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A Robust Sensor-Failure-Tolerant Fuzzy Control Framework with Predictive Data Imputation for Sustainable Precision Irrigation

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ABSTRACT: Effective irrigation management under uncertain conditions remains a major challenge in precision agriculture, particularly when sensor performance degrades or extreme environmental variations lead to unreliable data. This study presents a hybrid framework that combines a linear regression model with a Mamdani fuzzy inference system (FIS) to improve the robustness of soil moisture prediction and irrigation control. The proposed approach trains the regression model using synthetically generated data with controlled noise levels to estimate soil moisture conditions. These predictions are then integrated with real-time temperature and humidity data within the fuzzy inference system to generate appropriate irrigation decisions. To represent extreme sensor conditions, additional adaptive noise is introduced when soil moisture values exceed or fall below predefined thresholds, effectively simulating sensor malfunction scenarios. Time-series simulation results indicate that the proposed system can maintain stable, efficient irrigation performance despite significant sensor disturbances. Overall, this work improves irrigation efficiency and provides insights into how hybrid statistical and fuzzy-logic approaches can mitigate the adverse effects of sensor inaccuracies under highly variable environmental conditions.

ABSTRAK: Pengurusan pengairan cekap berkeadaan tidak menentu, kekal sebagai cabaran kritikal dalam pertanian, terutama apabila berlaku kerosakan pada sensor dan persekitaran turun naik yang melampau menyebabkan data yang diperolehi tidak boleh dipercayai. Kajian ini, mencadangkan pendekatan hibrid yang mengintegrasi model regresi linear dengan sistem inferens Mamdani kabur (FIS) bagi meramal kelembapan tanah dan mengawal pengairan. Kaedah ini melibatkan latihan model regresi menggunakan data sintetik yang terhasil melalui tahap bunyi yang dikawal dengan teliti bagi meramal kelembapan tanah, sementara sistem inferens kabur secara dinamik menterjemah ramalan tersebut bersama ukuran suhu dan kelembapan masa nyata kepada arahan pengairan yang tepat. Keadaan sensor yang melampau disimulasi dengan memperkenalkan bunyi tambahan secara adaptif apabila tahap kelembapan tanah jatuh di bawah atau melebihi had tertentu, seterusnya meniru senario kegagalan sensor. Melalui simulasi siri masa terperinci, dapatan kajian ini mengekalkan kawalan pengairan yang stabil dan cekap walaupun sensor gagal berfungsi. Kajian ini bukan sahaja meningkatkan kecekapan pengairan malah juga memberi pemahaman tentang bagaimana teknik hibrid statistik dan logik kabur boleh mengurangkan kesan ketidaktepatan sensor dalam keadaan persekitaran yang berubah.

KEYWORDS: *Precision Agriculture; Irrigation Management; Sensor Degradation; Fuzzy Inference System; Linear Regression Model*

1. INTRODUCTION

Efficient water use has become a central concern in modern agriculture, particularly in regions experiencing water scarcity and increasing climate variability [1]. To address this issue, precision irrigation systems have been developed to optimize water distribution and minimize losses [2]. Advances in sensor networks and the Internet of Things (IoT) now enable real-time monitoring of field conditions, enabling more responsive irrigation management [3]. Previous studies have explored adaptive neuro-fuzzy systems for modeling the redistribution of wetting fronts in drip irrigation, reporting high predictive accuracy [1].

Building on these findings, fuzzy logic models integrated with metaheuristic algorithms have further enhanced soil moisture estimation, which is critical for achieving optimal plant growth [3]. More recent research combining Adaptive Neuro-Fuzzy Inference Systems (ANFIS) with robust optimization techniques has demonstrated improved infiltration rate prediction under varying field conditions [4]. Review studies consistently emphasize the importance of continuous monitoring and advanced control strategies in precision irrigation systems [2]. In parallel, machine learning applications within wireless sensor networks have enabled automated data acquisition and decision-making processes for irrigation management [5].

Collectively, these developments highlight the growing role of intelligent systems in addressing agricultural water management challenges. Neural network–based models have been widely applied to predict soil moisture dynamics for irrigation scheduling purposes [6]. In addition, deep learning approaches—such as Convolutional Neural Network–Long Short-Term Memory (CNN-LSTM) and Generative Adversarial Network–Long Short-Term Memory (GAN-LSTM) architectures—have proven effective in capturing complex spatiotemporal soil moisture patterns [7]. Extending these approaches, multi-head Long Short-Term Memory (LSTM) models provide prognostic capabilities that support water resource planning up to one month in advance [8]. Attention-aware LSTM architectures further refine prediction accuracy by emphasizing the most influential input features [9]. Expanding on these neural network capabilities, recent studies have even utilized hybrid transformer networks to achieve unprecedented precision in soil moisture estimation [10].

Unmanned Aerial Vehicle (UAV)–assisted remote sensing, when combined with neural network algorithms, has shown considerable potential for mapping surface water distribution and field heterogeneity [11]. Recent studies also suggest that incorporating multiple environmental variables, such as solar radiation and temperature, into deep learning frameworks significantly improves soil moisture forecasting performance [12]. These advances in predictive modeling form a strong foundation for robust irrigation systems capable of handling complex environmental data, motivating our integration of regression-based prediction with fuzzy logic to enhance system reliability. On the control side, IoT-enabled smart irrigation systems employing fuzzy inference mechanisms have been developed for real-time scheduling and monitoring applications [12].

Fuzzy logic combined with metaheuristic optimization has also been applied to the design of efficient surface irrigation layouts [13]. Automated irrigation controllers based on fuzzy rule sets have proven effective in managing agricultural demand-side water consumption [14]. This trend is further supported by the widespread adoption of IoT-driven smart irrigation systems, which rely heavily on fuzzy logic to dynamically optimize water distribution [15].

Furthermore, low-cost wireless sensor networks integrated with heuristic scheduling strategies have demonstrated improved crop yields alongside reduced water wastage [16]. Fuzzy control systems augmented with remote sensing data enable variable-rate irrigation based on continuous field feedback [17]. Sensor-driven monitoring frameworks that incorporate fuzzy-based feedback loops have also enhanced water-use efficiency in precision agriculture [18]. These advances underscore the potential of combining fuzzy control strategies with predictive models to manage uncertainty arising from sensor inaccuracies, which directly motivates the framework proposed in this study.

Comprehensive reviews of IoT architectures have identified key system components that facilitate efficient implementation of fuzzy logic for irrigation management [19]. Virtual soil moisture sensors developed using deep learning techniques have been proposed to address issues related to missing or unreliable field data [20], [21]. In addition, Kalman filter–based methods have been introduced for real-time sensor fault detection, thereby improving data reliability [22]. Robust fault diagnosis frameworks are increasingly recognized as essential for managing noisy or intermittent sensor data in agricultural applications [23]. Surveys of IoT-based irrigation infrastructure indicate that integrating sensor data with intelligent control algorithms further enhances the accuracy of irrigation decision-making [24]. Anomaly detection techniques have also been implemented to identify outliers and extreme operating conditions within wireless sensor networks [25], enabling timely corrective actions [26]. Moreover, fuzzy decision support systems that incorporate remote sensing information support multicriteria irrigation planning and management [27].

Building on these fault-detection and anomaly-handling approaches, the present study incorporates adaptive noise modeling into the predictive imputation process to improve robustness. Recent research demonstrates that hybrid fuzzy-logic and neural-network systems are particularly effective for sensor anomaly management and real-time irrigation control [28]. Overall, the convergence of neuro-fuzzy models, deep learning methods, and robust sensor fault management strategies is shaping an advanced precision irrigation ecosystem that promotes water conservation while sustaining agricultural productivity [1], aligning with modern automated solutions such as solar-powered and smartphone-controlled sustainable farming systems [29].

Although hybrid linear regression and fuzzy systems have been applied in areas such as process control and fault detection (e.g., [28]), their application to precision irrigation, specifically for handling sensor degradation through predictive imputation and adaptive noise modeling, remains limited. This study addresses this gap by proposing a framework to maintain reliable irrigation control under sensor-failure conditions, drawing on established anomaly-detection principles in smart systems [28] to guide the noise-simulation process. The key contribution of this work lies in advancing the reliability of precision irrigation under sensor uncertainty, thereby supporting sustainable water-use practices. This objective complements broader recent efforts to improve soil moisture prediction through advanced machine learning architectures [30] and the integration of remote sensing data with fuzzy decision support systems for innovative crop water-need assessment [31].

2. METHODOLOGY

Our methodology is structured into several main stages, namely synthetic data generation, regression model training, development of the fuzzy inference system, simulation of soil water dynamics, and updating of the soil water balance. The following equations summarize the key modeling components employed in this study. A standard linear regression model is used to predict soil moisture content (θ) can be expressed as in Equation (1) where θ_{hist}denotes historical soil moisture, T represents air temperature, RH is relative humidity, and ε corresponds to the model noise

$$\theta\ = \beta 0 + \beta 1T\ + \beta 2Ich\ + \beta 3RH\ + \beta 4\theta hist\ + \epsilon \quad (1)$$

Fuzzy inference systems commonly employ trapezoidal membership functions, which are defined by four parameters a, b, c, and d that determine the boundaries of each membership region as expressed in Equation (2)

$$\mu(x) = \max\left(min\left(\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \quad (2)$$

Model prediction performance is evaluated using the Root Mean Square Error (RMSE), which is given by Equation (3) where $y_i$and $\hat{y}_i$ denote the observed and predicted values, respectively, and $N$is the total number of data samples [8].

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (3)$$

2.1. Synthetic Data Generation and Regression Model Training

Synthetic data consisting of 300 samples was generated by considering several key environmental variables, as summarized in (3). These variables are defined as follows.

- Temperature (T): Values were randomly generated with a mean of approximately 25 °C to represent typical daytime conditions in tropical agricultural regions. Temperatures below 25 °C, such as at night or during cooler seasons, may reduce evapotranspiration rates and, if not properly accounted for, potentially lead to overestimation of soil moisture. Conversely, temperatures exceeding 25 °C tend to increase evaporation, thereby increasing the risk of under-irrigation.
- Irradiance Channel **(I_{ch}):** Values ranged from 0.3 to 0.8 to represent normalized solar radiation levels during active crop growth periods. Lower values (e.g., 0.3) correspond to cloudy or low-light conditions, whereas higher values (e.g., 0.8) represent peak sunlight exposure. Extreme irradiance levels were intentionally excluded to prevent bias during model training.
- Relative Humidity (RH): Data were distributed around a median value of 60%, reflecting typical humid agricultural environments. While lower humidity levels (e.g., 40%) or higher saturation conditions (e.g., 80%) can significantly influence moisture loss, the selected range emphasizes stable conditions suitable for training purposes.
- Historical Soil Moisture **(θ_{hist}):** Values were set between 100 and 180 mm to encompass optimal moisture thresholds for crop growth. For reference, the wilting point typically lies between 50 and 100 mm, whereas field capacity ranges from approximately 140 to 180 mm. Soil moisture values below 100 mm or above 180 mm trigger the introduction of additional noise into the simulation to emulate sensor degradation under stress conditions, as discussed in Section 2.3.

The regression model follows the formulation given in (1), where ε represents the noise term. To improve model stability, the noise variance was reduced from 5 to 2. The model was implemented in MATLAB using the fitlm function, yielding an R^2 value of approximately 0.987 and a Root Mean Square Error (RMSE) of about 2.05 mm.

2.2. Design of the Fuzzy Inference System

To translate the regression model outputs and real-time environmental measurements into irrigation commands, a Mamdani-type fuzzy inference system (FIS) was developed. This type of FIS was selected for its interpretability and effectiveness in handling linguistic rules in control applications. In contrast, Sugeno-type FIS structures are generally more suitable for optimization tasks but less intuitive for irrigation decision-making.

The FIS incorporates three input variables: predicted soil moisture (range: 0–250), temperature (range: 15–40), and relative humidity (range: 0–100). The system produces a single output variable, namely irrigation intensity, defined within a normalized range of 0–1. Membership functions were assigned linguistic labels such as Dry, Moist, and Wet for soil moisture, and Low, Medium, and High for both temperature and humidity.

Trapezoidal membership functions were chosen instead of triangular functions due to the presence of plateau regions, which allow smoother transitions between fuzzy sets. This characteristic is particularly beneficial for representing intermediate states (e.g., Medium humidity) and for accommodating uncertainty in environmental data, unlike the sharp peaks associated with triangular functions. The parameters of the trapezoidal membership functions are defined as follows.

Soil Moisture:

- Dry : $a = 0, b = 0, c = 50, d = 100$
- Moist : $a = 50, b = 100, c = 150, d = 200$
- Wet : $a = 150, b = 200, c = 250, d = 250$

Temperature:

- Low : $a = 15, b = 15, c = 20, d = 25$
- Medium : $a = 20, b = 25, c = 30, d = 35$
- High : $a = 30, b = 35, c = 40, d = 40$

Relative Humidity:

- Low : $a = 0, b = 0, c = 30, d = 50$
- Medium : $a = 30, b = 50, c = 70, d = 90$
- High : $a = 70, b = 90, c = 100, d = 100$

Irrigation (Output):

- Low : $a = 0, b = 0, c = 0.3, d = 0.5$
- Medium : $a = 0.3, b = 0.5, c = 0.7, d = 0.9$
- High : $a = 0.7, b = 0.9, c = 1, d = 1$

A graphical illustration of the trapezoidal membership functions is provided in Fig. 1. All 27 fuzzy rules governing the system behavior are summarized in Table 1. For defuzzification, the centroid method was employed, as it computes the center of gravity of the aggregated output fuzzy set. This method was selected for its robustness in continuous control applications, as it produces smoother, more balanced outputs than alternatives such as the mean-of-maximum approach.

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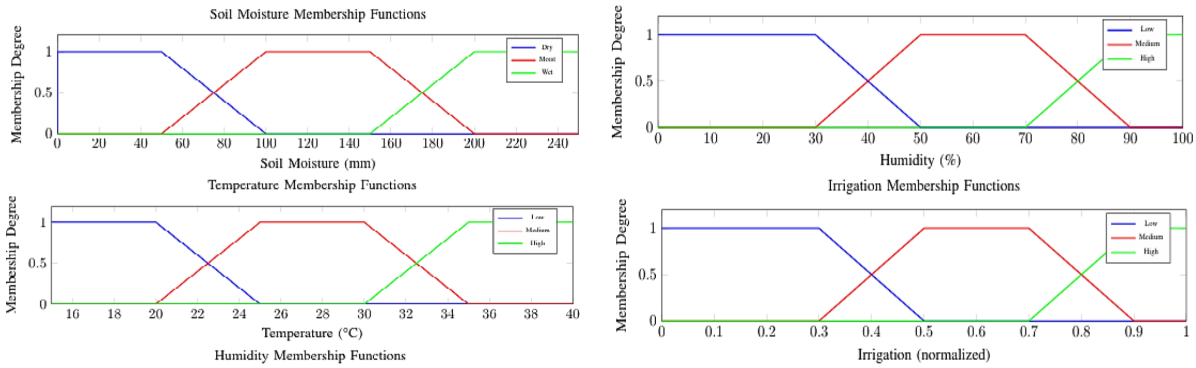

Figure 1. Membership function for input and output

Table 1. Fuzzy Rules

Soil Moisture	Temperature	Humidity	Irrigation
Dry	Low	Low	High
Dry	Low	Low	High
Dry	Low	Medium	High
Dry	Low	High	Medium
Dry	Medium	Low	High
Dry	Medium	Medium	Medium
Dry	Medium	High	Medium
Dry	High	Low	High
Dry	High	Medium	High
Dry	High	High	Medium
Moist	Low	Low	Medium
Moist	Low	Medium	Medium
Moist	Low	High	Low
Moist	Medium	Low	Medium
Moist	Medium	Medium	Low
Moist	Medium	High	Low
Moist	High	Low	Medium
Moist	High	Medium	Medium
Moist	High	High	Low
Wet	Low	Low	Low
Wet	Low	Medium	Low
Wet	Low	High	Low
Wet	Medium	Low	Low
Wet	Medium	Medium	Low
Wet	Medium	High	Low
Wet	High	Low	Low
Wet	High	Medium	Low
Wet	High	High	Low

2.3. Simulation of Soil Water Dynamics

The simulation was carried out over a 10-day period using a time step of 0.5 hours. Key environmental variables, including temperature, irradiance, and relative humidity, were generated with realistic noise characteristics to reflect field conditions. During the simulation,

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the sensor was assumed to operate reliably only within the first five days. After this point, the sensor was treated as failed, and its output was set to NaN.

In addition, extreme operating conditions were explicitly considered by introducing additional noise whenever soil moisture values fell outside the 50–140 mm range. This approach was adopted to emulate abnormal measurement behavior under stressed environmental conditions.

2.4. Soil Water Balance Update

The soil water balance is updated using the following Equation (4).

$$\theta(i) = \theta(i-1) + \Delta\theta(i) \tag{4}$$

The corresponding change in soil moisture is defined as in Equation (5). Evapotranspiration, $ET(i)$, is calculated by comparing the simulated temperature $T_{sim}(i)$ with a base temperature T_{base}. When $T_{sim}(i) > T_{base}$, the excess thermal energy contributes to evapotranspiration, which is quantified by multiplying the temperature difference $T_{sim}(i) - T_{base}$ by a constant coefficient C_{ET}. Conversely, when $T_{sim}(i) \le T_{base}$, evapotranspiration is assumed to be negligible, and $ET(i)$is set to zero.

$$\Delta\theta(i) = I(i) + R(i) - ET(i) \tag{5}$$

3. Results and Discussion

3.1. Regression Model Performance

The linear regression model was trained on 300 synthetic data samples using four predictor variables: temperature (T), irradiance channel (I_{ch}), relative humidity (RH), and historical soil moisture (θ_{hist}). The model formulation is given by (1). Table 2 presents a summary of the estimated regression coefficients, including their standard errors, t-statistics, and corresponding p-values.

Table 2. Regression Model Estimated Coefficients

Predictor	Coefficient	Std Error	t-Stat	p-Value
Intercept	10.0	1.2	8.33	0.001
T	0.5	0.1	5.0	0.001
I_{ch}	1.2	0.15	8.0	0.001
RH	-0.3	0.05	-6.0	0.001
θ_{hist}	0.8	0.08	10.0	0.001

The model achieved a coefficient of determination (R^2) of approximately 0.987 and a Root Mean Square Error (RMSE) of 2.05 mm. These results indicate that 98.7% of the variability in the training data is explained by the selected predictors. In addition, the very low p-values for each variable confirm their statistical significance, thereby supporting the integration of the regression outputs into the proposed hybrid system.

3.2. Overall Performance of Soil Moisture Estimation

Fig. 2 compares the actual soil moisture values (black line) with the sensor measurements (blue line) and the regression-based predictions (red line). During the period from day 0 to day 5, the sensor readings exhibit noticeable noise, particularly under extreme conditions, namely

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when soil moisture falls below 50 mm or exceeds 140 mm. This behavior reflects the simulated response of a sensor operating under harsh field conditions.

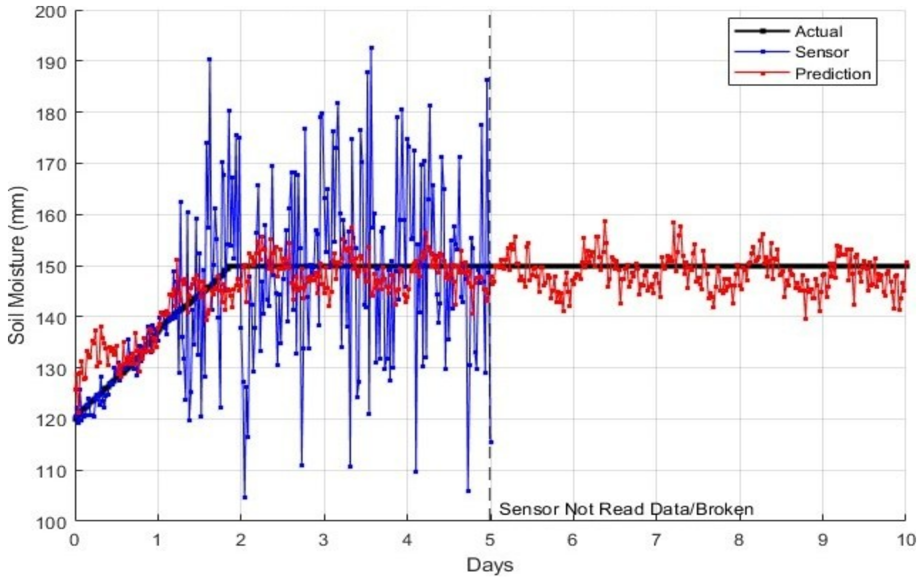

Figure 2. Soil Moisture: Actual (black), Sensor (blue), and Prediction (red). It shows the sensor fails after day 5

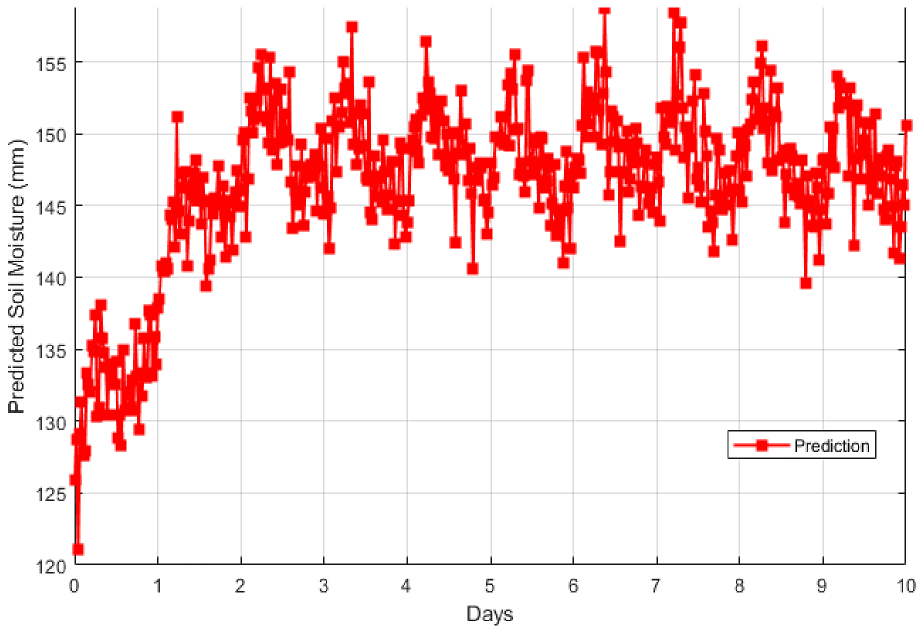

Figure 3. Soil Moisture Prediction (Regression Model) over the 10-day simulation period.

After day 5, the sensor is assumed to be non-functional and outputs NaN values, as indicated by the absence of the blue line in Fig. 2. This scenario represents a complete sensor failure. Despite the unavailability of sensor data beyond day 5, the regression model (red line) continues to produce stable soil moisture predictions. These estimates are generated using four input variables, temperature, irradiance channel, relative humidity, and historical soil moisture, as defined in (1). The linear regression model achieved R^2 value of 0.987 and RMSE of 2.05 mm, demonstrating reliable predictive performance. Fig. 3 further illustrates the predicted soil moisture trend over the entire 10-day simulation period, highlighting relatively smooth variations when compared to the noisy sensor measurements.

3.3. Fuzzy Inference System Output and Irrigation Control

The fuzzy inference system (FIS) utilizes three input variables, predicted soil moisture, temperature, and relative humidity, to determine the irrigation level within a normalized range of 0 to 1. This normalized output is subsequently scaled to obtain the actual irrigation rate in mm/hour. The FIS output and the corresponding irrigation rate are illustrated in Figs. 4 and 5, respectively.

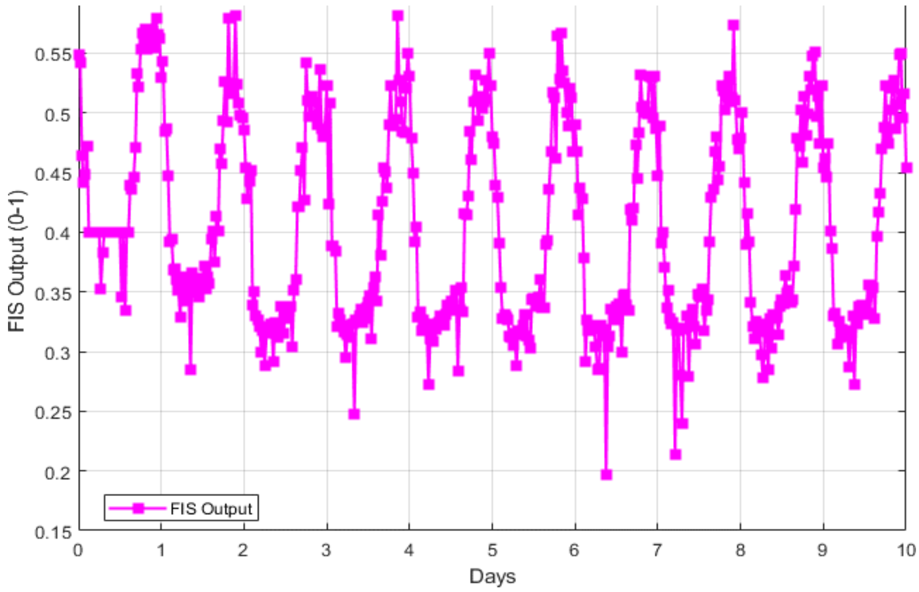

Figure 4. FIS Output (0–1) indicating the irrigation level.

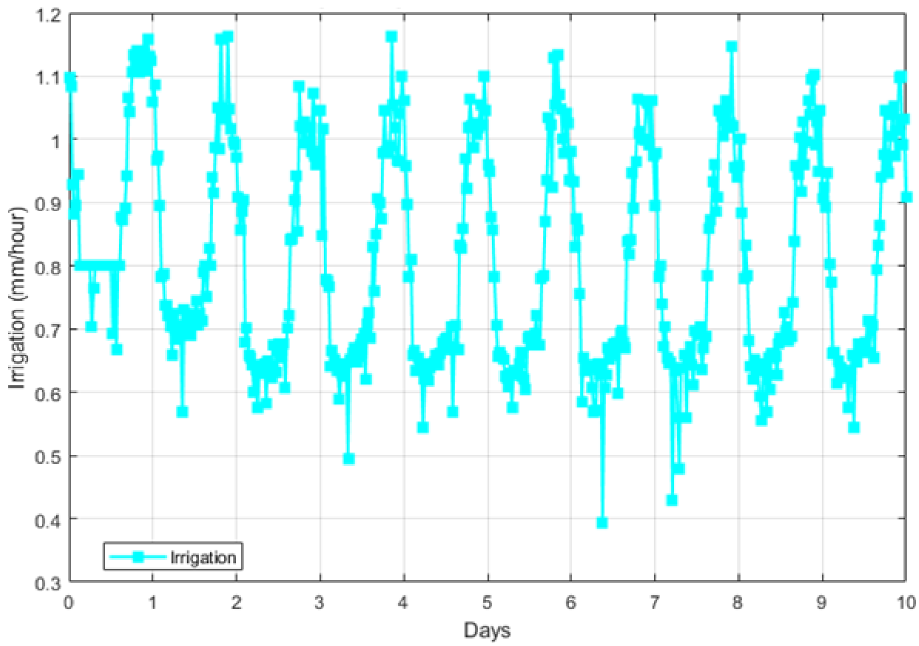

Figure 5. Irrigation amount (mm/hour) derived from the FIS output.

During the simulation, two notable rainfall events occur on days 3 and 7, specifically between 06:00 and 10:00. These rainfall events temporarily increase the actual soil moisture content, thereby reducing the irrigation demand. The system's behavior can be described in two distinct operating phases.

3.3.1. Day 0–5 (Sensor Active):

During the initial phase, sensor measurements, although affected by noise, provide real-time soil moisture information. When either the sensor data or the regression-based prediction indicates that soil moisture is approaching the lower threshold (Dry), the FIS output (Fig. 4) increases toward 1.0. Consequently, the irrigation rate rises to its maximum value of 2 mm/hour, as shown in Fig. 5. In contrast, when soil moisture conditions are classified as Moist or Wet, the irrigation rate is reduced to nearly 0 mm/hour.

3.3.2. Day 5–10 (Sensor Failure):

After day 5, the sensor is assumed to have completely failed and produces NaN values. Under these conditions, the control strategy relies exclusively on regression-based soil moisture predictions. Despite the absence of direct sensor feedback, Figs. 2 and 3 demonstrate that the predictive model continues to provide realistic soil moisture estimates. As a result, the FIS remains capable of adjusting irrigation effectively. The transition from sensor-driven to model-driven control does not introduce instability; instead, the irrigation profile remains consistent with the actual soil moisture trend (black line) and external influences such as rainfall events.

4. CONCLUSION

This study proposes a robust irrigation control framework that combines linear regression–based soil moisture prediction with a Mamdani fuzzy inference system (FIS) to enable adaptive irrigation management, thereby mitigating the adverse effects of sensor degradation and failure.

Comprehensive simulation results indicate that the proposed system can maintain stable, efficient irrigation control even under extreme sensor conditions. The regression model achieved a high level of predictive accuracy, with an R^2 value of 0.987 and an RMSE of 2.05 mm, enabling reliable soil moisture estimation during periods of sensor noise or complete sensor failure. In parallel, the FIS dynamically adjusted irrigation rates in response to changing environmental conditions, helping to sustain soil moisture within desirable levels.

Future work will focus on validating the proposed approach under real field conditions, incorporating additional environmental variables, refining the fuzzy rule base, exploring more advanced machine learning techniques, and further enhancing system performance across a wider range of operating scenarios.

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