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Real-Time Feedback For Crop-Specific Irrigation Strategies

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Abstract
This paper presents the development and simulation of a real-time, crop-specific, feedback-driven irrigation and fertilization management system designed to optimize the use of limited water and nutrient resources. Implemented using MATLAB Simulink and Python 3.7, the system integrates simulated multi-sensor inputs, PID controller, fuzzy inference, and actuator modeling to dynamically adjust irrigation and fertigation schedules based on soil moisture, nutrient content, temperature, and crop growth stages. An artificial neural network trained via transfer learning was employed to enhance predictive decision-making. Simulation results demonstrated that the irrigation model achieved 100% accuracy, while the fertilization model achieved over 91% accuracy. These findings underscore the system's potential to maintain optimal soil conditions, minimize water and fertilizer wastage, and improve crop growth outcomes. The research highlights the promise of real-time, AI-driven feedback systems in advancing precision agriculture, ensuring sustainable resource management, and supporting climate-smart farming practices.

Keywords: *Precision irrigation, fertigation, fuzzy logic, PID control, artificial neural networks, MATLAB Simulink.*

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I. Introduction

Water scarcity and climate variability pose significant threats to global food security, with agriculture consuming about 70% of global freshwater resources. Hence, inefficiencies in traditional irrigation often lead to substantial water losses and reduced resource sustainability (Gu et al., 2020; Ray & Majumder, 2024). Advances in precision irrigation, powered by ICT, IoT, and sensor networks, have enabled real-time monitoring of soil and environmental parameters, improving decision support systems (García et al., 2020; Morchid et al., 2025). Despite progress made, most existing smart irrigation systems primarily respond to external factors like soil moisture or weather, while insufficiently integrating internal plant development processes (Wilkening, 2023; Bhatti et al., 2023). Furthermore, the coupling of nutrient delivery with specific crop growth demands remains limited, often treating irrigation and fertigation as separate processes (Evans et al., 2013). This study addresses these gaps by simulatiing a real-time, crop-specific irrigation system that integrates multi-sensor feedback with phenology-driven decision models to synchronize water and nutrient supply with crop developmental stages.

II. Related Works

Earlier research highlights significant contributions to precision irrigation. Mishra et al. (2021) demonstrated IoT-enabled irrigation that saved up to 35% water by responding to soil moisture data. Zhang et al. (2020) explored fuzzy logic for irrigation scheduling in tomato farming, showing improvements over static methods. Patel and Gupta (2019) introduced machine learning for predicting irrigation needs, enhancing scheduling efficiency. Therefore, many systems lack integration of multi-input feedback that includes both soil-plant dynamics and nutrient requirements, and few adapt to specific crop growth stages or phenological milestones (Wilkening, 2023; Naziq et al., 2024). The current study builds on these foundations by coupling crop-specific moisture thresholds, nutrient demands, and growth measurements with advanced control logic for truly tailored irrigation and fertigation.

III. System Methodology

System Design

High-level system architecture was first designed to define the main components and data flow within the irrigation system. This architecture includes three major subsystems, which entail Sensor Input Subsystem (soil moisture, temperature, nutrient), Crop-Specific Irrigation Decision Unit, Actuation and Feedback Subsystem. This modular breakdown was implemented in MATLAB Simulink as shown in fig.1 for clarity and flexibility

A. **Sensor Input Simulation:** Generated dynamic signals for soil moisture, temperature, nutrient levels, and growth using MATLAB Simulink signal generators and lookup tables.

B. **Decision Logic:** Applied PID controllers and fuzzy inference systems to maintain optimal ranges specific to maize, tomato, and rice moisture needs. Various thresholds were selected based on the crop type as follows:

  i. **Maize**: 20%–40% optimal moisture range

  ii. **Tomato**: 30%–50% optimal moisture range

  iii. **Rice**: 50%–75% optimal moisture range

Rule-based logic triggered irrigation or fertigation when sensor values crossed critical thresholds. This module received sensor inputs and determined whether to turn irrigation ON or OFF based on predefined rules:

Rule 1: If soil moisture < lower threshold → Irrigation ON

Rule 2: If soil moisture > upper threshold → Irrigation OFF

C. **Actuation & Feedback:** Modeled actuator response through integrator and transfer function blocks to emulate water inflow effects on soil moisture.

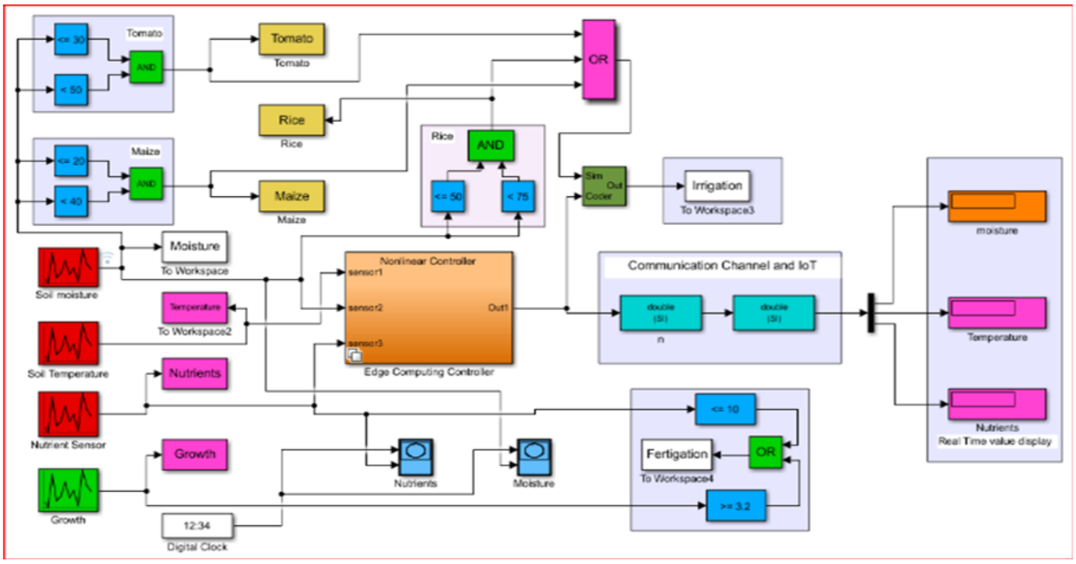


Fig.1. System Architecture showcasing various Modules

AI Model Training

An artificial neural network (ANN) was developed in Python 3.7 using transfer learning to predict irrigation and fertilization actions from sensor data. Sample dataset generated as shown in table 1 was used to train the Artificial Neural Network.

Time (s)	Moisture	Nutrients	Temp	growth
0	51.2	12.0	17.9	1.87
1	46.0	2.58	16.1	1.18
2	35.0	37.3	12.2	3.71
3	9.50	44.3	3.32	3.71
4	43.3	51.4	15.1	4.73
5	70.9	21.0	24.8	2.53
6	11.5	28.5	4.05	3.07
7	7.80	45.7	2.73	4.32
8	36.9	1.90	12.9	1.13

Model performance was evaluated using accuracy, precision, recall, F1 score, and confusion matrices. The leave-one-out cross-validation was used to ensure the model's generalization capabilities.

Accuracy is calculated by comparing the model's predictions with the actual labels in the validation dataset. The Formula for Accuracy used in this model evaluation is given by;

$$Accuracy = \frac{\text{True Positives} + \text{True Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}}$$

Precision is one indicator of a machine learning model's performance and the quality of positive prediction made by the model. The Formula for Precision used in this model evaluation is given by;

$$Prediction = \frac{\text{True Positives in all classes}}{\text{True Positives} + \text{False Positives in all classes}}$$

Recall measures how often a machine learning model correctly identifies positive instances (true positives) from all the actual positive samples in the dataset. The Formula for Recall used in this model evaluation is given by;

$$Recall = dividing\ the\ number\ of\ true\ positives\ by\ the\ number\ of\ positive\ instances$$

F1 score computes the average of precision and recall, where the relative contribution of both of these metrics is equal to F1 score. The best value of F1 score is 1 and the worst is 0. The Formula for F1 score is given by;

$$F1\ score = \frac{2\ (\text{Precision X Recall})}{\text{Precision } + \text{Recall}}$$

System Mathematical Model

The mathematical model for the physical concept is given as follows for the real-time feedback control of irrigation and application of fertilizer based on real sensor values of soil parameters. Factors that influence the irrigation frequency are:

Tomatoes optimum moisture requirement range is 30% to 50%. This implies that moisture content that is below this range should trigger the automated feedback for irrigation.

Mathematically shown in equation 1 and equation 2;

$$t = \begin{cases} 0, if\ 30 \leq Q\ \geq\ 50 \\ 1, \quad otherwise \end{cases} \qquad (1)$$

$$\mathrm{u}(t), = \sum_{k=30}^{50} \binom{n}{k} a^{n-k} \qquad (2)$$

Maize optimum moisture requirement range is 20% to 40%. This implies that moisture content that is below this range should trigger the automated feedback for irrigation.

Mathematically shown in equation 3 and equation 4;

$$m = \begin{cases} 0, if\ 20 \leq Q\ \geq\ 40 \\ 1, \quad otherwise \end{cases} \qquad (3)$$

$$\mathrm{u}(m) = \sum_{k=20}^{40} \binom{n}{k} a^{n-k} \qquad . \qquad (4)$$

Rice optimum moisture requirement range is 50% to 75%. This implies that moisture content that is below this range should trigger the automated feedback for irrigation.

Mathematically shown in equation 5 and equation 6 ;

$$r = \begin{cases} 0, if\ 50 \leq Q\ \geq\ 75 \\ 1, \quad otherwise \end{cases} \qquad (5)$$

$$\mathrm{u}(r) = \sum_{k=50}^{75} \binom{n}{k} a^{n-k} \qquad (6)$$

Irrigation for tomatoes is denoted by u(*t*), for maize is denoted by u(*m*), for rice is denoted by u(*r*), and for growth by u(*g*). The total irrigation (k) model is given by equation 7 and equation 8:

$$k = u(t) + u(m) + u(r) \qquad (7)$$

$$f(J) = \sum_{n=0}^{60} (t^{n-k} + m^{n-k} + r^{n+k}) \qquad (8)$$

Factors that influence the fertilization frequency are:

Nutrient requirement in the model is 0mg/kg to 60. However, nutrient content below the quantity of nutrient Q sensed triggers the automated fertilizer application feedback as shown in equation 9.

Where $Q \leq 10$

$$u(n), = \sum_{k=0}^{60} \binom{n}{k} a^{n-k} \quad (9)$$

Growth requirement in the model is 1 to 5. This implies that when the growth sensor senses growth not within the value of Q, automated fertilizer application feedback is triggered as shown in equation 10.

Where Q >= 3.2

$$u(g) = \sum_{k=3.2}^{5} \binom{n}{k} a^{n-k} \quad (10)$$

The fertilizer (k) model is given by the equations 11 and 12:

$$k = u(n) + u(g) \quad (11)$$

$$f(J) = \sum_{n=0}^{60} (n^{n-k} + g^{n+k}) \quad (12)$$

Simulation & Validation

Testing scenarios simulated variable crop types, moisture ranges (20–40% for maize, 30–50% for tomato, 50–75% for rice), and dynamic growth phases. Real-time system behavior was monitored via scopes and data exports to MATLAB workspaces, with additional graphical evaluations performed as shown in fig.2.

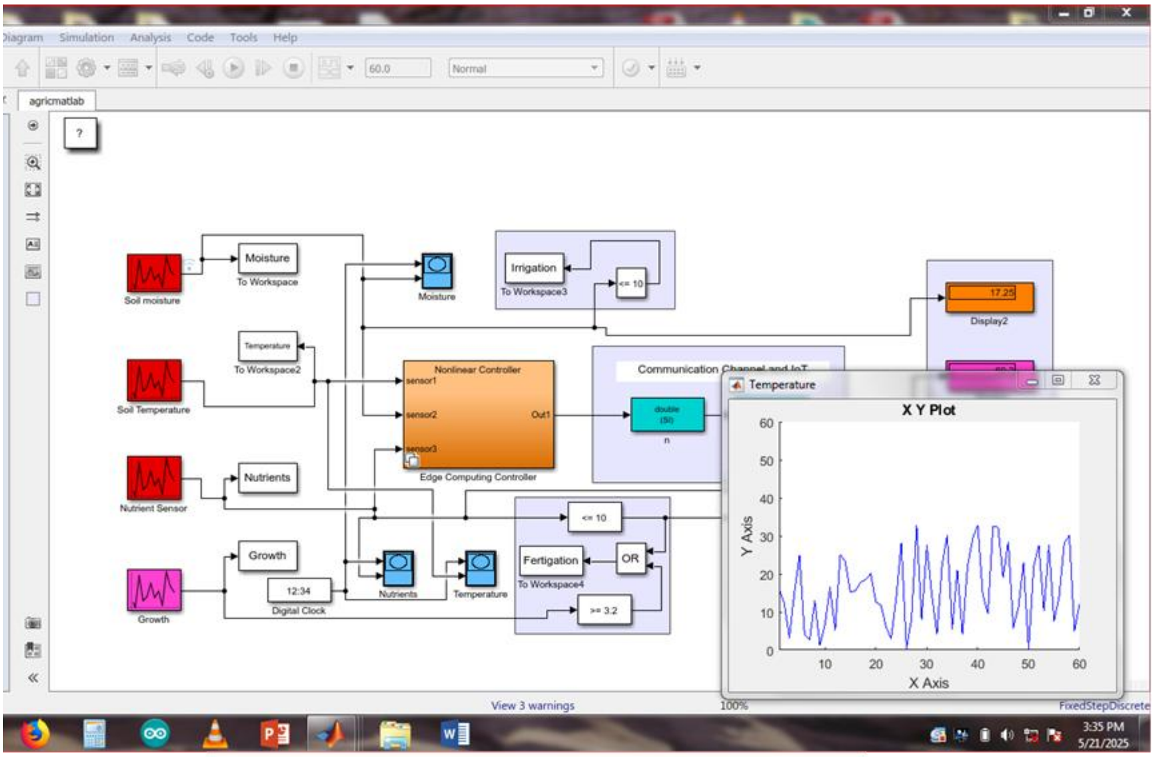


Fig.2: Test Simulation MATLAB environment

IV. Results Obtained

Simulation demonstrated that the system effectively maintained optimal moisture and nutrient levels. As seen in Table 2, irrigation was activated precisely when moisture fell below crop-specific thresholds such as <20% for maize, and fertigation responded to both nutrient concentration and growth metrics.

Time (s)	Moisture	Nutrients	Temp	growth	Crop-Specific Irrigation			Irrigation	fertigation
					Maize	Tomato	Rice		
1	33.6	5.05	11.7	1.36	0	0	1	1	1
2	17.3	35.9	6.06	3.61	1	1	1	1	1
3	8.61	22.8	3.01	2.66	1	1	1	1	0
4	39.3	38.5	13.7	3.80	0	0	1	1	1
5	80.4	50.0	28.1	4.64	0	0	0	0	1
6	1.10	41.9	0.38	4.04	1	1	1	1	1
7	23.3	14.4	8.15	2.04	0	1	1	1	0

8	93.3	2.61	32.6	1.18	0	0	0	0	1
9	22.6	40.4	7.93	3.94	0	1	1	1	1
10	78.5	18.0	27.5	2.31	0	0	0	0	0
11	41.0	34.7	14.3	3.53	0	0	1	1	1
12	11.9	41.6	4.17	4.02	1	1	1	1	1
13	63.4	54.5	22.2	4.96	0	0	0	0	1
14	86.2	20.0	30.1	2.46	0	0	0	0	0
15	15.8	13.5	5.53	1.98	1	1	1	1	0
16	60.1	54.0	21.0	4.93	0	0	0	0	1
17	11.7	39.7	4.11	3.89	1	1	1	1	1
18	62.6	41.4	21.9	4.01	0	0	0	0	1
19	83.5	35.8	29.2	3.60	0	0	0	0	1
20	94.0	3.99	32.9	1.29	0	0	0	0	1

The ANN models yielded strong results:

i. Irrigation model: Accuracy = 100%, F1 score = 1.0, Recall = 1.0, Precision = 1.0.

ii. Fertilization model: Accuracy = 91.7%, F1 score = 0.91, Recall = 87.5%, Precision = 95.6%.

Graphical plots shown in fig. 3 and fig.4 confirmed adaptive responses, irrigation cycles correlated tightly with moisture drops, while fertilizer application adjusted based on nutrient and growth readings. These results underline the system's ability to minimize over-irrigation and unnecessary fertilizer use.

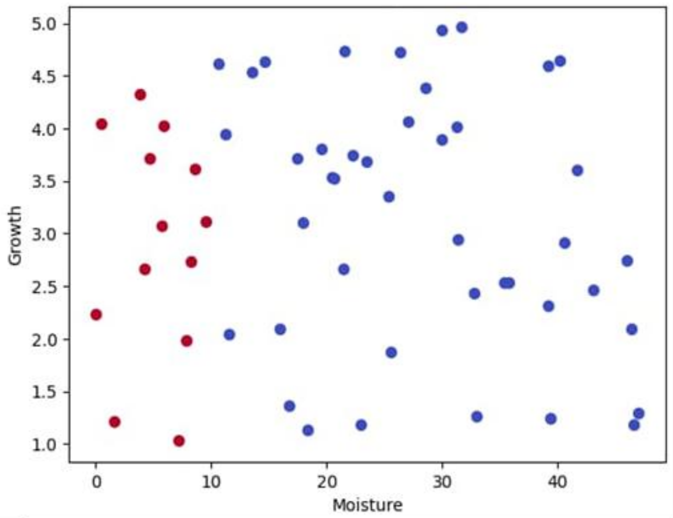
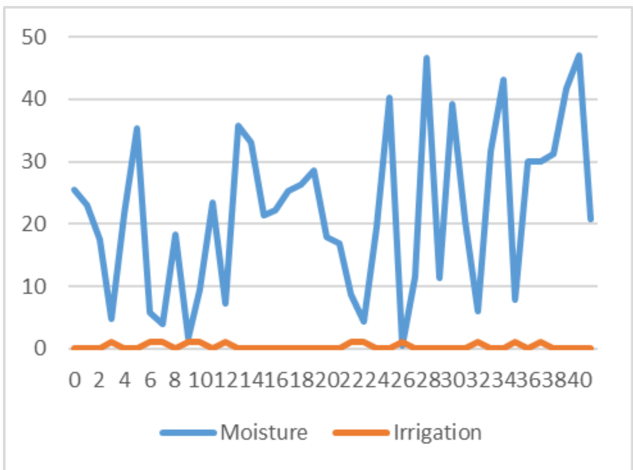


Fig. 3: Scattered plot of Growth vs Moisture



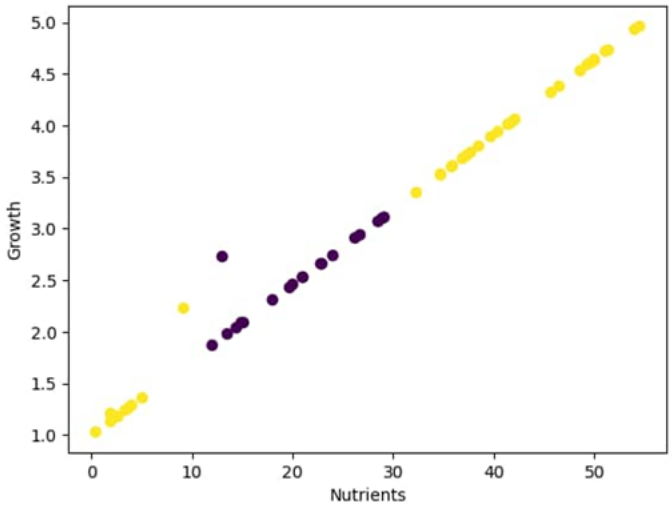
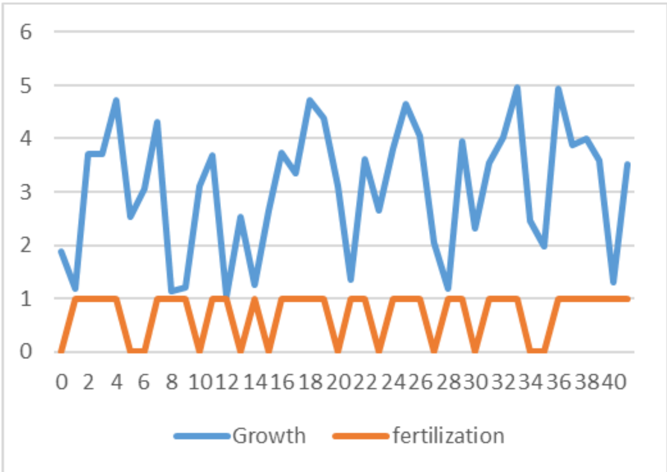


Fig.3: Plot of Growth vs Nutrient



V. Conclusion

This research demonstrates the feasibility and benefits of a real-time, crop-specific irrigation and fertilization system that integrates multi-sensor feedback, AI decision models, and advanced control logic. The approach offers substantial improvements in water and nutrient use efficiency, directly supporting sustainable agriculture. It is recommended that future work includes deploying prototype systems in actual farm settings, integrating reinforcement learning for continuous system adaptation, and developing farmer-friendly interfaces for widespread adoption. Such initiatives would further harness the power of smart irrigation systems to meet global food demands sustainably amid climate challenges.

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