Research Article

Optimizing Water Usage Through an Automated Smart Irrigation System for Sustainable Agriculture

Rohail Ali Khan[1], Muhammad Zia[1*], Muhammad Uzair Khan[1], Dawar Awan[1] and Naveed Jan[2]

[1]Department of Electrical Engineering Technology, University of Technology, Nowshera, Khyber Pakhtunkhwa, Pakistan; [2]Department of Information Engineering Technology, University of Technology, Nowshera, Khyber Pakhtunkhwa, Pakistan.

Abstract: The increasing water demands in irrigation highlight the necessity for a smart irrigation system capable of conserving approximately 80% of water usage. This study presents a model which optimizes the water usage averaging 3 to 4 liters per day, saving approximately 66% of water per day by automating the irrigation process, thereby reducing the need for continuous supervision. The system enhances water conservation by adjusting water delivery to plants and gardens based on their specific needs, making it suitable for agricultural fields, lawns, and parks. In addition to addressing seasonal crop demand, power availability is also crucial. Using batteries in PV systems increases costs, requires storage space, and raises environmental concerns. The proposed solution utilizes a hybrid model of maximum power point tracking (MPPT) approach, combining perturb and observe (P & O) with ANN algorithms, to enhance the energy extracted from a stand-alone PV panel up to 95%. This method optimizes the performance of the water pump and control circuitry, ensuring maximum energy utilization. A simulation model of the system was implemented to determine the most economically optimal design.

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***Correspondence:** Muhammad Zia, Department of Electrical Engineering Technology, University of Technology, Nowshera, Khyber Pakhtunkhwa, Pakistan; **Email:** zia.gikian@gmail.com
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Introduction

Agriculture consumes approximately 70% of global freshwater resources (Prazukin *et al.*, 2024; Singh, 2024), and in some regions, this figure can rise to as much as 85-90% due to the heavy reliance on irrigation (Gamal *et al.*, 2023). With the world's population continually growing and consequently increasing food production (Wang and Azam, 2024), the demand for water in agriculture is expected to remain high. Therefore, it is essential to develop and implement innovative methodologies that leverage smart technologies to ensure sustainable agricultural practices. Among these innovations, automated irrigation systems have shown remarkable potential, demonstrating water savings of up to 90% compared to traditional methods of crop watering (Pimentel *et al.*, 2004). However, powering such systems presents a unique set of challenges, particularly when considering the seasonal demand patterns of crops and the inherent variability of renewable energy sources like solar power (Sen and Bhattacharyya, 2014). Photovoltaic (PV) systems, widely utilized to harness solar energy, typically rely on batteries to store surplus energy, ensuring a balance between energy production and demand (Mohammad *et al*., 2014). Although effective, this method has several drawbacks. Batteries add to the overall investment costs, demand extra storage space, and pose environmental concerns due to their production, maintenance, and disposal. To address these issues, our project introduces an innovative solution that combines efficient irrigation with optimized solar power usage, promoting a more sustainable approach to agriculture.

Our proposed system automated smart irrigation system for sustainable agriculture (ASISSA) is designed to enhance irrigation efficiency by automatically regulating water flow based on real-time soil moisture levels. Maintaining proper soil moisture levels is crucial for plant health and water conservation in both agricultural and urban gardening practices (Alex *et al*., 2025). It consists of two integrated modules that perform distinct but complementary roles: Smart irrigation management and MPPT for PV systems to power up the system.

In agriculture, researchers are striving to reduce irrigation water usage for plants by exploring various technologies. The integration of advanced technologies, including computer vision and machine learning, is revolutionizing precision agriculture (Abourabia *et al*., 2024; Tasfe *et al*., 2024), health care system (Dhasarathan *et al*., 2024) and PV systems (Buratti *et al*., 2024). These approaches have been well-documented in literature. An automated irrigation system for smart agriculture using internet of things (AISSA), has deployed drip irrigation, sprinklers and solenoid valves, achieving 22.16% efficiency, however this system is dependent on internet availability (Ramachandran *et al*., 2018). Soil moisture-based irrigation control utilizes densitometry and volumetric techniques, which, although simple, depend on a soil water characteristic curve unique to the specific soil type (Breitmeyer and Fissel, 2017). However, these techniques require regular sensor maintenance to ensure optimal performance. Another approach, the intelligent automatic plant irrigation system, utilizes a moisture sensor to automate watering without the need for human intervention (Abba *et al*., 2019). The performance of the system, that uses a comparator Op-Amp and a timer to drive a relay for activating a motor, is affected by environmental conditions (Horowitz *et al*., 2022).

Furthermore, a real-time wireless smart sensor array has been developed to manage irrigation scheduling in cotton cultivation (Horowitz *et al*., 2022). This system is designed for specific crops, measuring soil moisture and temperature, but it is limited to certain crop types. Proper irrigation scheduling is essential for efficient water management in crop production, particularly in conditions of water scarcity.

Table 1: *Nomenclature used in this study.*

Symbol	Definition
S_m	moisture level
R_p	rain prediction
Ir	irradiance
S_t	solar temperature
α	required water
$\acute{\Gamma}_t$	on time
γ_A	current
β_V	voltage
δ_P	power
Ω_m	motor status
ϕ	MPPT point

Factors such as the amount of water supplied, the frequency of irrigation, and overall water usage play a significant role in determining efficiency of an automated irrigation system. IoT-based smart irrigation systems offer numerous advantages but also have some drawbacks. The initial investment needed for installing IoT devices and sensors can be quite significant, which may pose a challenge for small-scale farmers (Dhillon and Moncur, 2023). These systems rely on internet connectivity and a stable power supply, which may not be readily available in rural or remote areas, limiting their implementation. Additionally, the complexity of IoT technology can be a challenge, as farmers may need to acquire technical skills to operate and maintain the system effectively. Moreover, the transmission of data in these systems raises concerns about privacy and security, making them vulnerable to cyber threats. Table 1 summarizes the nomenclature used in the rest of the paper.

Main contributions

The following are the main contributions of this study:

1. Introduces an advanced smart irrigation system designed to optimize water usage by automatically adjusting irrigation based on real-time soil moisture data.
2. Automated deactivation of the motor during rainfall to conserve power.
3. Implementing a hybrid model based on ANN and P & O with the solar panel to significantly enhance efficiency, leading to substantial reductions in power consumption.

Motivation

The Figure 1 illustrates the global trend in water availability per capita from 1960 to 2060 (Molden *et al*., 2007). The red line represents the average amount of water available per person, measured in cubic meters per capita per year. Over the decades, there has been a clear decline in water availability, indicating increasing pressure on global water resources.

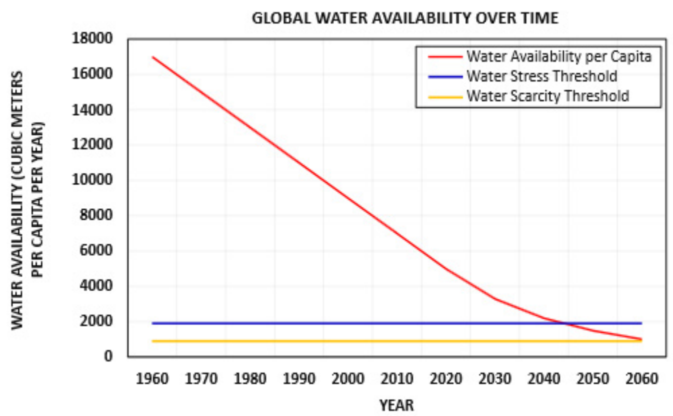

Figure 1: *Global water availability over time.*

Water stress threshold (1700 cubic meters per capita per year): Represented by the blue line, this threshold indicates the point at which water scarcity begins to affect human and environmental well-being (Liu *et al*., 2024).

Water scarcity threshold (1000 cubic meters per capita per year): Indicated by the orange line, crossing this threshold suggests severe limitations on water availability, impacting agricultural, industrial, and personal water use.

The rest of the paper is organized as follows: Section 2 presents the proposed system design in detail, while Section 3 provides a comprehensive discussion of the results achieved in this study. Finally, the conclusion section summarizes the overall findings and outlines potential future research directions.

Proposed system design

The automated smart irrigation system for sustainable agriculture (ASISSA) continuously tracks the maximum power point, adjusting the PV system for optimal power generation while integrating sensors and a control circuit to enhance water efficiency.

Irrigation system overview

The first module of our system is the smart irrigation system, which utilizes a soil moisture sensor that continuously monitors soil moisture levels. If the moisture level falls below a predefined threshold and there is no prediction of rain by the rain and irradiance sensors, the system activates the water pump, supplying the necessary water to the agricultural land to maintain optimal soil conditions for plant growth. Conversely, if the moisture level is adequate or rain is anticipated (as detected by the rain sensor), the system prevents unnecessary watering, thus conserving water. This approach minimizes human intervention, making the irrigation process more efficient and less labor-intensive. By using sensors, the system ensures that water is used only when needed, significantly reducing water wastage and promoting more sustainable farming practices.

The soil moisture sensor measures the moisture level in the soil, helping the system determine if watering is necessary (Evertt *et al*., 2012). The rain sensor detects rainfall, allowing the system to prevent unnecessary irrigation during rain (Trono *et al*., 2012). The irrigation sensor monitors the status and effectiveness of the irrigation process, ensuring water is being distributed properly. The water level sensor keeps track of the water supply available, ensuring the system doesn't attempt to irrigate when there's insufficient water. The block diagram of the proposed system is shown in Figure 2.

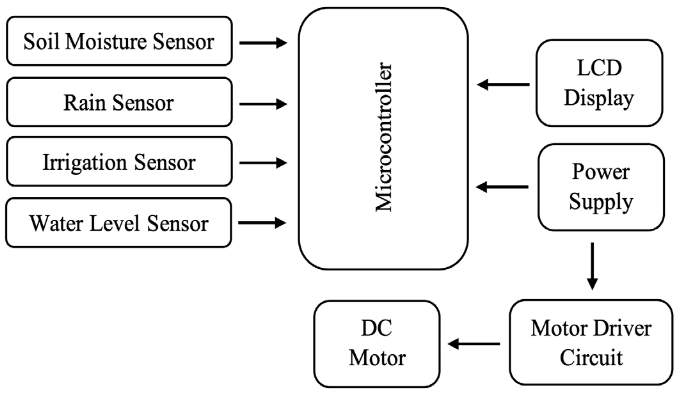

Figure 2: *Block diagram of smart irrigation system.*

The test area of the indoor agriculture chamber is 2ft × 2ft = $4ft^2$= 371612 mm^2 used, the volume of the chamber is calculated as V= $4ft^2$ × 2ft = $8ft^3$= 2.265e8 mm^3.

$$1 \text{ liter of water} = 0.0353\ ft^3 = 999584.685\ mm^3$$

Water depth is calculated by Equation 1.

$$D = \frac{V}{A} \quad ...(1)$$

$$D = 10 \text{ liters} \times 0.0353 \frac{ft^3}{liter} = 0.353 ft^3$$

$$D = \frac{V}{A} = \frac{0.353\ ft^3}{4\ ft^2} = 0.08825\ ft$$

$$D = 0.08825\ ft \times 304.8 \frac{mm}{ft} = 26.8986\ mm$$

Thus, 10 liters of water will fill the chamber to a depth of 26.8986 mm for hydroponic farming.

Key parameters of sensors

Key parameters of the moisture sensor, rain sensor, and irradiance sensor are given in Tables 2, 3, 4, respectively.

Table 2: *Key parameters of moisture sensor.*

Parameter	Specification
Sensor Type	Capacitive
Voltage Range	3.3V – 5V
Measurement Range	0-100%
Output Type	Analog (0-1023)
Sensitivity	High
Response Time	< 1 Second
Operating Temperature	-40°C to +85°C
Accuracy	±5%

Table 3: *Key parameters of rain sensor.*

Parameter	Specification
Sensor type	Resistive/Capacitive
Voltage range	3.3V – 5V
Detection area	Typically, 2-5 cm^2
Output type	Digital (High/Low) or Analog (0-1023)
Sensitivity	Adjustable or Fixe
Response time	< 1 Second
Operating temperature	-40°C to +85°C
Durability	Waterproof, UV Resistant
Power consumption	Low (Typically < 10mA)

How does a soil moisture sensor function and how to use it with arduino?

The soil moisture sensor measures the soil's moisture level and sends an analog signal to the Arduino as shown in Figure 3 (Radman and Radonjić, 2017). The Arduino processes this signal and compares it to preset thresholds defined in the code. If the moisture level falls below the set threshold, indicating dry soil, the Arduino activates the water pump to irrigate the plants. The system aims to maintain optimal soil moisture levels, thereby preventing both overwatering and underwatering.

Table 4: *Key parameters of irradiance sensor.*

Parameter	Specification
Sensor type	Photodiode or Photovoltaic
Voltage range	3.3V – 5V
Measurement range	0 to 2000 W/m^2
Output type	Analog (e.g., 0-5V) or Digital (PWM)
Sensitivity	High
Response time	< 1 Second
Operating temperature	-40°C to +85°C
Accuracy	±5%
Power consumption	Low (Typically < 20mA)

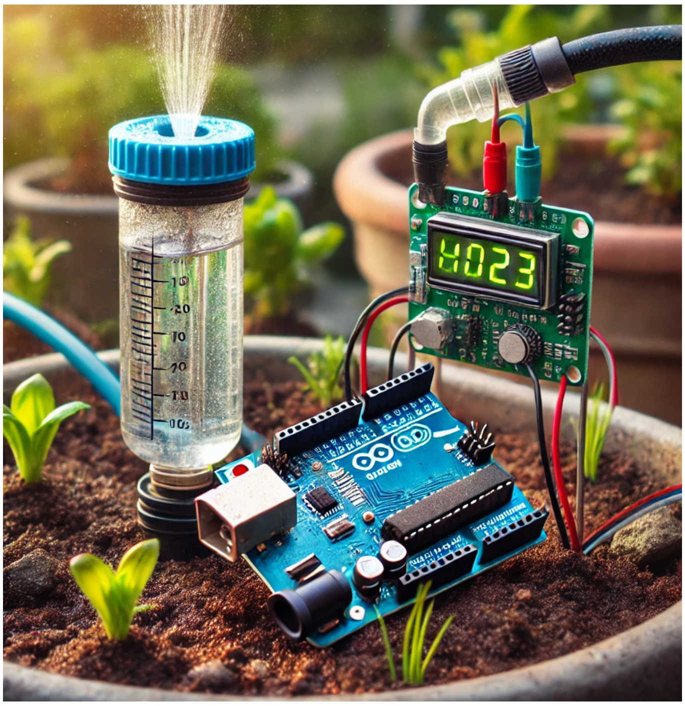

Figure 3: *Moisture senser interfacing.*

This setup demonstrates the practical implementation of a smart irrigation system, showcasing how integrating sensors and microcontrollers can lead to efficient and automated water management in

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agriculture. Analog value from the moisture sensor is mapped to percentage by using Equation 2.

$$M\ (\%) = \left(\frac{1023 - A_{out}}{1023}\right) \quad \dots(2)$$

Where M (%) is the soil moisture percentage, and A_{out} is the analog output reading from the sensor. 10 bits value of the sensor is converted to voltage by Equation 3.

$$V_{out} = \frac{A_{out}}{1023} x V_{CC} \quad \dots(3)$$

Where; A_{out} is the voltage corresponding to the sensor's analog output, and Vcc is the supply voltage (typically 3.3V or 5V).

Internal sensor calibration is given by Equation 4.

$$C_s = k \times (V_{out} - V_{dry}) + b \quad \dots(4)$$

Where C_s is the sensor reading, k is the calibration constant, V_{dry} is the output voltage in dry soil, and b is the offset value.

Working steps

The process starts with the system taking reading from the sensor as shown in Figure 4. At the first decision point, the system evaluates whether the moisture level is below the defined threshold, indicating insufficient soil moisture. If this threshold is met, the system initiates irrigation and simultaneously updates the display with the current moisture status. Next, the system checks the water level to ensure it remains above a critical threshold; if not, irrigation is stopped. If the water level is below this threshold, irrigation continues. This cycle repeats, ensuring efficient water usage by activating irrigation only when necessary. The process concludes once the soil moisture reaches adequate levels or when the system is manually stopped, thereby optimizing water conservation in agricultural practices.

Table 5 lists the main components used in the simulation and the corresponding connections to the Arduino UNO pins.

Algorithm

The following algorithm defines the operation of ASISSA, which effectively manages water flow and maximizes the energy extracted from PV module through MPPT tracking.

1: Input: R_p, S_m, I_r, S_t
2: Output: α, Γ_t, γ_A, β_V, δ_P
3: for setup do %Irrigation system
4: read→ R_p, S_m% Input data from the rain and moisture sensor
5: compute α, $\acute{\Gamma}_t$ %Compute the on time of the pump based on the volume of water required
6: activate Ω_m %Activate the water pump
7: end for
8: for setup do %For PV system
9: read→ I_r, S_t %Input date from the Irradiance and temperature sensors
10: compute ϕ %Track the MPPT
11: end for
12: end

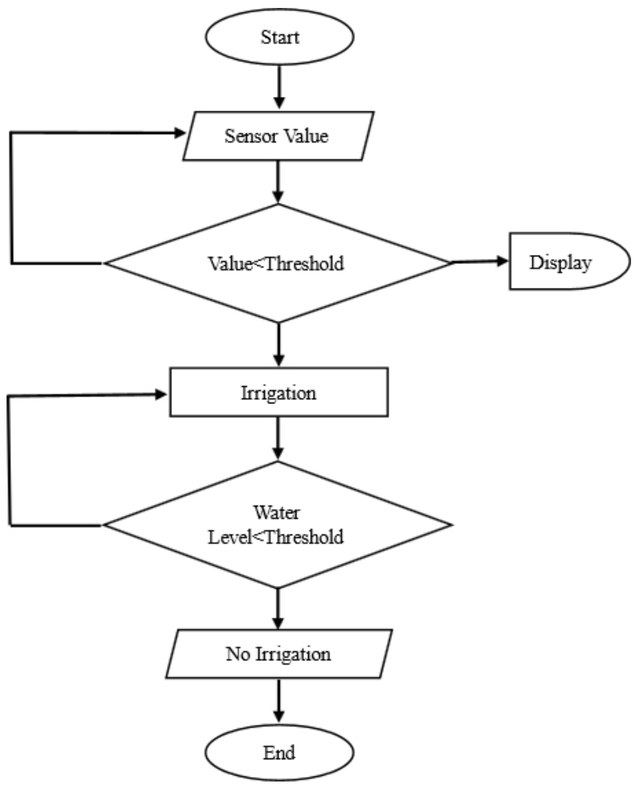

Figure 4: *Flow chart for the proposed system.*

Table 5: *Hardware interfacing.*

Component	Pin Description	Connecting Pin
Moisture Sensor	V_{CC}	5 V
	GND	GND
	A_{out}	A0
LCD Display	V_{CC}	5 V
	GND	GND
	SDA	A4 (SDA)
	SCL	A5 (SCL)
Motor Driver	Motor Output	Digital Pin

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Maximum power point tracking (MPPT) for PV systems

The second module focuses on maximizing the efficiency of solar energy usage. PV modules exhibit a non-linear power-voltage (P-V) characteristic that varies based on environmental factors such as solar irradiation and cell temperature (Pelap *et al*., 2016). Each environmental condition 1000W/m², 800 W/m², 600 W/m² and 400 W/m² produces a unique power-voltage curve with a distinct MPP, where the PV module operates most efficiently. To extract the maximum power from the PV modules, it is essential to continuously track and adjust the system to operate at the MPP, as illustrated in Figure 5 (Salas *et al*., 2006). The curve includes three key parameters: Open-circuit voltage (V_{oc}), short-circuit current (I_{sc}), and the MPP.

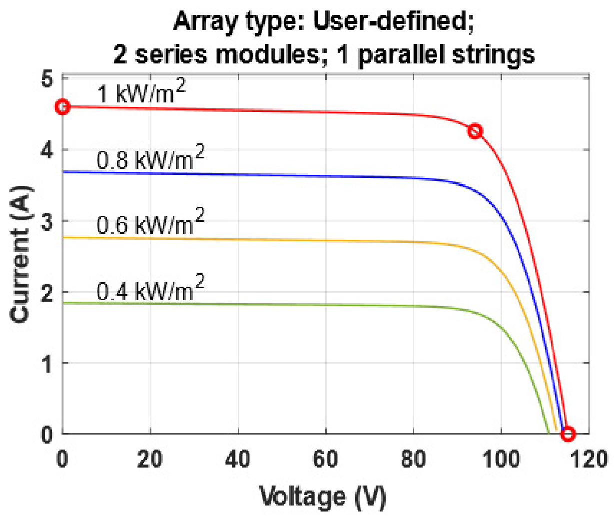

Figure 5: *I-V characteristics of the PV cell.*

The P-V characteristics of the PV cell are shown in Figure 6 (Yang *et al*., 2023). It depends on the open V_{oc}, the I_{sc} and the MPP.

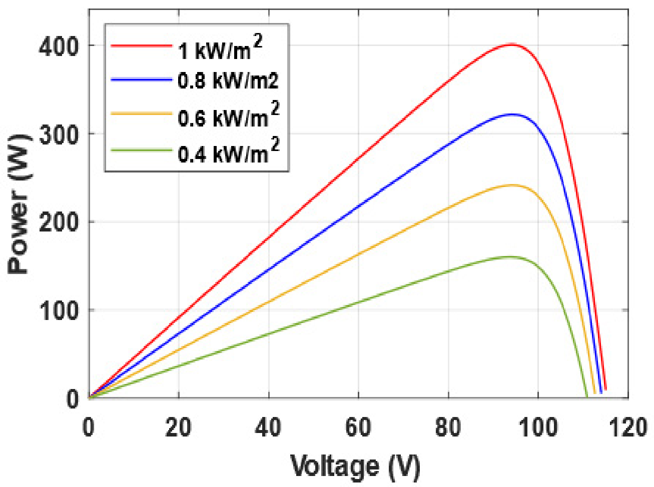

Figure 6: *P-V characteristics of the PV cell.*

The available net instantaneous power P_t, provided by the photovoltaic system during the day was estimated by the following Equation 5:

$$P_t = \begin{cases} \frac{I_t}{I_{ST}} P_{peak}[1-\beta(T_C - T_{ST})] \text{ if } I(t) > I_m \\ 0, I_t < I_m \end{cases} \quad ...(5)$$

Where; I_t is the irradiance (Wm^{-2}) on the solar, I_{ST} is the standard irradiance (1000 Wm^{-2}), P_{Peak} is the peak power (W) of the PV modules under standard conditions, β is the decay coefficient (0.004 $^0C^{-1}$ for silicon cell). Hove (2000), T_C represents the temperature of the cells in the module, while T_{ST} refers to the cell temperature under standard test conditions, and I_m is the threshold limit. The value of I_m should be lower for higher P_{Peak} values since the final power threshold can be reached with less irradiance. From Equation 1.

$$\frac{I_m}{I_{ST}} P_{peak}[1-\beta(T_C - T_{ST})] = P_{min} \quad ...(6)$$

$$I_m = \frac{P_{min}}{P_{peak}} \frac{I_{ST}}{[1-\beta(T_C - T_{ST})]} \quad ...(7)$$

Where P_{min} is the minimum power that can be used.

As irradiance is the function of time, it can be written as:

$$I_t = \frac{\cos\alpha}{\cos\alpha_z} I_{drt} + \frac{1+\cos\gamma}{2} I_{dt} + \rho \frac{1-\cos\gamma}{2}[I_{drt} + I_{dt}] \quad ...(8)$$

Where α represents the angle of incidence of direct solar radiation relative to the inclined collector plane, α_z is the angle of incidence of direct solar radiation relative to the horizontal plane, I_{drt} is the solar direct irradiance as a function of time (t) (Wm^{-2}), I_{dt} is the solar diffuse irradiance as a function of time t (Wm^{-2}), γ is the tilt angle of the PV modules.

The net power ultimately transferred to the water (P) is calculated using Equation 9.

$$P_{net} = \eta_{Pump} \cdot \eta_{AM} \cdot \eta_C \cdot P \quad ...(9)$$

Where η_C is the efficiency of the converter, η_{AM} is the efficiency of the asynchronous motor, and η_{Pump} is the pump efficiency.

In this study, conservative fixed efficiency values of 0.95 for the converter, 0.8 for the asynchronous motor, and 0.75 for the pump were used to evaluate the instantaneous PV power.

System design

In our system, we employ a hybrid model that combines ANN with the P&O method to achieve effective MPPT. The ANN component of the system is trained to predict the MPP based on historical and real-time environmental data, such as temperature and solar irradiance (Jlidi *et al*., 2024). The P&O algorithm then fine-tunes the operation by making small adjustments to the operating point and observing the resulting changes in power output (Tella *et al*., 2024). If the power output increases, the system continues adjusting in the same direction; if the output decreases, the adjustment is reversed. This hybrid method ensures that the PV system consistently operates at its Maximum Power Point (MPP), optimizing energy conversion efficiency.

Table 6: *Solar panel specifications.*

Parameter	Specification
Open circuit voltage V_{oc}	57.6 V
Short circuit current I_{sc}	4.6 A
Maximum output power	200.22 W
Voltage at maximum power	47 V
Current at maximum power	4.26 A

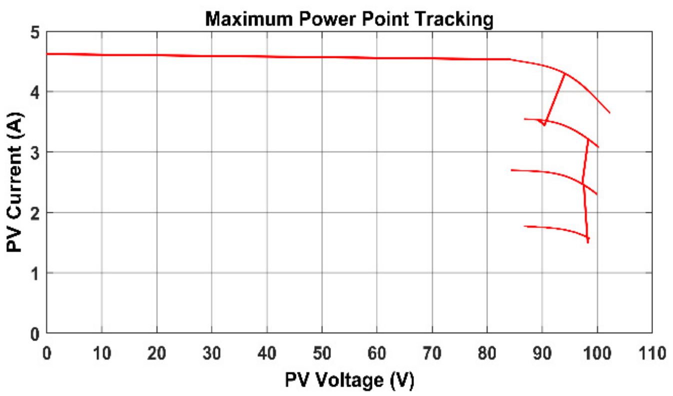

Figure 7: *MPPT tracking.*

The study focuses on a photovoltaic (PV) system where two modules are connected in parallel, with the current-voltage (I-V) characteristic curve demonstrating the relationship between current (Y-axis) and voltage (X-axis) as shown in Figure 7 (Katche *et al*., 2023). Each module has an open-circuit voltage (V_{oc}) of 57.6 V, a short-circuit current (I_{sc}) of 4.6 A, and consists of 60 cells. The modules operate at a maximum power point with a voltage (V_{mp}) of 47 V and a current (I_{mp}) of 4.26 A. The module specifications shown in Table 6 include temperature coefficients for V_{oc} and I_{sc}, -0.35502 %/°C and 0.06 %/°C, respectively, which adjust voltage and current based on temperature changes to maintain system efficiency. The I-V curve from the simulation highlights the decline in current as voltage increases beyond the maximum power point, showing where the MPPT algorithm is crucial for optimal power extraction as shown in the Figure 7.

Table 7 shows the system specifications. Two solar panels, each rated at 200.22 W, are connected in series.

Table 7: *System specifications.*

Parameter	Specification
Open circuit voltage V_{oc}	115.2 V
Short circuit current I_{sc}	4.6 A
Maximum output power	400.44 W
Voltage at maximum power	94 V
Current at maximum power	4.26 A

Software design

The software used in this work is the Arduino platform and Proteus Professional for smart irrigation control while MATLAB for maximum power tracking, which offers a variety of libraries to streamline programming.

Proteus simulation

The system shown in Figure 8 integrates multiple sensors to optimize water usage by assessing environmental conditions before activating the water pump. A soil moisture sensor measures the moisture level in the soil and transmits the data to the microcontroller, which serves as the system's central processing unit. Simultaneously, a rain sensor predicts potential rainfall, and an irradiance sensor measures sunlight intensity, both of which provide crucial information about weather conditions. If it is likely to rain, the system does not activate the water pump. The system's logic, managed by the Arduino, ensures that the motor only activates when the soil moisture is low and there is no imminent rain, as indicated by the rain sensor and low irradiance levels. This design conserves water by preventing unnecessary irrigation during rain or when moisture levels are sufficient, which is essential for sustainable agricultural practices. The system's status, including sensor readings and motor activity, is displayed on an LCD screen, providing real-time feedback to the user.

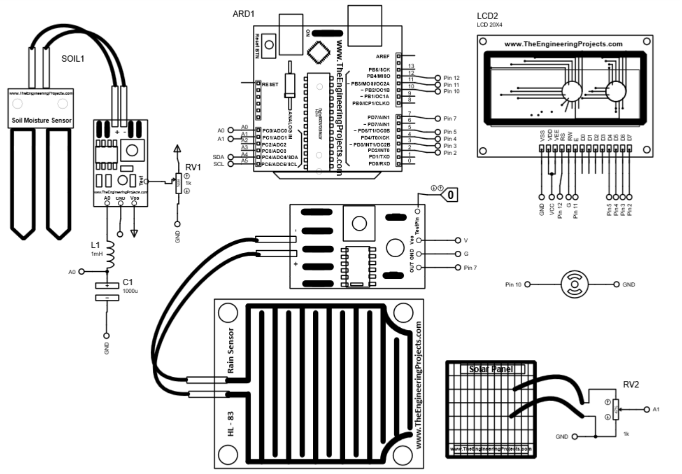

Figure 8: *Proteus simulation setup for the proposed study.*

Figure 9 displays the results of testing the smart irrigation system on a garden plant over seven days. The blue line represents the plant's daily water requirement in millimeters per day, while the red line shows the corresponding moisture readings from the Arduino, with digital values ranging from 500 to 1000.

The water requirement varies between 7.27 and 11.57 mm/day, as indicated by the fluctuations in the blue line. Meanwhile, the red line reflects the moisture readings, demonstrating how the system monitors soil moisture and adjusts irrigation accordingly. When moisture levels fall outside the preset range, the irrigation system automatically turns the water pump on or off to maintain optimal soil moisture.

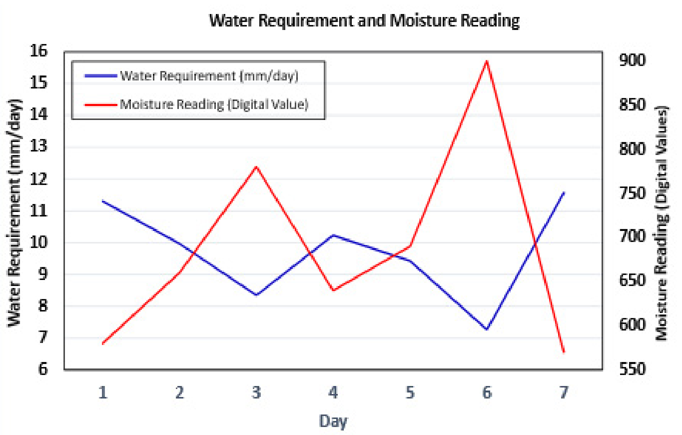

Figure 9: *Water requirement and moisture readings.*

Modeling and simulation of PV system

The system shown in Figure 10 presents a hybrid model that integrates P&O with ANN to generate an optimal PWM signal for precise MPPT. The output from the PV panels is processed by both P&O and ANN-based MPPT controllers, which collaborate to determine the ideal PWM signal. This signal is then used by a boost converter to ensure the system operates exactly at the maximum power point (Caceres and Barbi, 1999). The system continuously monitors efficiency, noting that efficiency tends to decrease as PWM increases. This design ensures that the boost converter consistently tracks the maximum power point, thereby optimizing the overall performance of the PV system.

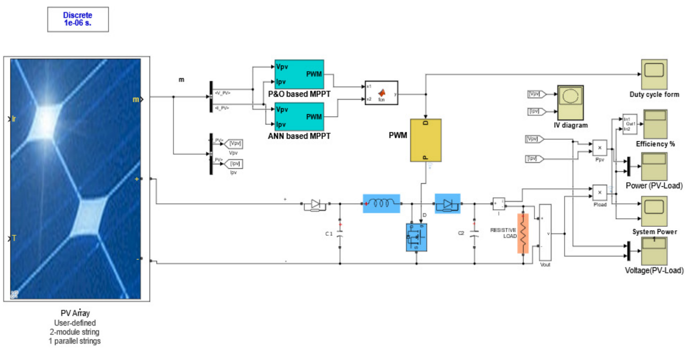

Figure 10: *Hybrid model of ANN and P&O.*

Booster converter parameters

$$V_{input} = 90.24\sim109.44\ V$$

$$V_{output} = 325\ V$$

$$P_{ratedpower} = 400\ W$$

$$I_{input} = \frac{Power}{Input\ Voltage} \quad \dots(10)$$

$$I_{input} = \frac{400}{90.24} = 4.433A$$

$$I_{output} = \frac{Power}{Output\ Voltage} \quad \dots(11)$$

$$I_{output} = \frac{400}{325} = 1.23A$$

$$f_{sw} = 5\ kHz$$

$$\Delta V = 1\%\ \text{of output voltage} = 3.25\ \text{V}$$

$$\Delta I = 5\%\ \text{of output voltage} = 0.22\ \text{A}$$

Inductor:

$$L = \frac{V_{ip}(V_{op} - V_{ip})}{f_{sw} \times \Delta I \times V_{op}} \quad \dots(12)$$

$$L = \frac{90.24(325 - 90.24)}{5000 \times 0.22 \times 325}$$

$$L = 59.2mH$$

Capacitance:

$$C = \frac{I_{ip}(V_{op} - V_{ip})}{f_{sw} \times \Delta V \times V_{op}} \quad \dots(13)$$

$$C = \frac{1.23(325 - 90.24)}{5000 \times 3.25 \times 325}$$

$$C = 54.6\mu F$$

Results and Analysis

Five tests were conducted on 4 sq ft area, as shown in Table 8, detailing the initial and final soil moisture levels, water pump status, and the time taken to reach the desired moisture threshold. In each test, the system successfully activated the water pump when soil moisture fell below the threshold level, raising it to the target range of 70% to 75% as required. The time taken to reach this range varied between 10 and 15 seconds, with longer durations typically corresponding to lower initial moisture levels. These results ensure precise water management while minimizing the need for manual intervention in agricultural settings.

Table 8: *Soil moisture levels and corresponding system actions.*

Test number	Initial moisture level (%)	Final moisture level (%)	Pump activation status	Time to reach threshold (s)
1	40	70	Activated	12
2	35	75	Activated	14
3	50	75	Activated	10
4	30	70	Activated	15
5	45	75	Activated	11

Table 9: *Soil Moisture levels and corresponding system actions.*

Test number	Initial moisture level (%)	Final moisture level (%)	Pump activation status	Time to reach threshold (s)	Water usage (Liters)
1	40	70	Activated	12	3.5
2	35	75	Activated	14	4.2
3	50	75	Activated	10	2.8
4	30	70	Activated	15	3.9
5	45	75	Activated	11	3.3

The test results in Table 9 show the time required to reach an adequate moisture level and provides an estimate for how long it would take to moisturize the land fully. The amount of water used by the land is also calculated. In each test, the system activated the pump due to low initial moisture, demonstrating its ability to automatically respond to varying moisture conditions. These results emphasize the system's effectiveness in optimizing water usage by dynamically adjusting water output based on real-time soil moisture data.

Figure 11 shows the initial soil moisture levels, which are below the threshold. It provides an estimate of the time required to supply enough water to the plants. The graph indicates that higher initial moisture levels result in faster achievement of the moisture threshold because less water is needed. This demonstrates the efficiency of our design in optimizing water use by adjusting output based on real-time soil conditions. The graph clearly illustrates the system's ability to conserve water while maintaining adequate moisture levels, supporting the goal of promoting sustainable agriculture.

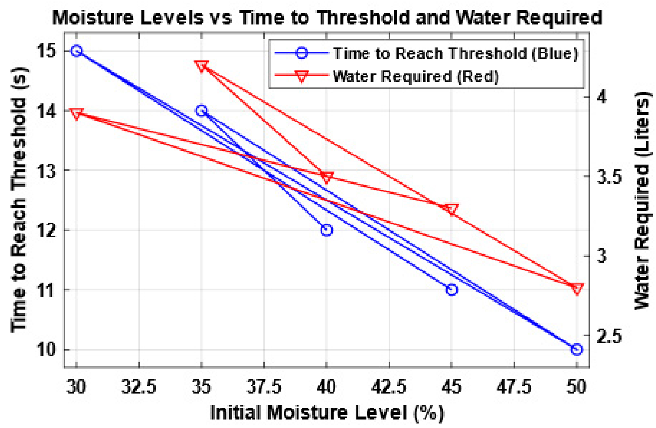

Figure 11: *Initial moisture level vs time to threshold and water usage.*

The system adjusts water delivery based on different moisture levels, ensuring the achievement of the final moisture levels defined by the system while also providing the estimated time to reach the threshold. The data also show that higher initial moisture levels require less water and lead to quicker attainment of the desired moisture level. Together, these findings confirm the system's capability to conserve water while maintaining optimal soil moisture, thereby promoting sustainable agricultural practices.

Figure 12 shows the irrigation patterns of the AISSA, ASISSA, and manual irrigation system for six days. The manual method shows an average of about 9 liters per day. The AISSA system adopts a more controlled approach, using approximately 7 liters per day, representing moderate water savings compared to the manual method. The ASISSA system, which is the proposed solution, significantly optimizes water usage, averaging between 3 to 4 liters per day. ASISSA demonstrates superior efficiency and adaptability, by adjusting to daily requirements. It saves approximately 66% of water daily compared to the manual method and around 42% compared to AISSA for the same irrigation area. ASISSA effectively adapts to varying water requirements, as observed on day 2 and day

3, by utilizing sensor data to take immediate action, even without relying on internet connectivity.

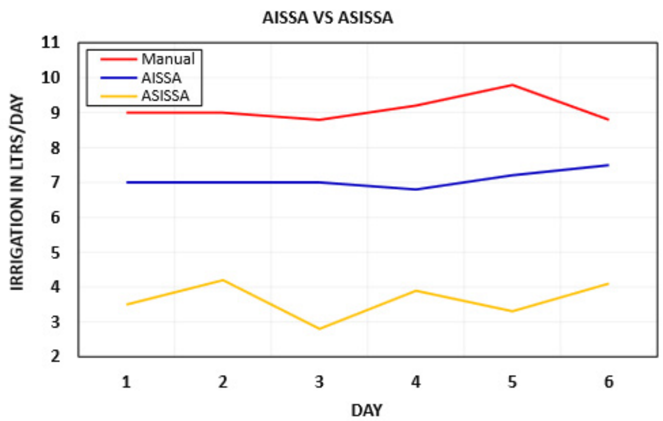

Figure 12: *AISSA vs ASISSA.*

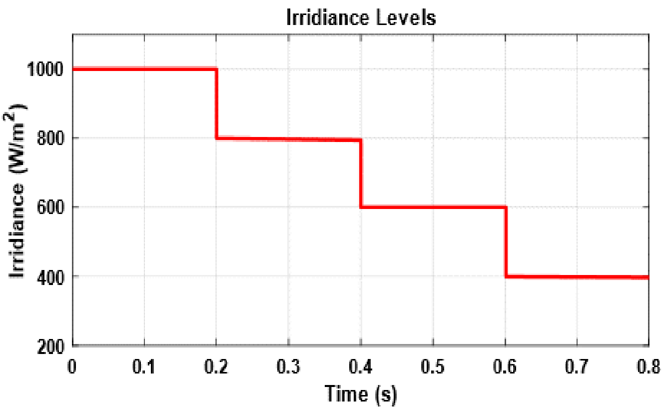

Figure 13: *Irradiance levels depicting different times of a day.*

Figure 13 shows different irradiance levels, as irradiance changes throughout the day, with a stepwise decrease in light intensity i.e., 1000 W/m^2, 800 W/m^2, 600 W/m^2 and 400 W/m^2 to simulate varying environmental conditions, such as cloudy weather or the lower irradiance levels during morning and evening. Each irradiance level represents a distinct reduction in light intensity, affecting the performance and efficiency of the PV system. Low irradiance indicates insufficient sunlight, resulting in reduced power output from the solar panel.

Figure 14 shows the PV power output as irradiance varies throughout the day, with levels reaching up to 1000 W/m^2. When irradiance is high, meaning the sun is bright and unobstructed, the PV system delivers maximum power. Conversely, when irradiance is low, indicating shadows on the PV panel or cloudy weather, the system does not produce full power. Each reduction in power output corresponds with the decrease in irradiance, demonstrating the direct impact of light intensity on the PV panel's performance, resulting in reduced power output.

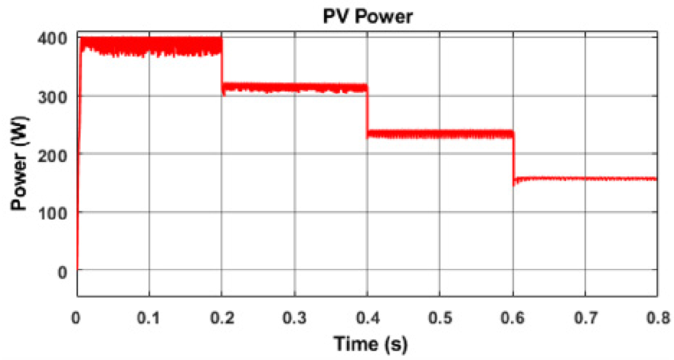

Figure 14: *PV Power.*

Figure 15 shows the power obtained from the PV system using a hybrid model by controlling the PWM on the current and voltage combination.

$$Average\ efficiency = \frac{Extracted\ power}{Ideal\ Power} \times 100\% \quad ...(14)$$

$$Average\ efficiency = 89.5\%$$

The average energy extracted from the PV system is 89.5%, and its efficiency varies between 85% and 95%. The decrease in power is due to cloudy weather when irradiance is low, demonstrating the hybrid model's effectiveness in consistently achieving near-maximum power under varying irradiance conditions.

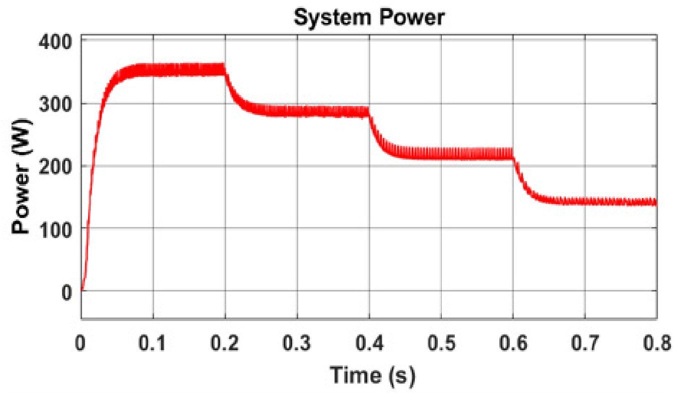

Figure 15: *System power.*

Conclusions

In this research, an irrigation system is designed to optimize both water usage and solar energy efficiency, thereby enhancing agricultural sustainability. A real-time soil moisture sensor automatically adjusts irrigation, maintaining an ideal 70%-75% moisture level and reducing water consumption by up to 60% compared to manual irrigation while ensuring adequate hydration for plants. To improve solar efficiency, a hybrid MPPT model combining P&O with ANN generates an optimal PWM signal, enabling the inverter to operate at the maximum power point and achieve 95% efficiency from PV panels, eliminating reliance on WAPDA power. This integrated approach maximizes resource utilization, significantly boosting agricultural productivity while offering a scalable and adaptable solution for sustainable farming. Future enhancements include integrating Wi-Fi or IoT devices to improve automation and adaptability in diverse agricultural settings. Additionally, in high-temperature regions with limited agricultural land and water scarcity, such as Mogadishu (Somalia) and Dubai (UAE), the system can be adapted for indoor or greenhouse farming, creating controlled environments suitable for cultivating vegetables and addressing key agricultural challenges.

Novelty Statement

This study introduces a smart irrigation system that optimizes water usage through automated con-trol while enhancing solar energy utilization with a hybrid MPPT (ANN + P&O) approach, ensur-ing efficient and sustainable irrigation in areas with limited grid access.

Author's Contribution

Dr. Dawar Awan: Conceptualization
Rohail Ali Khan: Methodology, software
Muhammad Zia: Writing – original draft, vali-dation
Muhammad Uzair Khan: Project Administration, formal analysis
Dr. Naveed Jan: Supervision

Conflict of interest
The authors have declared no conflict of interest.

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