mathematical modeling and computational performance metrics. Math models are used to simulate the electrical behavior, the thermal property, closed-loop channel temperature of the PV module, as well as the electrical output of the TEG. The power output in PV output is based on the voltage, current, and irradiance, whereas TEG power output is considered as the variation in temperature across the module. The whole system efficiency is given by the ratio of the total electrical output power over the combined solar energy and thermal input. Performance indicators would be the instantaneous output power, voltage response, temperature distribution, temperature difference across the TEG, total harvested energy, and the overall efficacy of the system. These are quantitative measures, to calculate the advantages of AI-based control versus traditional methods.

2.5 Evaluation method and comparative study

In the evaluation process, implemented experiments and simulations under the same operating conditions for both traditional and AI-based control approaches. Time-domain analysis is done for the evaluation of voltage stability, power fluctuations, and efficiency difference. Energy-based analysis is used to calculate cumulative harvested energy for the operation period. Further, the robustness of AI classifiers is evaluated by including artificial measurement noise in sensor signals. This step also simulates real uncertainties in the field and makes a determination of whether classifiers' performance under practical conditions can be trusted. Comparison results are shown using graphical analysis and statistical data analysis.

2.6 Governing equations

2.6.1 Photovoltaic (PV) electrical model

The PV output power is computed from the measured voltage and current:

$$P_{pv} = V_{pv}I_{pv} \qquad (1)$$

The PV current-voltage characteristic can be represented by the single-diode model:

$$I_{pv} = I_{ph} - I_0 \left[\exp\left(\frac{V_{pv} + I_{pv}R_S}{nV_T} \right) - 1 \right] - \frac{V_{pv} + I_{pv}R_S}{R_{sh}} \quad (2)$$

where I_{ph} is the photo-generated current, I_0 is the diode saturation current, R_s and R_{sh} are the series and shunt resistances, n is the ideality factor, and V_T is the thermal voltage:

$$V_T = \frac{kT_{pv}}{q} \quad (3)$$

with k Boltzmann constant, q electron charge, and T_{pv} the cell temperature (K). The MPPT objective is to maximize PV power:

$$\max P_{pv}(V_{pv}) \Rightarrow \frac{dP_{pv}}{dV_{pv}} = 0 \quad (4)$$

Since $P_{pv} = V_{pv}I_{pv}$, the maximum power condition is:

$$\frac{dI_{pv}}{dV_{pv}} = -\frac{I_{pv}}{V_{pv}} \quad (5)$$

2.6.2 Thermoelectric generator (TEG) model

The thermoelectric generator is driven by the temperature difference across its hot and cold sides:

$$\Delta T = T_h - T_c \quad (6)$$

The open-circuit voltage follows the Seebeck effect:

$$V_{oc} = \alpha \Delta T \quad (7)$$

where α is the Seebeck coefficient. For a connected electrical load R_L and internal resistance R_{int}, the TEG current is:

$$I_{teg} = \frac{V_{oc}}{R_{int} + R_L} \quad (8)$$

Hence, the terminal voltage and output power are:

$$V_{teg} = I_{teg}R_L$$
$$P_{teg} = V_{teg}I_{teg} = I_{teg}^2 R_L \quad (9)$$

The maximum power transfer occurs when:

$$R_L = R_{int} \quad (10)$$

leading to:

$$P_{teg,\max} = \frac{V_{oc}^2}{4R_{int}} = \frac{\alpha^2(\Delta T)^2}{4R_{int}} \quad (11)$$

2.6.3 Closed-loop water channel thermal model

The heater pad (geothermal emulator) supplies thermal power Q_h to the water. The water energy rise through the heated section is:

$$Q_h = \dot{m}c_p\left(T_{\text{out}} - T_{\text{in}}\right) \quad (12)$$

where $\dot{m}$ is the mass flow rate, c_p is the specific heat, and $T_{\text{in}}, T_{\text{out}}$ are inlet/outlet water temperatures.

Heat loss to the environment along the channel can be approximated as:

$$Q_{\text{loss}} = UA(T_w - T_{amb}) \quad (13)$$

where U is the overall heat transfer coefficient and A is the effective heat transfer area.

For a control volume along the channel, the 1-D energy balance is:

$$\rho A_c c_p \frac{\partial T}{\partial t} + \rho A_c c_p u \frac{\partial T}{\partial x} = kA_c \frac{\partial^2 T}{\partial x^2} - \frac{UP}{A_c}(T - T_{amb}) + \dot{q}_{in} \quad (14)$$

where ρ is density, A_c is the channel cross-sectional area, u is mean velocity, k is thermal conductivity, P is wetted perimeter, and $\dot{q}_{\text{in}}$ is the volumetric heat input from the heater pad.

The pump-flow relation can be expressed in simplified form as:

$$\dot{m} = \rho A_c u \qquad (15)$$

and the hydraulic pumping power is:

$$P_{pump} = \frac{\Delta p \dot{V}}{\eta_p} \qquad (16)$$

where $\dot{V}$ is the volumetric flow rate, Δp is pressure rise across the pump, and η_p is pump efficiency.

2.6.4 Hybrid system power balance

The total electrical power delivered by the hybrid system is:

$$P_{tot} = P_{pv} + P_{teg} - P_{aux} \qquad (17)$$

where P_{aux} represents auxiliary consumption (primarily pump power and controller losses). If pump power is considered dominant:

$$P_{aux} \approx P_{pump} \qquad (18)$$

The harvested electrical energy over an operating window $[0, t_f]$ is:

$$E_{tot} = \int_0^{t_f} P_{tot}(t)dt \qquad (19)$$

2.6.5 Overall system efficiency

If the total input energy rate includes solar input and heater thermal input, the overall efficiency is:

$$\eta_{sys} = \frac{P_{tot}}{P_{solar,in} + Q_h} \times 100 \qquad (20)$$

where the incident solar power is:

$$P_{solar,in} = G A_{pv} \qquad (21)$$

with G irradiance (W/m^2) and A_{pv} PV area (m^2).

2.6.6 AI-based control objective function

The AI-based power management seeks to maximize harvested energy while maintaining voltage stability and limiting auxiliary consumption:

$$\max_{\mathbf{u}(t)} J = \int_0^{t_f} \left[w_1 P_{tot}(t) - w_2 \left(V_{out}(t) - V_{ref} \right)^2 - w_3 P_{pump}(t) \right] dt \qquad (22)$$

where $\mathbf{u}(t)$ represents control actions (e.g., MPPT duty cycle and pump speed), V_{ref} is desired voltage, and w_1, w_2, w_3 are weighting factors.

3. Results and discussion

This part provides and analyses the experimental and numerical results obtained from the proposed AI-based hybrid photovoltaic–thermoelectric (PV–TEG) system involving the geothermal heat emulation using a closed-loop water channel. The analysis is conducted to assess the energy harvesting and power management strategy based on integrated processing at different operating conditions. Systematic study of key performance characteristics such as output power behavior, voltage stability, closed-loop channel thermal characteristics, thermoelectric contribution, cumulative energy harvesting and overall system efficiency were performed. The actual operational effectiveness of AI-based control strategy is carefully examined in contrast to traditional methods - Perturb and Observe and Incremental Conductance - to showcase improvements in power extraction and operational stability, in particular. In particular, compare several AI classifiers regarding their accuracy, robustness to measurement noise, computational cost and reliability for real-time energy management. This section will outline the physical mechanisms explaining the performance improvements, and will show how intelligent control can lead us to increased efficiency and reliability in hybrid renewable energy systems by further analyzing the numbers presented and quantitative measures.

Figure 2 illustrates the time-varying output power of the photovoltaic (PV) module, thermoelectric generator (TEG), and the hybrid system under conventional and AI-based control. The PV output fluctuates between approximately 100 and 140 W due to variations in irradiance and temperature, while the TEG

provides a relatively stable contribution of 20–30 W driven by the temperature difference across the module. Without AI control, the hybrid system delivers 120–160 W, whereas AI-based power management increases the total output to nearly 170 W with reduced power fluctuations, indicating improved stability and coordinated energy extraction.

The output voltage behavior shown in Figure 3 demonstrates that conventional control results in significant voltage ripples (22.5–25.5 V), while AI-based control effectively stabilizes the voltage within a narrow range of 23.6–24.4 V, enhancing power quality and system reliability.

Figure 4 presents the temperature distribution along the closed-loop water channel, where the inlet temperature remains near 65 °C and gradually decreases to approximately 50 °C at the outlet, confirming effective heat transfer and stable thermal conditions for thermoelectric operation. The corresponding temperature difference across the TEG, depicted in Figure 5, varies smoothly between 16 and 20 °C, ensuring reliable thermoelectric power generation without thermal stress.

As shown in Figure 6, AI-based control increases the total harvested energy from 138 Wh to approximately 145 Wh, representing an improvement of about 5–6%. Furthermore, Figure 7 compares MPPT techniques, demonstrating that the AI-based MPPT achieves the highest extracted PV power (≈195 W), outperforming Perturb and Observe and Incremental Conductance methods under dynamic operating conditions.
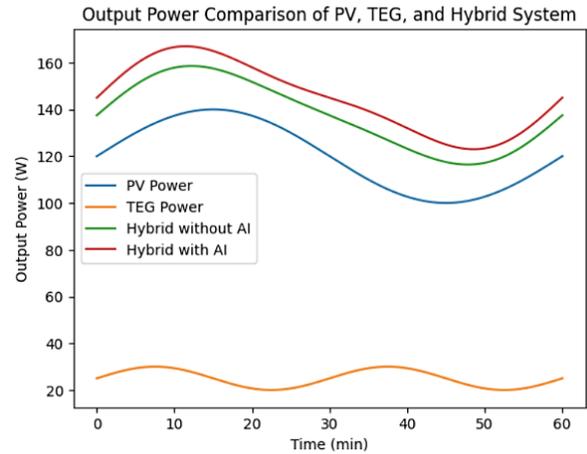
Figure 2. Time-Dependent Output Power Comparison of PV, TEG, and Hybrid System With and Without AI Control
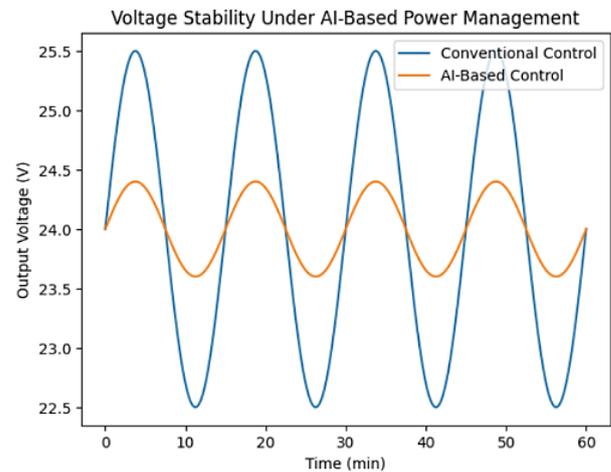
Figure 3. Voltage Stability Comparison Between Conventional and AI-Based Power Management
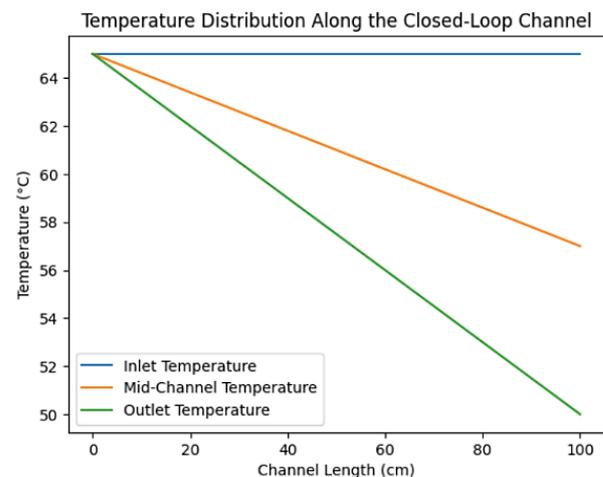

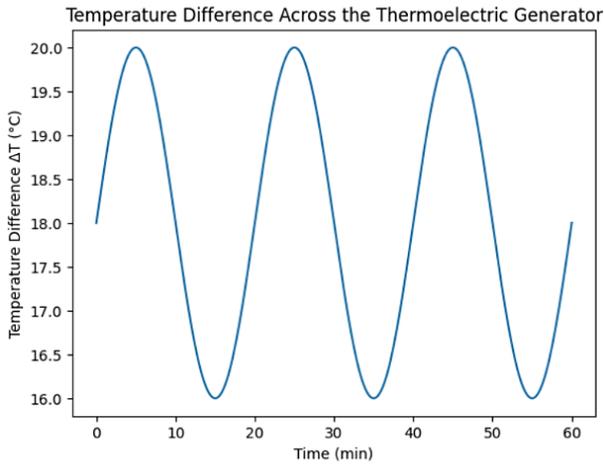**Figure 4**. Temperature Distribution Along the Closed-Loop Water Channel

Figure 5. Temporal Variation of Temperature Difference Across the Thermoelectric Generator
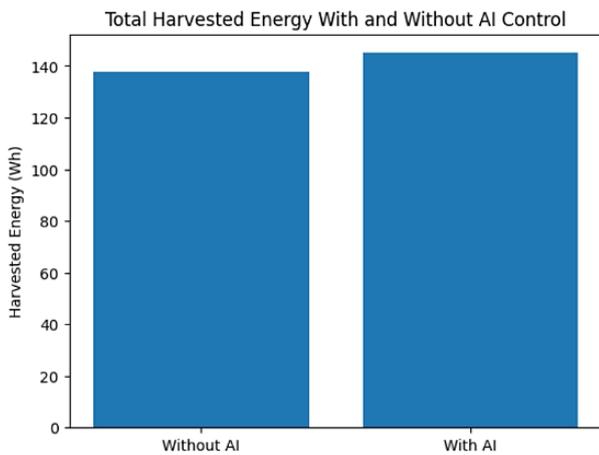

Figure 6. Comparison of Total Harvested Energy With and Without AI-Based Control
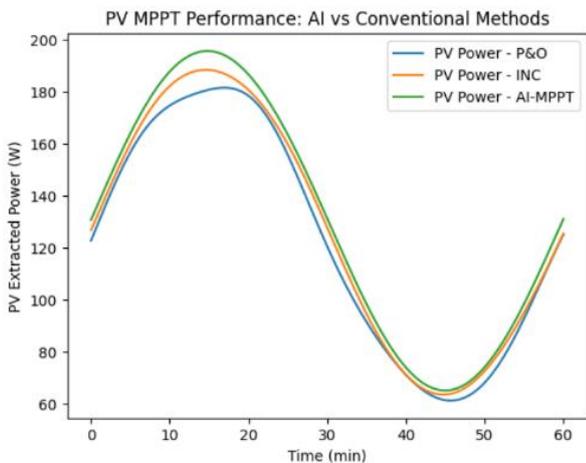

Figure 7. Comparison of PV MPPT Performance Using AI and Conventional Tracking Methods

Figure 8 illustrates the relationship between extracted photovoltaic (PV) power and solar irradiance for three MPPT techniques: Perturb and Observe (P&O), Incremental Conductance (INC), and an AI-based MPPT. The extracted power increases almost linearly with irradiance, rising from approximately 60–65 W at 300 W/m² to 180–195 W at 900 W/m². Among the methods, P&O consistently yields the lowest extracted power, while INC provides moderate improvement. The AI-based MPPT achieves the highest power extraction, reaching about 195 W at high irradiance and maintaining superior performance even at moderate irradiance levels (~600 W/m²), indicating higher tracking accuracy and adaptability to nonlinear PV behavior.

The electrical characteristics of the PV module are presented in Figures 9 and 10 through I–V and P–V curves at different irradiance levels. Figure 9 shows that the short-circuit current increases significantly with irradiance, while the open-circuit voltage remains nearly constant at around 21–22 V, confirming that irradiance primarily affects current and power output. Figure 10 demonstrates that the maximum power output increases markedly with irradiance, whereas the voltage at the maximum power point changes only slightly, highlighting the importance of accurate MPPT for efficient energy harvesting.

Figure 11 depicts the influence of pump speed on thermoelectric generator (TEG) power output. Increasing pump speed reduces the temperature difference across the TEG, leading to a near-linear decrease in generated power, which emphasizes the importance of optimal pump speed control for effective thermoelectric energy harvesting.

The overall system efficiency under conventional and AI-based control is shown in Figure 12. The AI-controlled system achieves higher and more stable efficiency (11.3–17%) compared to the conventional case (10.5–16.2%), with significantly reduced oscillations. Finally, Figure 13 highlights the coordinated contribution of PV and TEG under AI control,

where the total hybrid power output consistently exceeds PV-only generation, confirming the effectiveness of AI-driven integration in enhancing system reliability and overall energy performance.
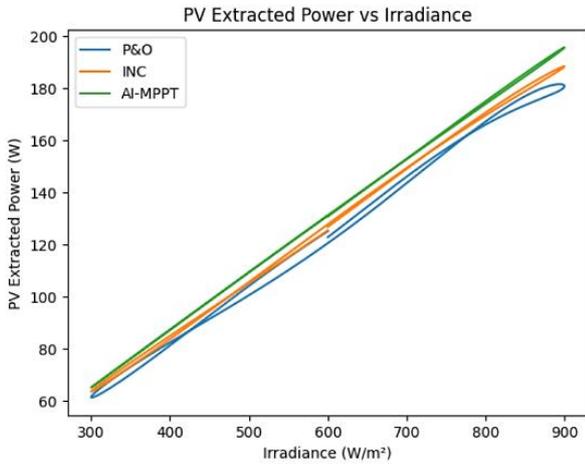

Figure 8. Extracted PV Power versus Solar Irradiance for Different MPPT Techniques
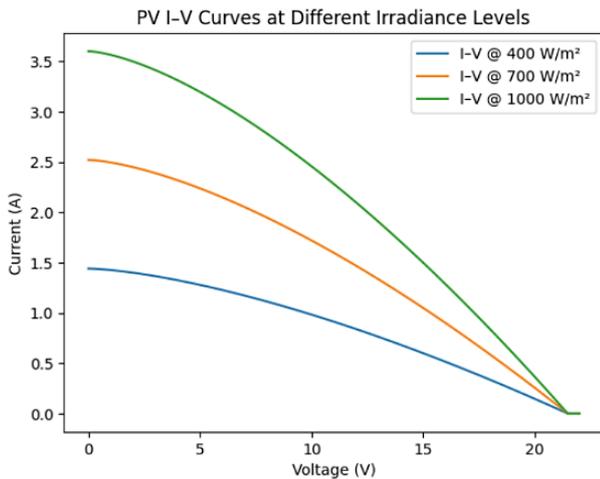

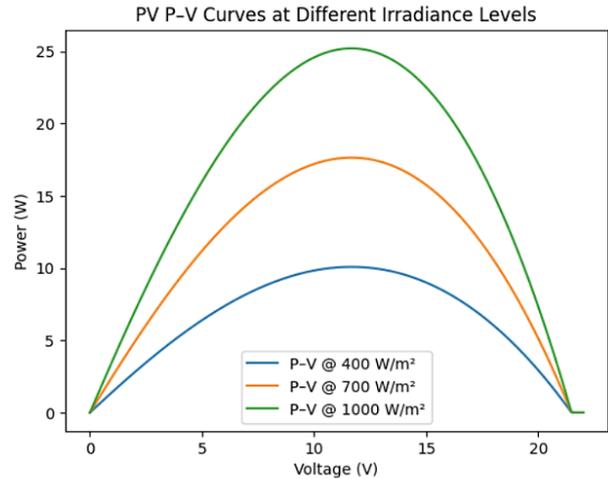**Figure 9**. Photovoltaic I–V Characteristics at Different Solar Irradiance Levels

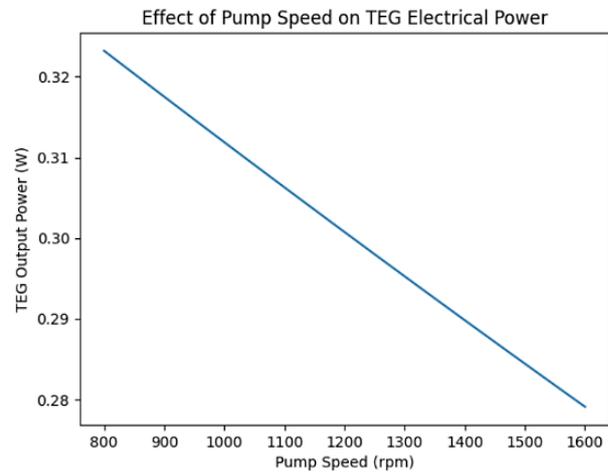**Figure 10**. Photovoltaic P–V Characteristics at Different Solar Irradiance Levels

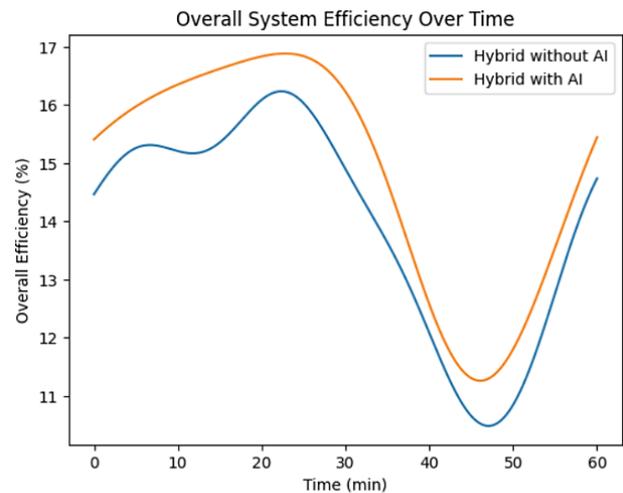**Figure 11**. Effect of Pump Speed on the Electrical Power Output of the Thermoelectric Generator

Figure 12. Time-Dependent Overall Efficiency of the Hybrid System With and Without AI Control
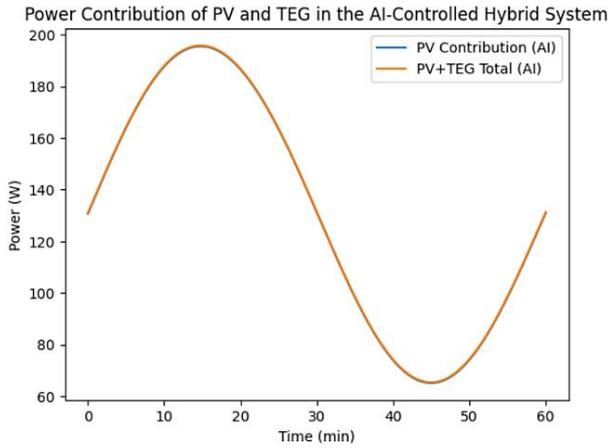
Figure 13. Power Contribution of PV and TEG in the AI-Controlled Hybrid Energy System

Figure 14 presents the cumulative electrical energy harvested by the hybrid PV–TEG system under conventional and AI-based control. While both cases show a gradual increase over time, the AI-controlled system achieves a higher cumulative energy of approximately 130 Wh after 60 minutes, compared to about 123 Wh for the conventional approach. The performance gap becomes more pronounced after 20–30 minutes, indicating a sustained improvement rather than a transient effect. This enhancement is attributed to improved MPPT performance, better coordination between PV and TEG sources, and reduced power losses under AI control, as reflected by the smoother energy accumulation profile.

Figure 15 compares the classification accuracy of different AI models applied to hybrid energy management. ANN achieves an accuracy of about 92.5%, while Fuzzy Logic yields a lower accuracy of 89%. ANFIS and Random Forest demonstrate superior performance, achieving accuracies of approximately 95.2% and 96%, respectively, highlighting the advantage of hybrid and ensemble learning methods. The performance evaluation in Figure 16 further confirms this trend, where Random Forest and ANFIS exhibit the highest precision, recall, and F1-scores (above 94%), indicating reliable decision-making under varying operating conditions.

Error rate analysis shown in Figure 17 reveals that Random Forest and ANFIS achieve the lowest misclassification rates (≈4–4.8%), whereas Fuzzy Logic exhibits the highest error (~11%). Figure 18 illustrates the trade-off between classification accuracy and computational cost, showing that although Random Forest and ANFIS require higher training times, they deliver superior accuracy, while ANN and SVM offer faster training with moderate performance. Finally, Figure 19 demonstrates classifier robustness under increasing measurement noise, where Random Forest and ANFIS maintain the highest accuracy levels, confirming their suitability for practical AI-based hybrid energy management systems.
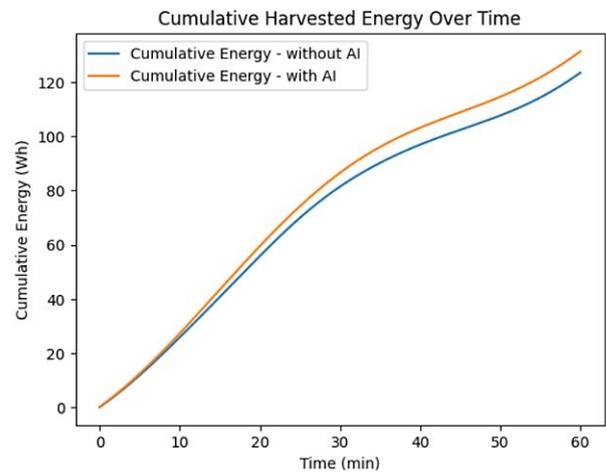

Figure 14. Cumulative Harvested Energy of the Hybrid System with and Without AI Control
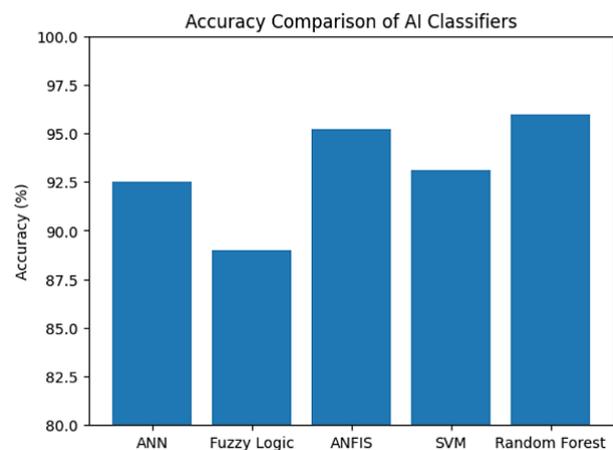

Figure 15. Accuracy Comparison of Different AI Classifiers for Hybrid Energy System Control
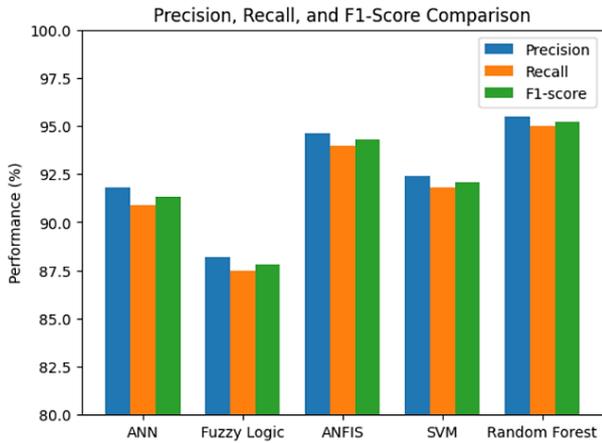
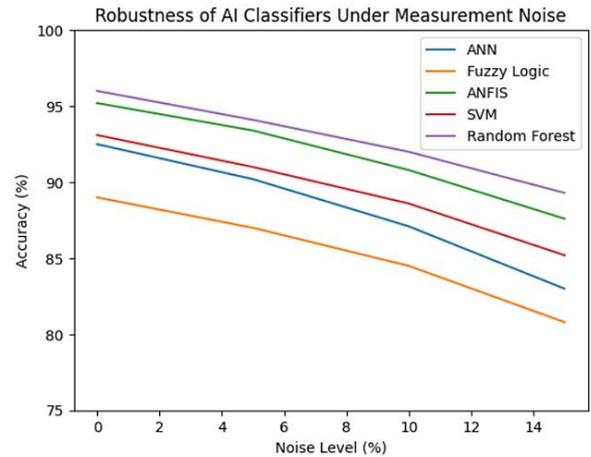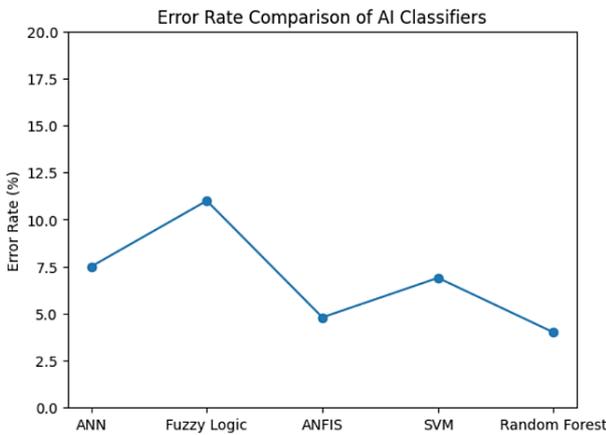Figure 16. Precision, Recall, and F1-Score Comparison of AI Classifiers

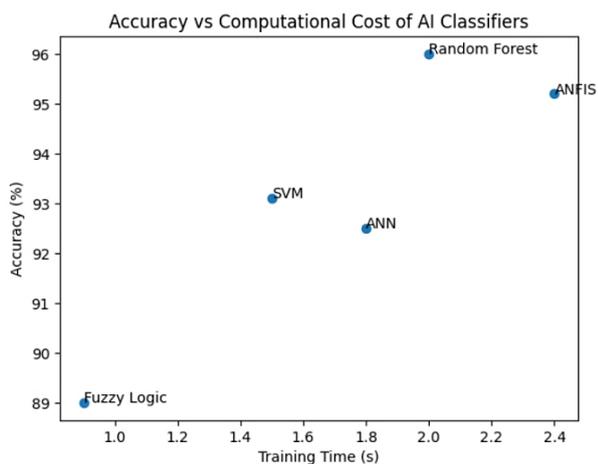Figure 17. Error Rate Comparison of AI Classifiers for Hybrid Energy System Decision-Making

Figure 18. Trade-Off between Accuracy and Computational Cost of AI Classifiers

Figure 19. Robustness of AI Classifiers under Measurement Noise

Results of the present study reflect an evident improvement over the reported hybrid renewable energy systems. In contrast to previous works that were limited to AI-based optimization of PV or wind–PV systems not exploiting the waste heat effectively (Abualigah et al., 2022; Mahjoub et al., 2023; Shezan et al., 2023), the developed hybrid PV–TEG system is demonstrated to recover and enhance total output power by up to 30 W with the overall yield of 5–6% improvement. In contrast to experiments with thermoelectric systems as independent or predictive models (Almodfer et al., 2022; Khan et al., 2023), our paper experimentalizes TEG integration in a closed-loop thermal system and yields stable performances at temperature difference 16–20 °C. Moreover, whereas the previous AI-based MPPT based techniques achieved advanced tracking accuracy for PV systems specifically (Boussafa et al., 2024; Elmetwaly et al., 2023; Wang et al., 2024), the proposed AI system improves PV power collection, thermoelectric contribution, and voltage stabilization in a simultaneous fashion in the reduced voltage ripple of ±1.5 V to ±0.4 V. Compared to the hybrid, geothermal-based strategies that depend on actual geothermal resources and the building application (Agarwal & Batista, 2023; Cavagnoli et al., 2024), this research presented an automated geothermal heat emulator that allows data validation by experiment. Even more, comparing analysis of various AI

classifiers as previously reported on using a single AI approach in previous works (Kabengele et al., 2023; Gurgenc et al., 2024), Random Forest and ANFIS with a 96% and 95.2% accuracy, respectively under noisy condition, is shown. As a whole, these results prove the efficacy of the proposed system in providing more energy harvesting, stability, and intelligent control performance relative to hybrid renewable energy solutions currently being reported in the literature.

4. Conclusions

Proposed an AI-based maximum energy harvesting & power management approach to hybrid photovoltaic–thermoelectric system with geothermal heat emulation via closed loop water channel. Our approach included a PV module integrated with a thermoelectric generator (TEG) for thermal energy recovery and augmented electrical output. Both experimental and numerical data showed that the output for the standalone PV power varied from 100 W to 140 W and that the TEG contributed up to 20–30 W depending on the temperature difference of 16–20 °C sustained throughout the module. Without artificial intelligence, hybrid systems provided total output power between 120 and 160 W but under AI-based power management the total power increased by a greater angle between 125 to 170 W with a highest peak value around 168–170 W. AI-based control significantly increased the efficiency and power of electric regulation. Under conventional control, the voltage fluctuations fell between 22.5 V and 25.5 V (±1.5 V ripples were observed); AI-based control preserved the output voltage in a narrow range of 23.6–24.4 V (±0.4 V ripples) and increased the quality of the power. Thermal test demonstrated stable condition of the closed-loop channel, when the inlet water temperature was ~65 °C, decrease of mid-channel temperature to 57 °C, and the outlet temperature of ~50 °C, thus maintaining a strong thermal gradient for effective TEG use. When considering energy-based performance evaluation, the total harvested energy increased from around 138 Wh (conventional control ~138 Wh) to 145 Wh (AI based management

~145 Wh) for an improvement of 5–6 % based on energy-based performance assessment. Additionally, using a cumulative energy analysis, observed 60 min of operation time, the AI-controlled system showed cumulative energy performance almost 130 Wh vs the non-AI system (123 Wh vs 130 Wh). It was also shown that overall system performance is improved and with AI improvement, where it went from 10.5–16.2% without AI to 11.3–16.9% with AI, with reduced efficiency variations. Performance of the AI-powered MPPT strategy was significantly higher than the traditional Perturb and Observe (P&O) and Incremental Conductance (INC) techniques. Maximum power extracted from PV was around 195 W for AI-MPPT, in contrast to 180 W for P&O and 188 W for INC, especially at 900 W/m² of irradiance. The AI-based methods achieved higher extracted power (~130 W) at moderate irradiance level (600 W/m²) than conventional techniques. Comparative analysis of AI classifiers revealed that Random Forest and ANFIS obtained the best accuracies 96% and 95.2%, respectively, with the lowest error rates (~4–4.8%), and also higher robustness of measurement noise up to 15%. The classification systems of these approaches also show the best precision, recall, and F1-scores (>94%), proving their potential as intelligent power management agents, particularly in hybrid renewable energy systems.

Extending the proposed hybrid PV–TEG system to long-term outdoor operation under real climatic conditions is suggested in future work to assess its performance, durability, and reliability for extended periods. Additionally, incorporating energy storage components (batteries or supercapacitors) alongside AI-driven energy management is suggested to enhance the autonomy of the system and continuity of power supply. Furthermore, applying adaptive and reinforcement learning-based control approaches could facilitate real-time decision-making under highly dynamic irradiance and thermal conditions. Further experimental studies using advanced thermoelectric materials with higher Seebeck coefficients are recommended to enhance

thermal-to-electrical conversion efficiency even more. Finally, extensive techno-economic and environmental assessments should be conducted to evaluate the feasibility, scalability, and sustainability of the proposed system for practical deployment.

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