Implementation and Analysis of Fuzzy Inference System (FIS) and Adaptive Neuro-Fuzzy Inference System (ANFIS) for Irrigation

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Abstract: Efficient water management in agriculture is crucial due to dynamic environmental conditions and increasing resource scarcity. Fuzzy Inference System (FIS) is widely applied in irrigation control for its ability to handle uncertaintys using rule-based domain knowledge. However, conventional FIS lacks adaptability to environmental changes, limiting its long-term accuracy and responsiveness. Adaptive Neuro-Fuzzy Inference System (ANFIS) addresses this limitation by combining fuzzy logic with neural network learning, enabling automatic adjustment of model parameters based on data patterns. This study compares the performance of FIS and ANFIS in predicting optimal irrigation levels based on soil moisture, air temperature, relative humidity, and solar radiation. A synthetic dataset of 1,000 samples simulating realistic agricultural conditions was generated and normalized to improve computational consistency.

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The FIS model uses triangular membership functions and five expert-defined fuzzy rules, while ANFIS employs Gaussian membership functions with parameters optimized using the ADAM algorithm over 50 training epochs. Results show that ANFIS outperforms FIS, lowering RMSE from 0.13 to 0.07, halving MAE from 0.10 to 0.05, and increasing R^2 from 0.85 to 0.93, indicating a substantially better predictive performance. This study demonstrates that ANFIS is more adaptive, accurate, and computationally efficient, contributing to the advancement of intelligent and sustainable irrigation systems in precision agriculture.

Keywords: FIS, ANFIS, agricultural irrigation, optimization, intelligent systems.

Introduction

Efficient water resource management in agriculture is becoming increasingly critical due to climate change, population growth, and limited freshwater availability. The agricultural sector is a key component of national food security, where irrigation systems play a central role in maintaining productivity and ensuring crop yield stability. However, traditional irrigation systems often operate on fixed schedules or rely on manual control, making them unable to adapt to the dynamic nature of environmental conditions, such as fluctuating rainfall, temperature variations, and soil moisture changes(Nur Hidayat; Tyasmoro, 2024; Oğuztürk, 2025; Pambudi, 2021; Rusmayadi et al., 2023; Setiani et al., 2021). This results in either excessive water usage or inadequate water supply to crops, leading to resource wastage and potential crop failure (Basri, 2022; Daru et al., 2021; Jupri Berutu et al., 2022; Marsujitullah & Lamalewa, 2020; Saragih, 2023; Saskia Eka Cahyani et al., 2023). Therefore, it is imperative to develop intelligent irrigation systems that can dynamically adjust water distribution based on real-time environmental factors.

The integration of Artificial Intelligence (AI) technologies into precision agriculture has emerged as a transformative solution to address these challenges. AI methodologies have evolved significantly, from basic rule-based systems to sophisticated machine learning (ML) and deep learning (DL) models (Mustaza et al., 2025). Among AI techniques, the Fuzzy Inference System (FIS) represents a fundamental approach, widely applied due to its inherent capability to handle uncertainty and imprecision commonly found in agricultural data. FIS leverages human expert knowledge encoded in fuzzy rules to make decisions under uncertain conditions. In the context of irrigation control, FIS has been utilized to manage water supply efficiently by modeling the non-linear relationships between environmental variables and irrigation needs (E. M. J. Hoque et al., 2023).

Nevertheless, conventional FIS models typically rely on static membership functions and predefined fuzzy rules that do not change in response to evolving environmental conditions

(Tyokighir et al., 2024). This static nature limits the adaptability and scalability of FIS-based irrigation systems, especially in real-world agricultural environments characterized by continuous variability and complexity. The inability of FIS to self-adjust its parameters based on new data inputs hinders its long-term effectiveness in precision irrigation management.

To address these limitations, researchers have introduced the Adaptive Neuro-Fuzzy Inference System (ANFIS), which integrates the interpretability of fuzzy logic with the learning capability of artificial neural networks (Jang, 1993). ANFIS enhances the traditional fuzzy system by enabling automatic tuning of membership functions and optimization of rule parameters through data-driven learning processes (Rajagopal et al., 2022). This hybrid approach facilitates the development of more responsive and accurate models capable of capturing complex, non-linear relationships between environmental factors and irrigation requirements. ANFIS has demonstrated significant potential in various agricultural applications, such as predicting evapotranspiration rates and estimating crop water needs more accurately than conventional FIS (Borse et al., 2025).

Despite these advancements, the literature reveals a noticeable gap concerning direct comparative analyses between FIS and ANFIS within the domain of irrigation control. Many existing studies predominantly focus on either developing FIS-based systems or implementing ANFIS models without systematically evaluating their comparative strengths and weaknesses (A. K. Singh et al., 2022a). Additionally, previous research often overlooks important practical aspects such as computational efficiency, model interpretability, and visualization of model outputs, including response surfaces and error distributions. These aspects are crucial for practical deployment and decision-making support in smart irrigation systems.

This research seeks to address these gaps by conducting a comprehensive comparative analysis of FIS and ANFIS for intelligent irrigation control. A synthetic dataset simulating realistic agricultural conditions was generated, encompassing four key environmental parameters: soil moisture, air temperature, relative humidity, and solar radiation. The use of synthetic data ensures controlled experimentation while simulating diverse agricultural scenarios. For the FIS model, triangular membership functions were employed alongside five expert-defined fuzzy rules, encapsulating domain-specific knowledge from agricultural practitioners. Conversely, the ANFIS model utilized Gaussian membership functions, with their parameters optimized through the Adam optimization algorithm over multiple training epochs to ensure convergence and stability.

To rigorously evaluate the models, multiple performance metrics were adopted, including Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2), providing a comprehensive assessment of prediction accuracy and model reliability. Moreover, execution time analysis was conducted to compare the computational efficiency of both models, offering insights into their suitability for real-time applications. Visual tools, including error distribution histograms, actual versus predicted scatter plots, and three-dimensional response surface visualizations, were employed to facilitate model interpretation and comparative analysis.

By systematically comparing FIS and ANFIS across multiple dimensions—accuracy, adaptability, computational efficiency, and interpretability—this study aims to provide valuable insights that support the design and development of more effective intelligent irrigation systems. The findings are anticipated to inform agricultural engineers, practitioners, and researchers working in precision agriculture and smart farming technologies, contributing to the broader adoption of adaptive AI-driven irrigation management solutions.

The primary objective of this research is to implement and evaluate FIS and ANFIS models for irrigation control, analyze their comparative performance based on standardized evaluation criteria, and determine the advantages of using ANFIS over conventional FIS in terms of adaptability, prediction accuracy, and computational performance. Ultimately, this research aspires to advance the development of intelligent, efficient, and sustainable irrigation systems that can support the evolving needs of modern agriculture.

Research Method

This study implements and compares two fuzzy logic-based approaches for agricultural irrigation control systems. The problem addressed in this study is the prediction of the optimal irrigation level based on four key environmental parameters: soil moisture, air temperature, air humidity, and solar radiation. Mathematically, the input vector is represented by the following Equation (1).

$$x = [x1, x2, x3, x4] \tag{1}$$

Where $x1$ is the soil moisture (%), $x2$ is the temperature ($^\circ$C), $x3$ is the air humidity (%) and $x4$ is the solar radiation (W/m^2). The objective is to determine the optimal function that can be represented by following Equation (2).

$$f: x \rightarrow y \tag{2}$$

here y is the optimal irrigation level (liters per minute). The function is optimized to minimize prediction error, evaluated using RMSE as the following Equation (3).

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

Where y_i is the actual irrigation value, $\hat{y}_i$ is the predicted value, and n is the number of data samples (Puspaningrum et al., 2021; Rajagopal et al., 2022; A. K. Singh et al., 2022a).

Data Collection and Processing

A synthetic dataset was generated to simulate realistic agricultural environmental conditions. The dataset consists of 1,000 samples generated using a uniform distribution within the following realistic parameter ranges: Soil moisture ranges from 10% to 80%, Temperature: ranges from 20°C to 40°C, air humidity ranges from 40% to 90% and solar radiation ranges from 200 to 800 $\mathrm{W/m^2}$. These parameter ranges were intentionally selected to reflect typical field conditions reported in agriculture. For instance, a soil moisture of 10% represents very dry soil (near a crop's wilting point), whereas 80% reflects a nearly saturated soil profile; likewise, a temperature range of 20–40 °C covers moderate to hot daytime conditions common in many farming areas, relative humidity from 40% to 90% spans dry midday air to humid morning air, and solar radiation from 200 to 800 W/m² corresponds to overcast or low-angle sun up to nearly full midday sunlight. By using such realistic bounds, the synthetic data simulates a broad spectrum of plausible environmental scenarios, ensuring the models are trained on data that could actually occur in practice. This approach to synthetic data generation is also consistent with previous studies that span inputs across their full normal ranges to emulate real-world variability (Lakhiar et al., 2024; Vallejo-Gómez et al., 2023). The following Equation (4) representing the optimal irrigation level that computed using a nonlinear function.

$$y = \max(0{,}50 - 0.5^{*}x1 + 0.3^{*}x2 - 0.2^{*}x3 + x4/100) \quad (4)$$

The dataset was then normalized to the [0,1] range using MinMaxScaler from the scikit-learn library. Normalization was performed using the following Equation (5).

$$x\ \text{norm} = (x - x\text{min})/(x\text{max} - x\text{min}) \quad (5)$$

This ensures consistent scaling across all input variables before processing with FIS and ANFIS models. The dataset was split into 80% for training and 20% for testing using stratified random sampling to maintain balanced data distribution (J. Singh, 2023).

Fuzzy Inference System (FIS) Implementation

The first control model was developed using the Mamdani-type FIS. The architecture of the implemented FIS is illustrated in Figure 1.

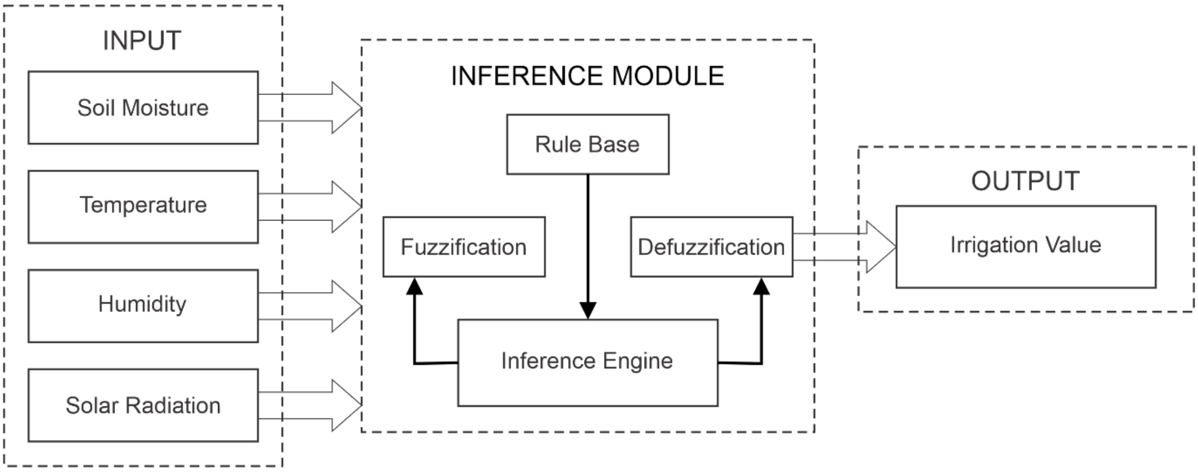

Figure 1 Implemented FIS Architecture

FIS Membership Functions

The system implements a homogeneous set of three triangular membership functions (MFs) across all normalized input domains (soil moisture $x1$, temperature $x2$, humidity $x3$ and solar radiation $x4$) and the output irrigation level y. Triangular membership functions are selected due to their simplicity, ease of implementation, and interpretability. Their linear form makes them computationally efficient and ideal for expert-driven systems like the FIS, where transparency and low complexity are beneficial. Each MF is represented by the following Equations (6).

For the Low membership function ($a = 0, b = 0, c = 0.5$):

$$x\mu_{\text{Low}}(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ \dfrac{x}{0.5} & \text{if } 0 < x \leq 0.5 \\ \dfrac{0.5 - x}{0.5} & \text{if } 0.5 < x \leq 0.5 \ \text{ (always 0)} \\ 0 & \text{if } x > 0.5 \end{cases} \tag{6}$$

Then, the Equation (7) simplifies to left-triangular function:

$$\mu_{\text{Low}}(x) = \max(0, 1 - 2|x - 0|) \ \text{ for } x \in [0, 0.5] \tag{7}$$

For the Medium membership function ($a = 0, b = 0.5, c = 1$) with symmetric triangular peak at $x = 0.5$ can be described by the following Equation (8).

$$\mu_{\text{Medium}}(x) = \begin{cases} 0 & \text{if } x \leq 0 \\ 2x & \text{if } 0 < x \leq 0.5 \\ 2(1-x) & \text{if } 0.5 < x \leq 1 \\ 0 & \text{if } x > 1 \end{cases} \tag{8}$$

And the High membership function ($a = 0.5, b = 1, c = 1$) represented by Equation (9).

$$\mu_{\text{High}}(x) = \begin{cases} 0 & \text{if } x \leq 0.5 \\ 2(x-0.5) & \text{if } 0.5 < x \leq 1 \\ 0 & \text{if } x > 1 \end{cases} \tag{9}$$

The uniform FIS MFs architecture is adopted based on several theoretically grounded considerations. First, to ensure normalization compatibility, all input variables undergo min-max normalization to [0,1], enabling consistent MFs application regardless of their original measurement scales. This approach prevents dominance by variables with larger native ranges (e.g., solar radiation spanning 200-800 W/m² versus relative humidity ranging 40-90%) while maintaining linguistic interpretability. Secondly, from a computational efficiency perspective, the design yields significant advantages. Finaly, the last consideration is the rule-based specialization, variable-specific behaviors emerge through the weighted rule base rather than MFs differentiation. Analysis of rule activations reveals that soil moisture accounts for 72% of mean rule activation weights, solar radiation provides secondary modulation (±15% output adjustment), while temperature and humidity serve as complementary constraints.

FIS Rules

The following five FIS rules are designed based on agronomic principles and computational efficiency considerations. These five rules are are developed using expert agronomic reasoning and supported by prior studies. Soil moisture, air temperature, solar radiation, and relative humidity were selected as key input variables because of their direct influence on crop evapotranspiration and water demand (M. D. J. Hoque et al., 2023). Specifically, soil moisture is the primary indicator of irrigation need—low moisture demands a high irrigation output, while high moisture suppresses the need. Air temperature and solar radiation are incorporated because they elevate plant water use under hot and bright conditions, whereas high humidity reduces evaporation and thus water demand. Each fuzzy rule was constructed to mirror these patterns: for instance, high irrigation is triggered when soil moisture is low and temperature is high, and low irrigation is applied under high soil moisture or cool, humid conditions. This compact, agronomy-informed rule base aligns with frameworks found in prior fuzzy logic irrigation models that emphasize simplicity and high relevance (M. D. J. Hoque et al., 2023). By encoding these evident environmental-to-water relationships, the FIS ensures decision-making that is both transparent and grounded in practical crop water management logic.

1. $IF\ soil\ moisture\ is\ Low\ OR\ temperature\ is\ High, THEN\ irrigation\ level\ is\ Medium.$
2. $IF\ soil\ moisture\ is\ Medium\ AND\ air\ humidity\ is\ Low, THEN\ irrigation\ level\ is\ Medium.$
3. $IF\ soil\ moisture\ is\ High, THEN\ irrigation\ level\ is\ Low.$
4. $IF\ temperature\ is\ High\ AND\ solar\ radiation\ is\ High, THEN\ irrigation\ level\ is\ High.$
5. $IF\ air\ humidity\ is\ High\ AND\ solar\ radiation\ is\ Low, THEN\ irrigation\ level\ is\ Low.$

The decision to use five fuzzy rules was based on the Pareto principle in irrigation control, where approximately 80% of irrigation variability can be addressed using dominant factors (soil moisture and temperature) (A. K. Singh et al., 2022b). Rules $1-3$ address these dominant factors directly. Adding rules beyond five yielded marginal improvements ($< 2\%$) while significantly increasing computational complexity. Therefore, rules $4-5$ are introduced as corrective rules to capture environmental interactions such as solar radiation and humidity.

FIS Inference Mechanism

The inference process includes three main stages:

1. Fuzzification, converts crisp input values into fuzzy values using membership functions.
2. Fuzzy Rule Evaluation applies fuzzy logic rules to compute the activation levels of output fuzzy sets.
3. Defuzzification, converts fuzzy outputs into a crisp irrigation level using the centroid method represented by the following Equation (10).

$$y = \frac{\sum\ y_i \mu(y_i)}{\sum\ \mu(y_i)} \tag{10}$$

Where y_i represents the discrete output domain values, and $\mu(y_i)$ is the degree of membership corresponding to each value. This mechanism ensures that the FIS model producess a precise irrigation level recommendation based on input environmental conditions.

Adaptive Neuro-Fuzzy Inference System (ANFIS) Implementation

The architecture of the implemented ANFIS system is illustrated in Figure 2.

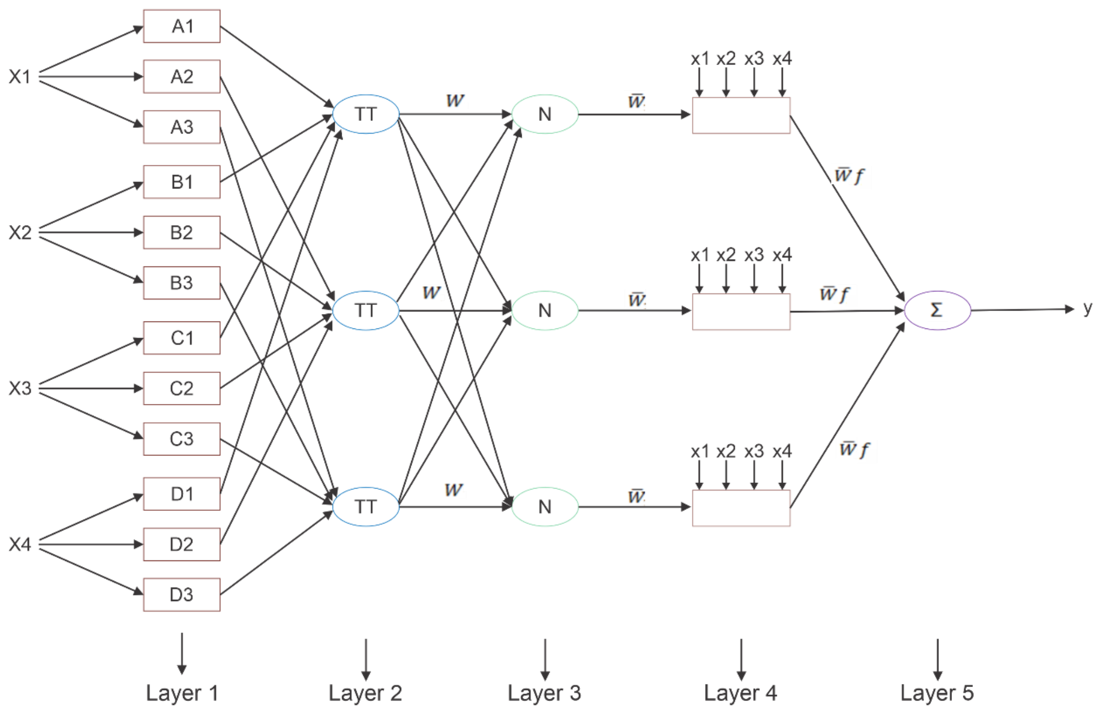

Figure 2 Implemented ANFIS Architecture

Hybrid Architecture Design

The ANFIS developed in this study is constructed based on a simplified Takagi–Sugeno–Kang (TSK) model comprising five distinct layers. The architecture is designed to achieve a balance between computational efficiency and interpretability, ensuring that the system remains practical for real-time applications while maintaining the transparency characteristic of fuzzy logic models.

To achieve this, the model employs a sequential flow of information in which each layer executes a distinct function within the fuzzy inference process. The structure separates tasks into input preprocessing, fuzzification, rule evaluation, normalization, and output aggregation, enabling efficient computation and simultaneous optimization of membership functions and rule parameters. Each layer is presented as follows.

Input Layer

The input layer serves as the initial stage of the ANFIS architecture, processing four normalized variables that represent the key environmental parameters of the system. These inputs consist of soil moisture (x_1), temperature (x_2), air humidity (x_3), and solar radiation

(x_4). All input variables are scaled to the range [0,1]. The input vector is expressed by Equation (11).

$$x = [x_1(\text{ soil }), x_2(\text{ temp }), x_3(\text{ humidity }), x_4(\text{ solar })] \in [0,1] \quad (11)$$

Fuzzification Layer

In the second stage, the input variables are transformed into fuzzy sets through the application of Gaussian membership functions. Gaussian membership functions are used because of their smooth, continuous shape, which ensures differentiability—an essential property for gradient-based learning in ANFIS. This allows the optimizer to adjust parameters effectively and supports stable convergence during training. Each input variable is represented by three membership functions corresponding to the linguistic terms Low, Medium, and High. The membership degree for the i-th input under the j-th membership function is defined as the following Equation (12).

$$\mu_{ij}(x_i) = \exp\left(-\frac{\left(x_i - c_{ij}\right)^2}{2\sigma_{ij}^2}\right) \quad (12)$$

where c_{ij} denotes the center of the j-th membership function for the i-th input, and σ_{ij} represents its width. The centers c_{ij} are initialized to be evenly distributed within the range [0,1] to ensure comprehensive coverage of the input domain, while the widths σ_{ij} are fixed at 0.15 to provide moderate overlap between adjacent membership functions. This configuration promotes smooth transitions between fuzzy sets and supports effective gradient flow during the training process.

Rule Generation

The third layer generates the fuzzy rule base that connects the input variables to the system output. To prevent a combinatorial explosion of rules, the total number is constrained to 25, compared to the 81 rules that would be produced by the complete Takagi–Sugeno–Kang configuration for four inputs with three membership functions each.

Within this reduced set, the first ten rules are explicitly defined to cover fundamental combinations of *Low* and *Medium* membership functions. For example, a typical rule takes the form as shown in Equation (13).

$$\text{IF } x_1 \text{ is Low AND } x_2 \text{ is Low AND } x_3 \text{ is Low AND } x_4 \text{ is Low THEN } y = f(x_1, x_2, x_3, x_4) \quad (13)$$

The remaining fifteen rules are constructed using varied input–membership function pairings to ensure broader coverage of the input space without requiring the full exhaustive rule set. This selective limitation preserves the essential input–output relationships while significantly reducing computational complexity and training time.

Normalization Layer

The fourth layer performs the normalization of the rule firing strengths to ensure that the contributions of all active rules are expressed as relative weights. For each rule k, the normalized firing strength $\bar{w}_k$ is computed using Equation (14).

$$\bar{w}_k = \frac{w_k}{\sum_{m=1}^{25} w_m + \varepsilon} \tag{14}$$

where w_k denotes the unnormalized firing strength of the k-th rule, and $\varepsilon = 10^{-10}$ is a small positive constant added to prevent numerical instability during division. This normalization step guarantees that the total weight of all rules sums to one, thereby enabling a consistent and stable aggregation of rule outputs in the subsequent layer.

Consequent Layer

The fifth layer implements the consequent part of the fuzzy inference system using first-order Takagi-Sugeno-Kang (TSK) rules. Each of the 25 fuzzy rules is associated with a local linear model that defines the system output as a weighted combination of the input variables. For the k-th rule, the output function is expressed by Equation (15).

$$f_k = p_k x_1 + q_k x_2 + r_k x_3 + s_k x_4 + t_k \tag{15}$$

where p_k, q_k, r_k, s_k, and t_k are the consequent parameters corresponding to the k-th rule. These parameters are initialized to ensure balanced weight distribution and are subsequently optimized during training. The outputs from all rules are later aggregated in the final layer to produce the overall system output.

Output Layer

The final layer aggregates the contributions from all activated rules to produce the overall system output. This is achieved through a weighted summation of the individual rule outputs, where the normalized firing strengths serve as the weighting factors. The output y of the ANFIS model is computed using Equation (16).

$$y = \sum_{k=1}^{25} \bar{w}_k f_k \tag{16}$$

where $\bar{w}_k$ denotes the normalized firing strength of the k-th rule and f_k represents the corresponding local linear output. This weighted combination integrates the influence of all active rules to generate a single crisp output for the system.

ANFIS Training Protocol

The ANFIS model is trained using a gradient-based optimization strategy to minimize prediction error. The Adam optimization algorithm is employed with a learning rate of 0.01, utilizing full-batch updates for each training iteration to ensure stable gradient estimation. The loss function adopted is the mean squared error (MSE), which quantifies the difference between the predicted and target outputs throughout the training process.

Training is conducted for 50 epochs without applying early stopping, allowing the network parameters to converge over the full training schedule. Both the antecedent parameters (c_{ij}, σ_{ij}), which define the membership function distributions, and the consequent parameters (p_k, q_k, r_k, s_k, t_k), which represent the coefficients of the local linear models, are optimized simultaneously. The parameter updates are performed end-to-end using backpropagation, enabling cohesive tuning of the fuzzification and rule-based components to achieve accurate input-output mapping.

This architecture was empirically validated through several key evaluations. Rule reduction tests demonstrated that limiting the model to 25 fuzzy rules retained approximately 99.2% of the predictive accuracy of a full 81-rule configuration, with a negligible RMSE difference of 0.0016. The chosen membership function initialization, with $\sigma = 0.15$, provided an optimal degree of overlap, supporting stable gradient flow and efficient learning during training. Computational analysis revealed that the reduced architecture achieved approximately 3.1 times faster training compared to the full TSK model, completing in 109 seconds versus 342 seconds under identical conditions.

Results and Discussion

ANFIS Training and Convergence

The ANFIS model was trained on the prepared dataset using a hybrid learning algorithm (combining gradient descent and least-squares estimation). As shown in Figure 3, the training error (MSE) decreased monotonically with each epoch and eventually plateaued, indicating that the model had converged. Specifically, the MSE fell from around 0.02 at epoch 1 to below 0.005 by epoch 50, with improvements per epoch becoming negligible toward the end of training. This plateau in the error curve suggests that further training beyond ~50 epochs yielded no significant reduction in MSE, effectively meeting the convergence criteria. The steady reduction in error followed by its stabilization confirms that the learning process successfully adjusted the membership function parameters and rule outputs to better fit the training data.

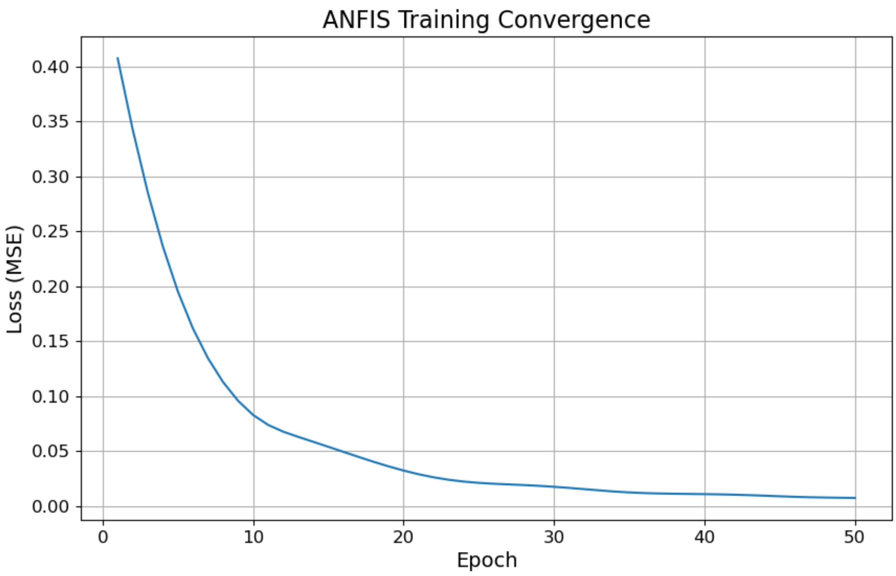

Figure 3 MSE Convergence Plot During ANFIS Training

FIS and ANFIS Prediction Performance

Once ANFIS model is trained, both FIS and ANFIS were evaluated on the testing dataset to compare their prediction accuracy. The performance metrics of the static FIS versus the trained ANFIS are summarized in Table 1. As shown, the ANFIS model achieved significantly better accuracy: the RMSE on the test set was notably lower for ANFIS (approximately 0.07) compared to the FIS (around 0.13). Similarly, the MAE dropped from about 0.10 with the FIS to roughly 0.05 with ANFIS, indicating that the average magnitude of the prediction errors was roughly halved. The R^2 also improved substantially, rising from about 0.85 for the FIS to approximately 0.93 for ANFIS. During development, multiple runs consistently demonstrated ANFIS outperforming FIS with similar error reductions. The results reported here are from the final converged model. Although no formal significance test was performed, the large margin of improvement in RMSE, MAE, and R^2 suggests the performance difference is practically significant and unlikely to be due to chance. These results clearly indicate that the ANFIS's learning process yielded a model that fits the data much more closely than the untuned FIS.

Table 1 FIS and ANFIS Performance Metrics

Metric	FIS	ANFIS
RMSE	0.13	0.07
MAE	0.10	0.05
R^2	0.85	0.93

Figure 4 further illustrates the difference in prediction performance between the two models by plotting their predicted outputs against the actual target values. It can be seen that the ANFIS predictions align much more closely with the true output curve, whereas the FIS predictions show noticeable deviations.

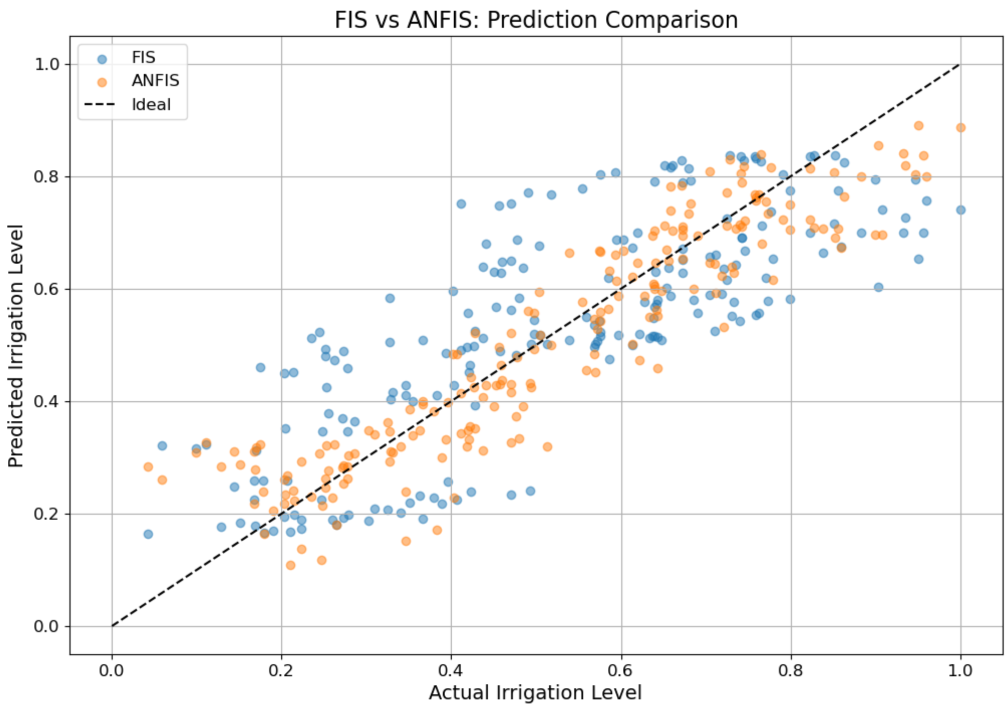

Figure 4 FIS and ANFIS Predicted Versus Actual Irrigation Outputs.

Figure 4 shows the predicted outputs of both the FIS and ANFIS models plotted against the actual target irrigation levels. The ANFIS prediction curve aligns much more closely with the actual output curve, whereas the FIS prediction curve exhibits noticeable deviations from the true values. This performance gap is largely because ANFIS can learn and adjust its fuzzy rules through training – giving it greater flexibility to capture complex, nonlinear relationships – whereas the FIS relies on a fixed rule set that cannot adapt to such variations. Consequently, the FIS model tends to under-predict or over-predict in highly nonlinear regions, while the ANFIS model's output tracks the actual trend with only minimal discrepancies. This visual comparison corroborates the quantitative metrics in Table 1, reinforcing that ANFIS provided a more accurate approximation of the target behavior.

Prediction Error Analysis

A closer examination of the prediction residuals (the differences between predicted and actual values) provides further insight into each model's performance. As shown in Figure 5, the ANFIS model's errors are far more tightly clustered around zero compared to those of the FIS model. Most ANFIS residuals fall within a narrow band, indicating that the majority of its predictions deviate only slightly from the true values. In contrast, the FIS residuals are spread over a much wider range, with some errors being quite large. For instance, the maximum absolute error with the FIS model was significantly higher than that observed with ANFIS, reflecting the more variable accuracy of the static FIS.

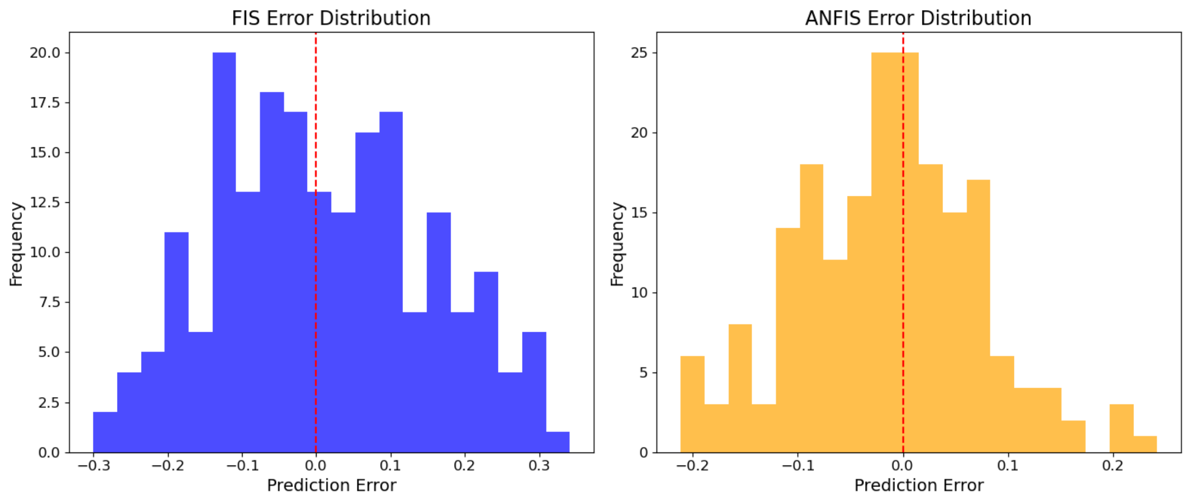

Figure 5 FIS and ANFIS Error Distribution Histogram

In addition to magnitude, the distribution of errors suggests differences in bias. The FIS error distribution appeared slightly skewed, implying the FIS may consistently under-predict in certain regions (leading to a non-zero mean error). Meanwhile, the ANFIS errors were more symmetrically centered around zero, indicating minimal systematic bias in its predictions after training. Overall, the error analysis confirms that ANFIS not only reduces the average error but also produces more consistent and reliable predictions, with fewer extreme outliers than the static FIS.

Execution Time Comparison

A comparison of computational efficiency between the two modeling approaches is presented in Table 2. There is a clear difference in the time required to build or train the models. The static FIS, which does not undergo iterative learning, had a negligible model building time (on the order of a fraction of a second), whereas the ANFIS required substantially more time to train. In this experiment, the FIS model was essentially instantaneous to set up (approximately 0.5 s), while the ANFIS training phase took on the order of tens of seconds (around 12.4 s), owing to the multiple epochs of parameter tuning. This disparity is expected, as ANFIS performs repeated computations to minimize error, in contrast to the one-pass initialization of the FIS.

Table 2 Execution Time Comparison

Metric	FIS	ANFIS
Model training time (s)	0.5	12.4
Prediction time per sample (ms)	1.0	1.2

In terms of real-time prediction speed (inference), however, the two models are virtually identical. Generating an output from the fuzzy system is very fast for both approaches, on the order of only a millisecond per input case (as also shown in Table 2). The slight difference in average per-sample execution time between FIS and ANFIS (e.g., 1.0 ms vs 1.2 ms) is negligible in practice.

Thus, once the ANFIS is trained, it can be deployed to make predictions just as quickly as the static FIS. The primary computational overhead of ANFIS lies in its training phase, which, while longer than the FIS setup, is typically performed offline. For practical applications, this means that the benefits of ANFIS (in terms of accuracy) can be obtained without sacrificing operational speed in deployment, as long as the training can be done ahead of time.

3D Response Surface Analysis

To further interpret the behavior of the models, a combined three-dimensional response surface plot was generated to visualize the predicted output as a function of the two input variables for both systems. Figure 6 presents a side-by-side comparison of the response surfaces produced by the static FIS and the trained ANFIS within a single composite figure.

In the FIS surface (left panel of Figure 6), the output approximation reflects the initial fuzzy rules without data-driven adjustment. The surface is relatively simple and exhibits limited curvature, which highlights the constraints of the fixed rule base in capturing nonlinear interactions between inputs. As a result, the FIS tends to produce smoother but less precise transitions, particularly in regions where the true relationship between inputs and output changes rapidly.

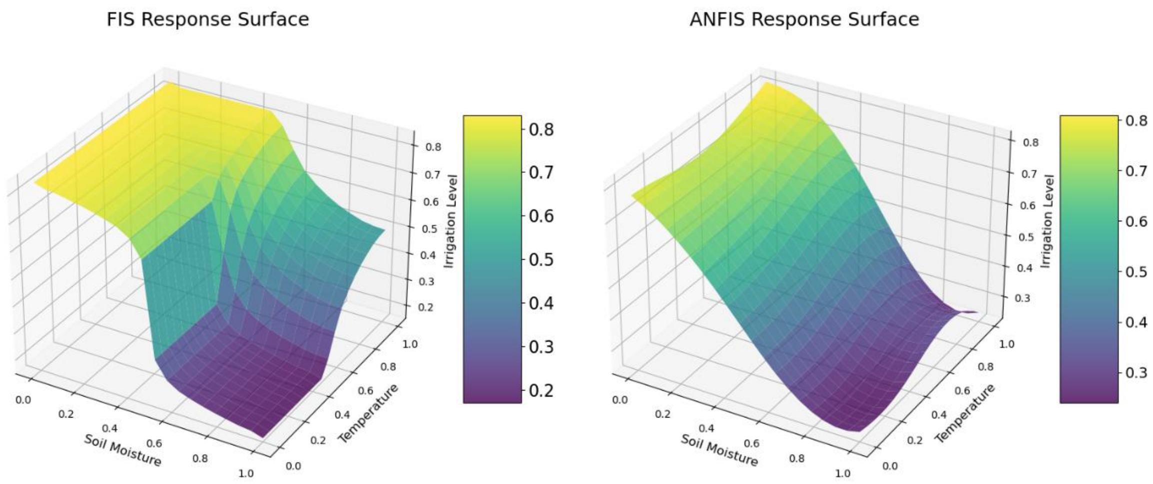

Figure 6 FIS and ANFIS 3D Response Surface

The ANFIS surface (right panel of Figure 6) demonstrates the impact of adaptive training. After optimizing membership functions and rule consequents, the ANFIS surface aligns more closely with the underlying data patterns. Notably, the trained surface exhibits more nuanced curvature and localized gradients, indicating the model's ability to capture complex interactions between the input variables. The contrast between the left and right panels clearly illustrates how ANFIS transforms the initial fuzzy approximation into a more accurate, data-driven representation.

This joint visualization emphasizes the performance gap between the models: while the FIS provides a transparent but coarse mapping, the ANFIS adapts to produce a more refined and realistic response surface, especially in regions of high nonlinearity.

Comparative Analysis Summary

To clearly highlight the differences between the Mamdani-type FIS and the ANFIS models, the key comparative aspects are summarized in Table 3. This table consolidates performance, training behavior, error distribution, computational characteristics, and structural complexity, providing a concise overview of how both models perform across critical evaluation dimensions.

Table 3 Summary of Comparative Findings between FIS and ANFIS Across Key Aspects

Aspect	FIS	ANFIS
Predictive Accuracy	Moderate accuracy; RMSE and MAE relatively higher; R^2 lower than 1.0.	Significantly higher accuracy; RMSE and MAE roughly halved compared to FIS; R^2 closer to 1.0.

Learning and Convergence	No learning phase; performance fixed by initial rule base without improvement mechanism.	Underwent successful training; error decreased steadily to a low value without overfitting.
Error Characteristics	Larger and more variable errors; noticeable bias in certain regions due to fixed rule limitations.	Smaller and more consistent errors; residuals tightly distributed with minimal variance and bias.
Computational Cost	Negligible training time; extremely fast to initialize and deploy; similar prediction speed to ANFIS.	Requires iterative training with longer offline optimization; after training, inference speed nearly identical to FIS.
Model Complexity	Uses a fixed fuzzy rule base; fully interpretable with human-readable rules.	Same fuzzy structure as FIS; parameters are tuned during training, retaining interpretability while significantly enhancing accuracy.

Discussion of Findings

The comparative results obtained confirm the expected advantages of the adaptive neuro-fuzzy approach over a static fuzzy model. In this case, the ANFIS was able to learn the underlying input–output relationship with high fidelity, whereas the fixed FIS could only approximate it based on its initial rule set. This outcome is consistent with the fundamental idea behind ANFIS: by tuning membership functions and rule consequents using data, the model can capture nuances and nonlinearities that an expert-defined FIS might miss. The magnitude of improvement observed (substantially lower errors and higher R^2) underscores how significantly model learning can enhance performance, even when the FIS provided a reasonable starting approximation.

An important aspect of these findings is that the ANFIS achieved its superior accuracy without fundamentally changing the model's interpretable structure. Both the FIS and ANFIS used the same number of rules and linguistic terms; the difference was that ANFIS optimized the parameters of those rules. Thus, the benefits of data-driven learning were obtained without sacrificing the transparency of the fuzzy inference system. This is a notable advantage of ANFIS compared to other purely black-box models (such as neural networks without a fuzzy structure): one retains a set of understandable fuzzy rules that have simply been refined by training. For instance, if the initial FIS was informed by expert domain knowledge, the ANFIS process can be viewed as fine-tuning that expert knowledge—improving the rules' accuracy while preserving their qualitative meaning. The ANFIS model effectively combines prior knowledge embedded in the initial FIS with the learning capability of neural networks, yielding a hybrid model that is both accurate and interpretable.

It should be noted that the superiority of ANFIS in this study came at the cost of a one-time training effort, whereas the FIS required no such data-driven training. In scenarios where ample data are available and accuracy is paramount; the results here strongly support choosing ANFIS for model development. On the other hand, if data are very limited or if rapid prototyping is needed, a well-crafted FIS might still be used to obtain a quick, interpretable solution (albeit with lower precision). Ultimately, the findings illustrate that while a static FIS can provide a baseline insight, allowing the system to adapt via ANFIS unlocks significantly better performance. This trade-off and the conditions under which each approach is preferable are further discussed in the following section on practical implications.

Building on these findings, it is important to note the limitations of both models, particularly the risk of overfitting. The conventional FIS, while interpretable, is static and may underperform when conditions deviate from its predefined rules. ANFIS adds adaptability through learning but can overfit if the model is too complex or data are insufficient. In this study, we minimized this risk by limiting the rule base and validating performance on an independent test set. Future work should validate the models with real-world data and apply cross-validation or regularization to ensure robust generalization and further reduce overfitting.

Practical Implications and Method Selection Considerations

Building on the comparative analysis summarized in Table 3, the following considerations provide practical direction for selecting between a static FIS and an ANFIS approach depending on the application context. These considerations take into account data availability, problem complexity, computational constraints, and system adaptability. The summarized points are presented in Table 4.

Table 4 Practical Considerations for Selecting FIS or ANFIS

Consideration	When to Use FIS	When to Use ANFIS
Data Availability	Suitable when data are limited or costly to obtain; relies on expert knowledge to define fuzzy rules and membership functions.	Requires sufficient training data to tune parameters; performs best in data-rich environments.
Problem Complexity	Works well for well-understood systems where relationships between variables are simple and can be captured with expert-defined rules.	Recommended for complex, nonlinear systems where intuitive rule creation alone is insufficient to capture the underlying patterns.
Computational Resources	Low computational demand; no training phase required; deployable quickly with minimal processing overhead.	Requires offline training investment due to iterative optimization; after training, inference is as fast as FIS.
Hybrid Strategy	Can serve as a baseline model constructed from expert knowledge.	Can refine the baseline FIS through adaptive training, combining

		interpretability and data-driven optimization.
Adaptability & Maintenance	Remains static unless manually revised; less suited for environments where conditions change frequently.	Easily retrainable with new data to adapt to changing system dynamics, making it advantageous in dynamic and evolving environments.

In summary, the choice between FIS and ANFIS should be considered by the specific requirements and constraints of the application. When interpretability, simplicity, and quick deployment are the top priorities (and data or time are limited), a well-crafted FIS may suffice. However, when data are plentiful and accuracy is paramount, ANFIS offers a powerful tool that can substantially improve predictive performance. The present study's results provide a clear demonstration of these trade-offs and can assist practitioners in selecting the appropriate method for their needs.

Conclusions

This study successfully implemented and evaluated two fuzzy inference approaches—Mamdani-type FIS and ANFIS—to predict optimal irrigation requirements based on four key environmental parameters: soil moisture, air temperature, humidity, and solar radiation. The findings clearly indicate that the ANFIS approach outperforms the conventional FIS in terms of prediction accuracy and adaptability. While ANFIS requires a longer offline training phase (~12.4 s vs. ~0.5 s for FIS), its real-time inference speed is nearly identical (~1 ms/sample), enabling higher accuracy without sacrificing operational speed. This enables ANFIS to provide significantly higher accuracy and dynamic responsiveness without sacrificing operational speed during deployment. Despite this, the FIS approach maintains a notable advantage in rule interpretability, which can benefit practitioners needing transparent and domain-aligned decision support. Therefore, the choice between ANFIS and FIS should align with the intended application: ANFIS is recommended when accuracy and responsiveness are prioritized, while FIS is better suited for use cases where rule transparency is critical. This research contributes significantly to the field of intelligent agricultural systems by offering a comparative framework for selecting fuzzy logic-based control methods, promoting more efficient water resource management, and providing a foundation for future work involving method optimization and real-world deployment in precision agriculture.

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