

Adaptive Irrigation System Based on Evapotranspiration and Soil Moisture Sensing for Precision Agriculture

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Abstract

Agriculture in Uganda faces mounting pressures from escalating food demand, climate variability, and declining freshwater availability, with irrigation alone accounting for over 80% of total freshwater withdrawals. To address the limitations of conventional evapotranspiration (ET) controllers—which often depend on expensive meteorological instrumentation—this study proposes a cost-effective, sensor-minimal approach that utilizes only ambient temperature and relative humidity measurements from a DHT11 sensor, combined with soil moisture sensing. ET estimation is performed using a Sugeno-type Adaptive Neuro-Fuzzy Inference System (ANFIS) trained via a hybrid learning algorithm that integrates least-squares estimation for linear parameters with gradient descent for nonlinear membership function tuning. The ANFIS model, achieving a mean absolute error of 0.035 and a coefficient of determination (R^2) of 0.988, was implemented in MATLAB to generate ET values in real time. These values are evaluated alongside in-field soil moisture readings by an ESP32 microcontroller to determine optimal irrigation scheduling. The system incorporates both automatic and manual control modes, accessible through a MATLAB-based PC graphical user interface and an Android mobile application via Wi-Fi, enabling responsive and scalable deployment. This architecture delivers a precise, affordable, and adaptable irrigation management solution suitable for resource-constrained agricultural environments in Uganda.

Keywords: Evapotranspiration; precision agriculture; adaptive irrigation; ANFIS

1. Introduction

The advancement of agricultural science and technology, along with the growing need for global food security, has brought the precise and efficient use of water resources to the forefront of sustainable agricultural practices (Xing & Wang, 2024).

Efficient water management is essential in agriculture, particularly in the face of increasing water scarcity and climate variability (Behura et al., 2025). It is noted that to meet the growing needs for agriculture, most populations have adopted irrigation.

Irrigation refers to the deliberate application of water to soil to support plant growth, especially in areas where natural rainfall is insufficient or irregular (Gamal et al., 2025). It involves the controlled distribution of water using various methods and technologies such as pumps, pipes or tubes, sprinklers, and drip systems. Beyond simply providing moisture, irrigation helps maintain optimal soil conditions, improves crop yields, and supports agricultural productivity throughout dry seasons (Genemo et al., 2023). Modern

irrigation systems integrate automation, sensors, and water-saving techniques to enhance efficiency and reduce wastage (Ehteram et al., 2021; Tace et al., 2022).

Traditional irrigation systems either follow fixed schedules or rely on expensive commercial Evapotranspiration (ET) controllers that require a wide range of meteorological inputs (Jamroen et al., 2020). These include solar radiation, wind speed, temperature, humidity, and atmospheric pressure parameters that demand specialized and costly sensors (R.G. Allen, 1998). Consequently, these solutions are inaccessible to many small-holder farmers, especially in developing countries like Uganda (Mokhtarzadeh et al., 2025).

In this project, an Adaptive Neuro-Fuzzy Inference System (ANFIS) was used to develop an artificial intelligence model capable of learning the relationship between multiple climatic inputs and the target output of evapotranspiration (ET). The target ET values were computed using the FAO-56 Penman–Monteith model, which is widely regarded as the standard for estimating reference ET in agricultural water management (Han et al., 2024).

A Sugeno-type ANFIS was specifically employed due to its ability to model complex, nonlinear relationships with high computational efficiency (Haider et al., 2022), making it suitable for real-time applications in irrigation control. The Sugeno approach combines fuzzy logic’s capacity to handle imprecision and uncertainty with the adaptive learning capability of neural networks (Chen & Tat Pham, 2001)

In a Sugeno-type ANFIS:

- Inputs (temperature and humidity) are first fuzzified into linguistic variables using membership functions (Benzaouia et al., 2023).
- Rule base consists of IF–THEN rules, where the THEN part is a mathematical function (often linear) of the inputs rather than a fuzzy set.
- Rule firing strengths are normalized, and the system computes a weighted average of the rule outputs, yielding a crisp output without a separate defuzzification step.
- The model parameters, including membership function shapes and rule output coefficients, are tuned using a hybrid learning algorithm that combines gradient descent (for nonlinear parameters) and least-squares estimation (for linear parameters).

Advantages of this Application

- Real-time performance: Low computational cost makes it feasible for deployment on microcontrollers like the ESP32.
- Smooth output surface: Ensures stable irrigation control decisions.
- Data adaptability: Learns from historical weather and ET data, improving accuracy over time.
- Integration with physical models: By training on Penman–Monteith computed ET values, the ANFIS model inherits the theoretical robustness of the physical model while gaining adaptive capabilities.

In the proposed irrigation system, the trained Sugeno ANFIS model processes live sensor data and estimates current ET, which is then evaluated alongside soil moisture readings to determine optimal irrigation scheduling.

2. Methodology

This chapter discusses step by step how the study was conducted to achieve the desired output.

2.1 Requirements Elicitation

The requirements were obtained by reviewing the existing literature about the various systems. An understanding of the existing automatic irrigation systems was used to determine some requirements of the designed system.

2.2 Data Collection

The following data collection methods were used for this project.

- i) **Historical climatic data:** This was collected from Uganda National Meteorological Authority. This included wind speed, solar radiation, humidity, temperature and vapor pressure.
- ii) **Literature survey:** This method involved reading of published documents over the internet, in text books, journals and documents from organizations and institutions regarding the system control design, automation methodologies and overall design of drip irrigation systems.

2.3 Data Analysis

The main aim of this was to extract the project requirements from all the collected data to aid in the development of the system. Software packages like cropwat and climwat (FAO), excel, MATLAB were used to process the data that helped in the design of the AI model and eventually simulation of the system.

2.4 Determining the Reference Crop Evapotranspiration

The reference crop ET was used as a target in training of the AI model

According to (RG. Allen, 1998) there are various methods of calculating the ETo value and these include the FAO Penman-Monteith method, Blarney-Criddle method, Pan Evaporation method, Radiation method, and Hargreaves equation

The FAO Penman-Monteith method is internationally accepted as standard method for the definition and calculation of the reference crop evapotranspiration.

The FAO Penman-Monteith equation is given as:

$$ET_o = \frac{0.408\Delta(R_n - G) + \frac{900\gamma U_2(e_s - e_a)}{T + 273}}{\Delta + \gamma(1 + 0.34U_2)} \dots \dots \dots \text{equation 2.0}$$

Where; ET_o = Reference evapotranspiration (mm/day), R_n = Net radiation at the crop surface (MJ/m²/day), G = Soil heat flux density (MJ/m²/day), T = Mean daily air temperature at 2 m height (°C), U₂ = Wind speed at 2 m height (m/sec), e_s = Saturation vapor pressure (kPa),

e_a = Actual vapor pressure (kPa), (e_s-e_a) = Saturation vapor pressure deficit (kPa), Δ = Slope of saturation vapor pressure curve at temperature (kPa/°C), γ = Psychrometric constant (kPa/°C (RG. Allen, 1998)

Cropwat , Climwat and Ms excel were used to compute and arrange the Penman Moneith based evapotranspiration. The outputs were a target during training of the model

Table 1:FAO Cropwat 8.0 PenMAN Evapotranspiration

Month	Min Temp	Max Temp	Humidity	Wind	Sun	Rad	ETo
	°C	°C	%	km/day	hours	MJ/m ² /day	mm/day
January	18.0	28.3	68	294	7.4	20.1	4.89
February	18.0	28.2	69	294	7.5	21.0	5.00
March	18.0	27.5	74	294	6.5	19.7	4.56
April	17.5	26.0	82	277	6.0	18.4	3.82
May	17.5	25.3	84	294	6.1	17.6	3.51
June	17.1	25.1	80	311	6.2	17.1	3.56
July	16.5	25.0	79	311	5.6	16.5	3.54
August	16.3	25.5	81	294	5.8	17.6	3.65
September	16.5	26.5	79	294	6.0	18.6	4.00
October	16.8	27.1	77	268	6.2	18.9	4.16
November	17.2	27.1	76	251	6.2	18.4	4.11
December	17.3	27.1	74	277	6.9	19.1	4.30
Average	17.2	26.6	77	288	6.4	18.6	4.09

Table 1 shows the computation of average evapotranspiration values for each month based on penman monteith for over 30 years. It is based on major parameters of temperature, humidity, windspeed and solar radiation

2.5 Training of ANFIS

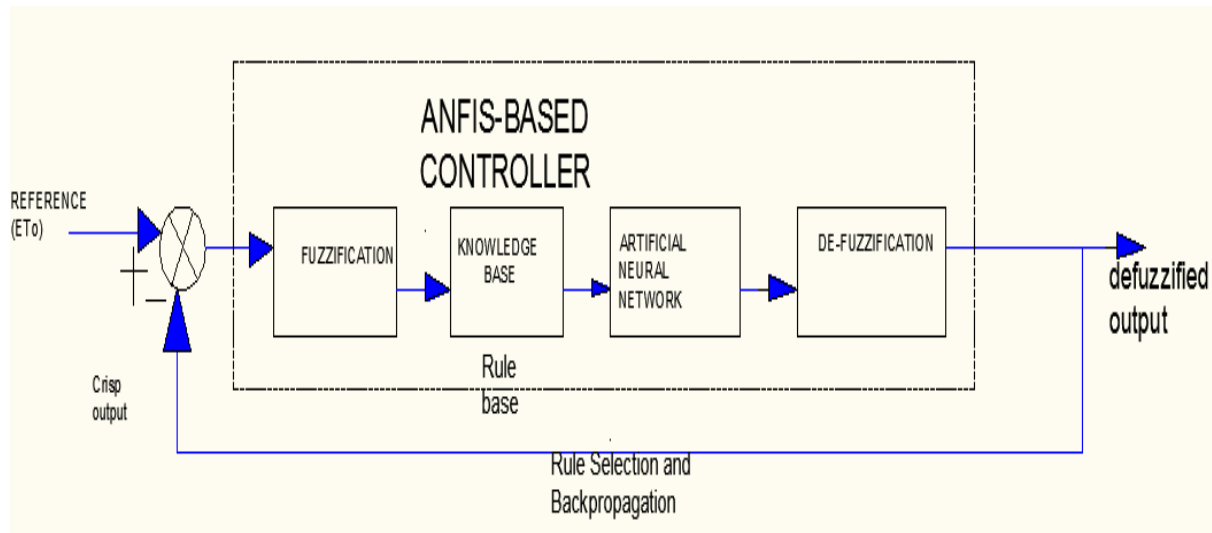


Fig. 11: Anfis Based Controller Training

Figure 1 illustrates supervised learning of the model with known targets(reference ETo) and how error is propagated back until it is minimized. Hybrid Algorithm was used as follows

- a) Forward pass: in this pass, the input data flows through the ANFIS network, and output is calculated using the current premise and consequent parameters.
- b) Error propagation: The error between the predicted output and the actual output is calculated

- c) Backward pass(Gradient Descent): In the backward pass, error is propagated backwards through the network and the consequent parameters are updated using gradient descent.
- d) Least Squares Estimate(LSE): After the backward pass, the premise parameters are updated using the least squares estimate method.

The ANFIS model was trained by five inputs obtained from engineered features(these represent the two inputs of temperature and humidity but feature engineering was done to introduce nonlinearity present in the FAO Penman Monteith). These included;

- i) Temperature(Temp)
- ii) Temperature squared(Temp²)
- iii) Humidity(Humid)
- iv) Humidity squared (Humid²)
- v) and the interaction term (Temperature × Humidity).

Table 2: Table shows Future engineered data for two years

Temperature	Humidity	TempSquared	HumidSquared	Temp x Humidity	Evapotranspiration
23.2	61	538.24	3721	1415.2	4.68
23.3	65	542.89	4225	1514.5	5.48
22.4	68	501.76	4624	1523.2	4.48
21.6	70	466.56	4900	1512.0	3.80
21.5	73	462.25	5329	1569.5	3.57
21.9	69	479.61	4761	1511.1	4.00
21.7	73	470.89	5329	1584.1	3.64
21.9	66	479.61	4356	1445.4	3.35
22.5	70	506.25	4900	1575.0	3.83
21.9	72	479.61	5184	1576.8	3.92
22.3	70	497.29	4900	1561.0	3.55
22.5	63	506.25	3969	1417.5	3.88
22.9	68	524.41	4624	1557.2	3.77
22.8	71	519.84	5041	1618.8	3.44
24.2	71	585.64	5041	1718.2	3.18
21.9	70	479.61	4900	1533.0	4.06
22.5	73	506.25	5329	1642.5	4.00
21.9	72	479.61	5184	1576.8	3.02
21.7	70	470.89	4900	1519.0	3.26
21.8	67	475.24	4489	1460.6	2.88
21.5	70	462.25	4900	1505.0	3.87
21.4	68	457.96	4624	1455.2	3.52
22.1	70	488.41	4900	1547.0	2.82
22.1	69	488.41	4761	1524.9	3.26

A Sugeno-type fuzzy inference system with 243 rules was created using MATLAB's genfis1 and ANFIS functions. The model was trained over 100 epochs using a hybrid algorithm

ANFIS Rules: (40 out of 243)

1. IF Temp is Low AND Temp² is Low AND Humid is Low AND Humid² is Low AND Temp×Humid is Low THEN ET is Low
2. IF Temp is High AND Temp² is High AND Humid is Low AND Humid² is Low AND Temp×Humid is High THEN ET is Medium
3. IF Temp is Medium AND Temp² is Medium AND Humid is Medium AND Humid² is Medium AND Temp×Humid is Medium THEN ET is Medium
4. IF Temp is High AND Temp² is High AND Humid is High AND Humid² is High AND Temp×Humid is High THEN ET is High
5. IF Temp is Low AND Temp² is Low AND Humid is High AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
6. IF Temp is High AND Temp² is High AND Humid is Medium AND Humid² is Medium AND Temp×Humid is High THEN ET is High
7. IF Temp is Medium AND Temp² is Medium AND Humid is High AND Humid² is High AND Temp×Humid is High THEN ET is High
8. IF Temp is Low AND Temp² is Low AND Humid is Medium AND Humid² is Medium AND Temp×Humid is Low THEN ET is Low
9. IF Temp is Medium AND Temp² is Medium AND Humid is Low AND Humid² is Low AND Temp×Humid is Low THEN ET is Low
10. IF Temp is High AND Temp² is High AND Humid is Low AND Humid² is Low AND Temp×Humid is Low THEN ET is Medium
11. IF Temp is Low AND Temp² is Low AND Humid is Medium AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
12. IF Temp is Medium AND Temp² is High AND Humid is Low AND Humid² is Medium AND Temp×Humid is Medium THEN ET is Medium
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14. IF Temp is Low AND Temp² is Medium AND Humid is High AND Humid² is Medium AND Temp×Humid is Low THEN ET is Low
15. IF Temp is Medium AND Temp² is Low AND Humid is Medium AND Humid² is Medium AND Temp×Humid is High THEN ET is Medium
16. IF Temp is High AND Temp² is High AND Humid is Medium AND Humid² is Low AND Temp×Humid is Medium THEN ET is Medium
17. IF Temp is Medium AND Temp² is Medium AND Humid is Low AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
18. IF Temp is Low AND Temp² is Low AND Humid is High AND Humid² is Medium AND Temp×Humid is High THEN ET is High
19. IF Temp is High AND Temp² is Medium AND Humid is Low AND Humid² is Low AND Temp×Humid is Medium THEN ET is Medium

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22. IF Temp is Medium AND Temp² is Low AND Humid is High AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
23. IF Temp is High AND Temp² is High AND Humid is Medium AND Humid² is High AND Temp×Humid is High THEN ET is High
24. IF Temp is Low AND Temp² is Low AND Humid is High AND Humid² is Medium AND Temp×Humid is Medium THEN ET is Medium
25. IF Temp is Medium AND Temp² is Medium AND Humid is Medium AND Humid² is High AND Temp×Humid is High THEN ET is High
26. IF Temp is High AND Temp² is Medium AND Humid is Low AND Humid² is Medium AND Temp×Humid is Low THEN ET is Medium
27. IF Temp is Low AND Temp² is High AND Humid is Medium AND Humid² is Low AND Temp×Humid is Low THEN ET is Low
28. IF Temp is Medium AND Temp² is High AND Humid is High AND Humid² is High AND Temp×Humid is High THEN ET is High
29. IF Temp is High AND Temp² is Low AND Humid is Low AND Humid² is Medium AND Temp×Humid is Medium THEN ET is Medium
30. IF Temp is Low AND Temp² is Medium AND Humid is Medium AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
31. IF Temp is Medium AND Temp² is Medium AND Humid is High AND Humid² is Low AND Temp×Humid is Medium THEN ET is Medium
32. IF Temp is High AND Temp² is High AND Humid is High AND Humid² is Medium AND Temp×Humid is High THEN ET is High
33. IF Temp is Low AND Temp² is Low AND Humid is Medium AND Humid² is High AND Temp×Humid is High THEN ET is Medium
34. IF Temp is Medium AND Temp² is Low AND Humid is Low AND Humid² is High AND Temp×Humid is Low THEN ET is Low
35. IF Temp is High AND Temp² is Medium AND Humid is Medium AND Humid² is Medium AND Temp×Humid is High THEN ET is High
36. IF Temp is Low AND Temp² is High AND Humid is High AND Humid² is High AND Temp×Humid is Medium THEN ET is Medium
37. IF Temp is Medium AND Temp² is High AND Humid is Low AND Humid² is Low AND Temp×Humid is Low THEN ET is Low
38. IF Temp is High AND Temp² is Low AND Humid is High AND Humid² is Medium AND Temp×Humid is High THEN ET is High
39. IF Temp is Low AND Temp² is Medium AND Humid is Low AND Humid² is High AND Temp×Humid is Medium THEN ET is Low
40. IF Temp is Medium AND Temp² is Medium AND Humid is Medium AND Humid² is Medium AND Temp×Humid is High THEN ET is High

2.6 Statistical Analysis

Two commonly used parameters to measure the accuracy of predictive models include the Mean Absolute Error and Coefficient of Determination (Robeson & Willmott, 2023). The following formulae were used;

Mean Absolute Error (MAE)

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \dots \dots \dots \text{equation 3.0}$$

- y_i : Actual values.
- \hat{y}_i : Predicted values.
- n : Number of observations.

Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \dots \dots \dots \text{equation 4.0}$$

- Numerator: Residual Sum of Squares (RSS).
- Denominator: Total Sum of Squares (TSS).
- \bar{y} : Mean of actual values.

3. System Design

The system has the following modules on its architecture as shown in the block diagram

ESP32 microcontroller for data processing and actuation, DHT11 sensor for measuring ambient temperature and humidity, Soil moisture sensor for detecting in-field water levels, MATLAB-based PC application for ET computation and GUI control and an Android mobile app for remote manual override and monitoring via Wi-Fi.

Sensor data is transmitted from the ESP32 micro controller to MATLAB via serial communication.

The trained ANFIS model estimates current Evapotranspiration, which is evaluated along with soil moisture levels to determine irrigation needs. The system supports both automatic and manual modes.

Design Components in Appearance

1. Soil Moisture Sensor (Fig. 2)

- ❖ **Function:** Detects the volumetric water content in the soil.
- ❖ **Role:** Provides real-time data on soil dryness/wetness for irrigation decisions.

2. ESP32-S3 Microcontroller Unit (Fig. 3)

- ❖ **Function:** A powerful MCU with Wi-Fi and Bluetooth connectivity.
- ❖ **Role:** Acts as the brain of the system—collects sensor data, communicates with MATLAB PC, controls relays, and connects to the mobile app.

3. Buck Converter (Fig. 4)

- ❖ **Function:** DC-DC step-down converter (e.g., 12 V → 5 V).
- ❖ **Role:** Supplies stable 5 V power to ESP32 and sensors from a 12 V source.

4. Transistor (Fig. 5)

- ❖ **Function:** Semiconductor switch or amplifier.
- ❖ **Role:** Acts as an interface to drive the relay module safely from the MCU's low-power GPIO pin.

5. Relay Module (Fig. 6)

- ❖ **Function:** Electromechanical switch.
- ❖ **Role:** Allows the ESP32 to control high-voltage devices such as pumps or solenoid valves.

6. DHT11 Sensor (Fig. 7)

- ❖ **Function:** Measures ambient **temperature** and **humidity**.
- ❖ **Role:** Supplies climatic parameters required for evapotranspiration (ET) estimation.

7. Perf Board (Fig. 8)

- ❖ **Function:** Prototyping board with a grid of copper pads/holes.
- ❖ **Role:** Holds circuit connections, ensuring neat and permanent assembly of components.

8. Power Adapter (Fig. 9)

- ❖ **Function:** Converts mains **220 V AC** to **12 V DC** output.
- ❖ **Role:** Primary power source for the buck converter and relay circuits.

Together, these components integrate into a **smart irrigation controller**: sensors gather data, ESP32 processes it and communicates with MATLAB (ANFIS-based ET model) and a mobile app, while actuators (relay + pump/valve) execute irrigation automatically or manually.

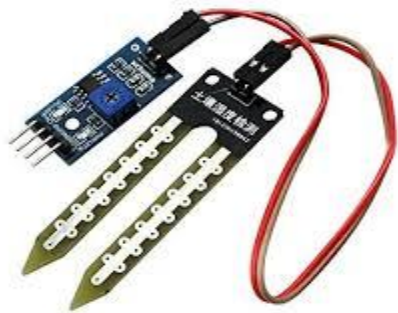


Fig. 22: Soil moisture sensor



Fig. 3: Esp32 - s3 MCU



Fig. 43: Buck converter to convert 12V dc to 5Vdc

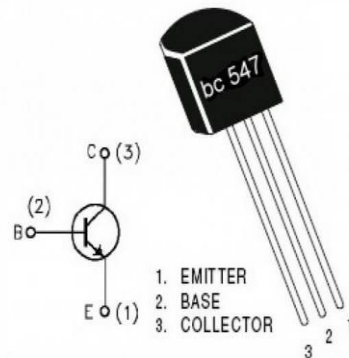


Fig. 4: Transistor to enable smooth switching between MCU and Relay module

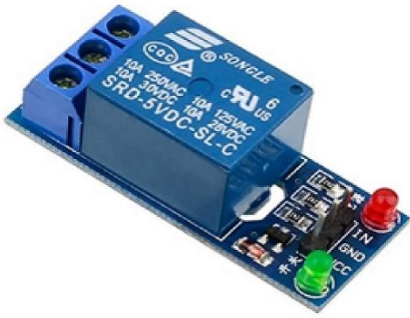


Fig. 6: Relay module for switching with higher voltage



Fig. 7: DHT11 sensor for Temperature & Humidity

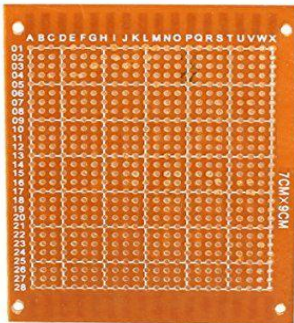


Fig 8: Perf board to hold the circuit 12Vac



Fig. 9: Power adapter, allowing in 220Vac outputting

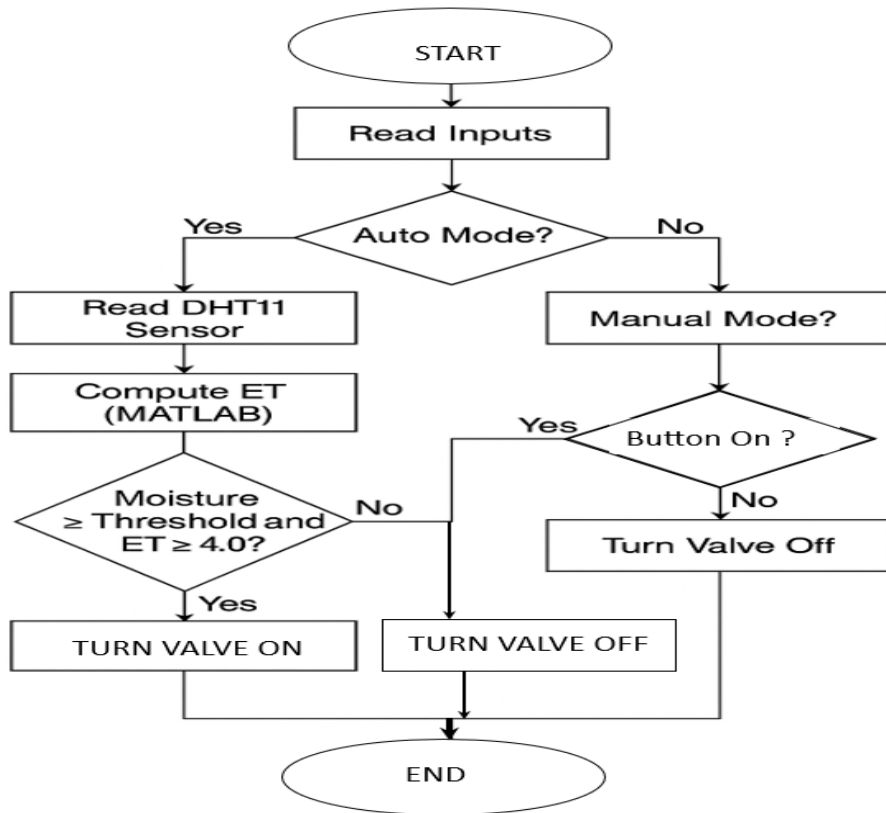


Fig. 10: Flow diagram

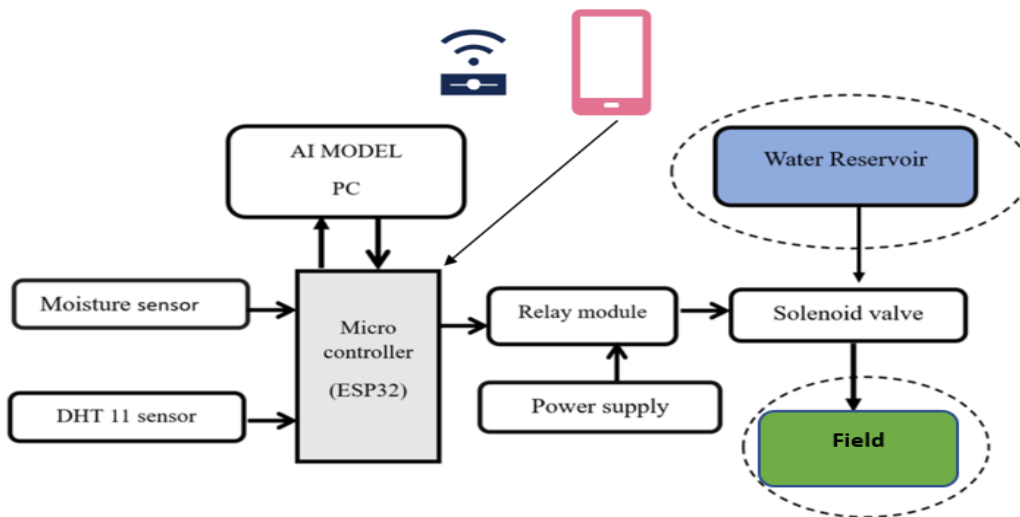


Fig. 51: Control system block diagram

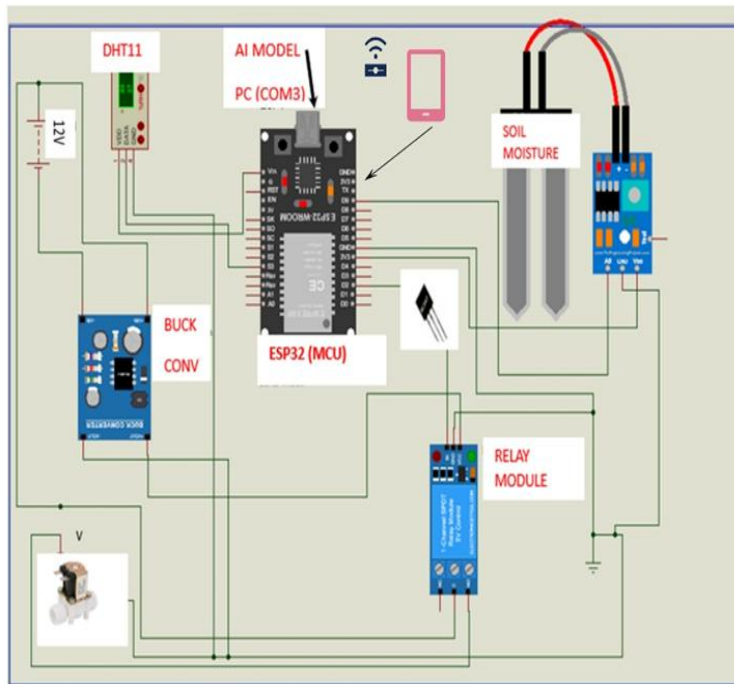


Fig. 126: layout of the control system

Drip Irrigation

In this project, drip irrigation was used since its very water efficient. Drip irrigation is a method of supplying water directly to the root zone of plants in a slow, steady manner through a network of valves, pipes, tubing, and emitters. Instead of flooding the entire field or spraying large areas, drip systems release water in small amounts directly at the base of each plant (Yang et al., 2023). This minimizes evaporation and runoff, making it one of the most water-efficient irrigation methods (Sarula et al., 2023), (Morianou et al., 2023), (Genemo et al., 2023).



Fig. 73: Prototype with water reservoir and control box

3. Results and Discussion

The trained ANFIS model, with a low MAE of 0.035 and high R^2 of 0.988, accurately replicated Penman-Monteith ET values using limited inputs. Field tests confirmed seamless integration with the ESP32 microcontroller for effective irrigation control. The system offers both manual and automated modes via Android and PC interfaces, with button response times ranging from 25 to 40 milliseconds, ensuring near-instant feedback for users. Real-time visualization of temperature and humidity plots provides valuable insights into environmental conditions, enabling timely decision-making and fine-tuning of irrigation schedules. This approach reduces hardware costs while enhancing precision by incorporating **real-time soil** moisture data and crop water demand estimations. See figure 14 and 15 for the user interfaces

Figure 14 shows a mobile-based control and monitoring platform that allows users to remotely monitor soil moisture, ET, and irrigation status via Wi-Fi, supports manual override of irrigation (switch pump/valve ON or OFF) and displays real-time field conditions in a user-friendly layout while figure 15 shows a PC-based application with GUI built in MATLAB. This Receives sensor data from ESP32 via serial communication, runs the trained ANFIS model to compute real-time evapotranspiration (ET), evaluates ET alongside soil moisture readings to trigger automatic irrigation and offers a visualization panel for monitoring climate variables and irrigation events.



Fig. 148: Android App interface

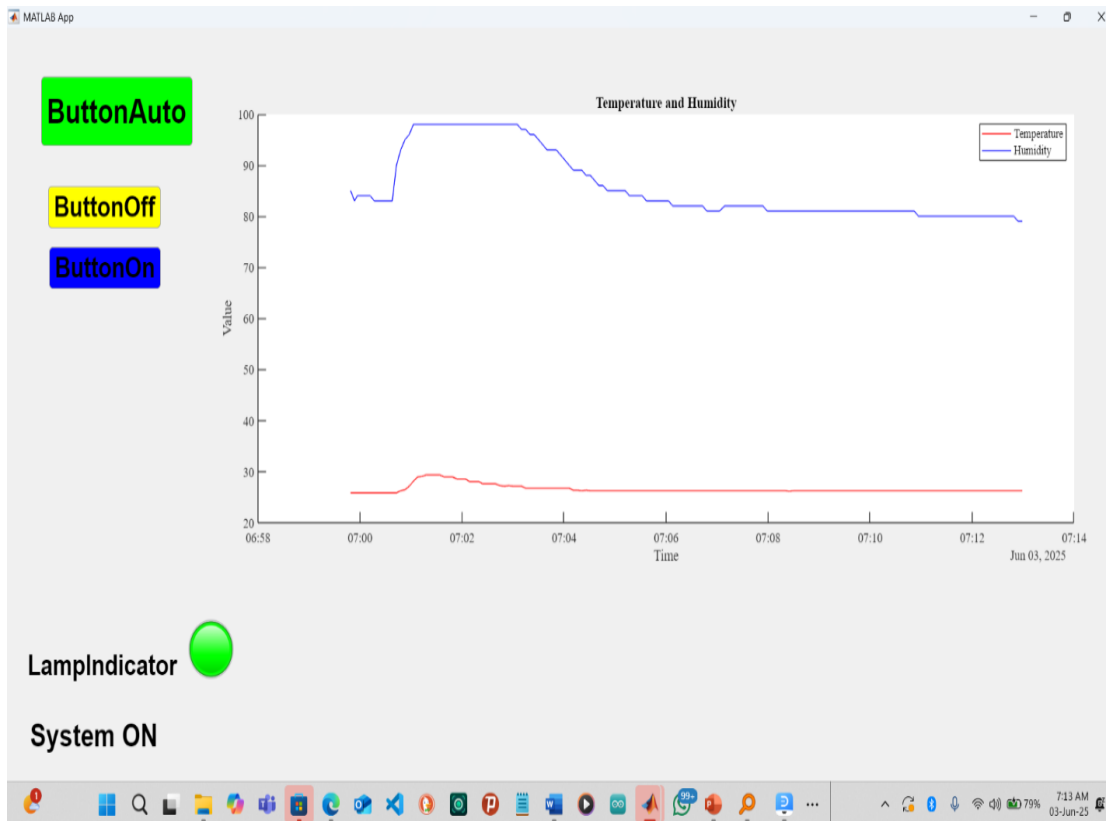


Fig. 15: Matlab App interface

4. Conclusion

This research presents an adaptive irrigation system that integrates an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based evapotranspiration (ET) estimation model with real-time soil moisture sensing and intuitive user interfaces. The trained ANFIS model achieved a low Mean Absolute Error (MAE) of 0.035 and a high coefficient of determination (R^2) of 0.988, demonstrating its strong capability to accurately replicate Penman-Monteith ET values using limited input variables. These results highlight the potential of intelligent data-driven models to serve as efficient alternatives to conventional ET estimation methods.

Field implementation confirmed the successful integration of the trained ANFIS model with the ESP32 microcontroller for real-time irrigation control. The system's dual-mode operation, offering both manual and automated control, achieved rapid response times between 25–40 milliseconds, ensuring smooth and reliable performance in practical agricultural settings. Additionally, the use of both Android and PC-based interfaces enhanced system flexibility, providing remote monitoring, control, and real-time visualization of environmental parameters and irrigation events.

The system's architecture effectively combines soil moisture data with ET-based crop water demand estimations, enabling precise irrigation scheduling while significantly reducing the need for costly weather stations and complex infrastructure. This contributes to overall cost reduction and makes advanced irrigation technology more accessible to smallholder farmers. Moreover, its scalable and adaptable design allows deployment in both small-scale farms and large commercial agricultural operations.

The findings of this study carry important implications. First, the integration of ANFIS with low-cost IoT hardware provides a practical pathway to improve water-use efficiency by applying water only when required. Second, timely and data-informed irrigation decisions can enhance crop productivity and support sustainable agricultural practices. Third, the affordability and flexibility of the system lower the technological entry barrier for resource-limited farmers, supporting wider adoption of precision

irrigation. Finally, by improving water resource management and crop yields, this system contributes to broader goals of food security and climate-resilient agriculture.

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