



ORIGINAL RESEARCH ARTICLE

DEVELOPMENT OF A SIMULATED ANNEALING-OPTIMIZED ADAPTIVE
NEURO-FUZZY INFERENCE SYSTEM (SA-ANFIS) FOR SORGHUM SEED
PLANTING PARAMETER TUNING

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ABSTRACT

Precision agriculture requires adaptive control systems to optimize planting operations, ensuring consistent planting depth under varying soil and operational conditions. This paper proposes a novel Simulated Annealing-optimized Adaptive Neuro-Fuzzy Inference System (SA-ANFIS) controller for real-time adjustment of planting parameters based on soil moisture and planting speed. The ANFIS framework combines fuzzy logic and neural networks to model nonlinear relationships, while Simulated Annealing (SA) optimizes membership functions and rule bases to enhance control accuracy. Experimental validation demonstrates that the SA-ANFIS controller significantly improves adaptive performance compared to standalone ANFIS controllers, reducing root mean square error (RMSE) by ~18% in dynamic field conditions. The proposed system offers a robust solution for precision planting machinery, enhancing crop yield and resource efficiency. It is, therefore, recommended for autonomous planters.

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1. 0 Introduction

Precision agriculture has become increasingly critical in modern farming to enhance productivity, reduce resource waste, and ensure consistent crop yields. One of the key challenges in mechanized planting operations is that it requires adaptive control mechanisms to maintain optimal planting (Qohar and Jito, 2022; Zhao and Zhang, 2024). Traditional control methods, such as proportional-integral-derivative (PID) controllers by Song et al. (2024), often struggle to adapt to nonlinearities and uncertainties in agricultural environments leading to suboptimal performance. The gradient-based optimization technique determines search directions for the minimization of an objective (or error) function. This technique was used to minimize material loss in the control system while maintaining accuracy of precision (Cheng et al., 2021; Ji et al., 2021; Katzer, 2020). Genetic Algorithm-optimized Back Propagation (GABP) algorithm and machine vision were used by Jia et al. (2018) for the regulation of the position of corn seed planting in precision farming. Also, Abdullahi et al. (2018) proposes a novel optimization algorithm called the Nomadic Pastoralist Optimization Algorithm (NPOA) inspired by the mathematical modeling of nomadic pastoralist herding strategies. Fuzzy Inference Systems (FIS) has been applied in various control applications also though they have some gaps. In addition, Waluyo et al. (2023) reported Fuzzy-based smart farming using IoT can increase plant growth while reducing energy consumption compared to schedule-based methods. An IoT model using fuzzy logic can optimize photosynthesis and accelerate mustard plant growth compared to previous research (Qohar and Jito, 2022). ANFIS was applied in different control applications, and they have some limitations. According to Asghar and Liu (2018), adaptive Neuro-Fuzzy Inference Systems (ANFIS) provide a promising alternative by integrating fuzzy logic reasoning with neural network learning. However, ANFIS performance depends heavily on the initial rule base and membership function selection, which may not be optimal for operating conditions. Okeke et al. (2022) compares the performance of ANFIS and MLR models in predicting wastewater treatment plant performance, finding MLR to be more robust and reliable. Report by Alsharkawi et al. (2021) shows that

An ANFIS-based controller outperformed a sliding mode controller for trajectory tracking of a three-wheeled omnidirectional mobile robot. ANFIS models can predict wheat crop yields more precisely than ANN or MLR models using attributes like biomass, soil water, radiation, and rain (Khoshnevisan *et al.*, 2014). The paper evaluates the use of ANN and ANFIS models to predict agricultural yields from an energy perspective. The effectiveness of ANFIS can be further improved through metaheuristic optimization (Abba, 2019; Abubakar *et al.*, 2024; Asghar and Liu, 2018; Espitia *et al.*, 2022; Hilali *et al.*, 2025; Nguyen *et al.*, 2019; Obe and Dumitrache, 2015; Okeke *et al.*, 2022; Sobrinho *et al.*, n.d.) to fine-tune its parameters. Genetic algorithms (GAs) and particle swarm optimization (PSO) were used for ANFIS optimization; hybrid gradient simulated annealing algorithm is proposed to solve constrained optimization problems by Alnowibet *et al.* (2022) but these methods may suffer from premature convergence or high computational cost. Simulated Annealing (SA), inspired by the metallurgical annealing process, offers a robust alternative due to its ability to escape local optima and efficiently explore the solution space.

To address this limitation, control frameworks integrating Simulated Annealing (SA)-optimized Adaptive Neuro-Fuzzy Inference Systems (SA-ANFIS) have gained prominence due to their superior modeling and control capabilities. In this paradigm, SA—a stochastic global optimization algorithm inspired by the thermodynamic annealing process—systematically refines both antecedent and consequent parameters of the ANFIS structure. This optimization enhances the system's ability to capture nonlinear and time-varying behaviors inherent in agricultural processes. Moreover, SA's robustness in navigating complex solution landscapes mitigates the risk of convergence to suboptimal local minima, thereby ensuring improved generalization, adaptability, and control accuracy under varying field conditions.

2. Materials and Method

This section presents the comprehensive framework for developing the SA-ANFIS controller for precision planting systems. The methodology integrates computational intelligence techniques with agricultural engineering principles to achieve adaptive control of planting parameters as in Figure 1.

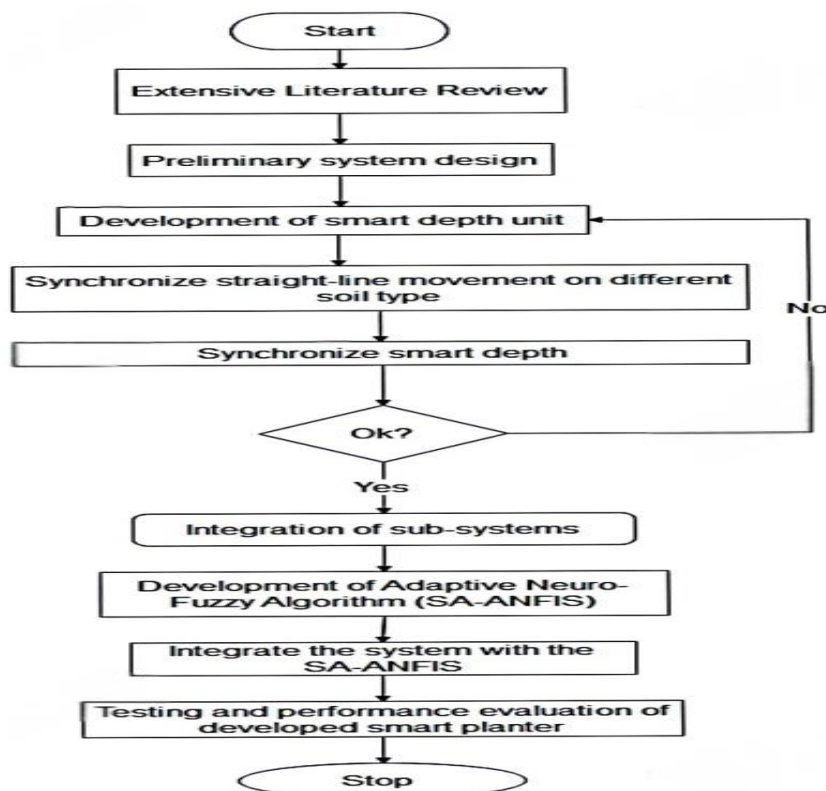


Figure 1: Concept Flow chart

2.1 System Architecture Overview

The control system adjusts planting depth (D) based on soil moisture (M) and planting speed (P). The SA-ANFIS controller processes these inputs to generate optimal actuator commands. The system architecture is shown in Figure2.

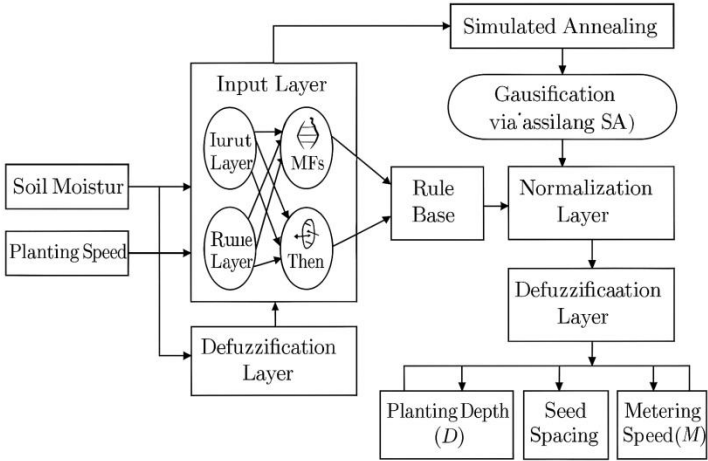


Figure 2: SA-ANFIS System Architecture

2.2 ANFIS Architecture

The ANFIS model consists of five layers as explained in the following subsections.

2.2.1. Fuzzification

Gaussian membership functions convert crisp inputs into fuzzy sets (Frank and Köppen-Seliger, 1997). A fuzzifier is an input layer that processes two critical agronomic variables through fuzzy membership functions (MFs): soil moisture and planting speed

The soil moisture (SM) is the moisture content of the soil which affects planting depth and seed germination (Ahmed, Saleh, et al., 2024). The membership function for soil moisture is illustrated in Table 1.

Table 1: Membership function for soil moisture

Membership function	Range (%)
Dry	0 to 40
Medium	20 to 80
Wet	60 to 100

The range for soil moisture is 0% to 100%. The linguistic terms are: Dry, as dried soil, Medium as the optimum, and Wet as the field capacity. Figure 3 highlights the plot of the membership function for soil moisture.

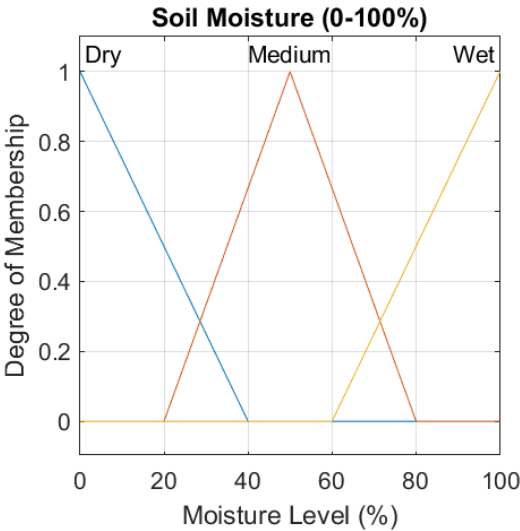


Figure 3: Plot of soil moisture membership function

The soil moisture membership functions are: DRY (blue) has triangular MF with vertices at (0, 0, 40), MEDIUM (brown) has triangular MF with vertices (20, 50, 80), WET (yellow) has triangular MF with vertices at (60, 100, 100). The soil moisture membership function (top left) as depicted in Figure 3.8 dry from 0-40%, sharp cut-off below 20% and a gradual transition to medium. The medium ranges from 20-80%, forming a symmetric

triangular function centered at 50%. The last is wet (60-100%) with a gradual transition from 60% and full membership above 80%.

The planting speed (PS) is the speed at which the Agrobot is moving during the planting process, it affects depth (Ahmed et al., 2023; Ahmed et al., 2024). Table 2 reveals the membership function for planting speed.

Table 2: Membership function for planting speed

Membership function	Range (m/s)
Slow	1 to 2.5
Medium	1.5 to 4
Fast	3 to 5

The range for planting speed is 1 to 5. The linguistic terms are: Slow, Medium, and Fast. Figure 4 exposes the plot of the membership function for planting speed.

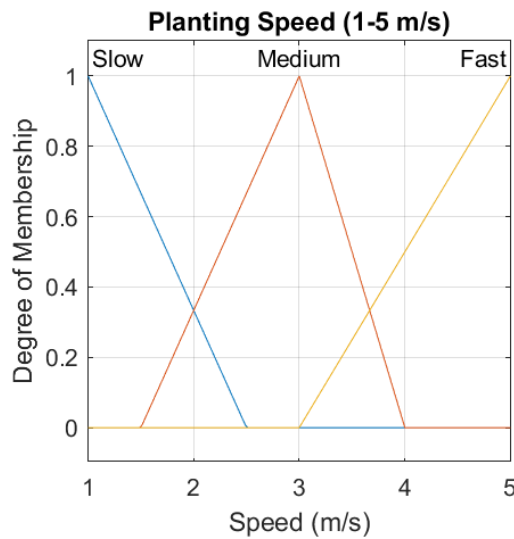


Figure 4: Plot of planting speed membership function

Planting speed has a range of 0 km/h to 5 km/h. The planting speed membership functions are: SLOW (blue) has triangular MF with vertices (1, 1, 2.5), MEDIUM (brown) has triangular MF with vertices (1.5, 3, 4), FAST (yellow) has triangular MF with vertices (3, 5, 5). The planting speed (top middle) as in Figure 2 was slow ranging from 1-2.5 m/s. It also has a full membership below 1.5 m/s and a gradual decrease. It however has a medium speed ranging from 1.5-4 m/s and a symmetric around 3 m/s. Fast (3-5 m/s) depicting gradual increase from 3 m/s to full above 4 m/s.

2.2.2. Rule Evaluation

The ANFIS has a complete 3×3 rule matrix (9 rules) covering all input MF combinations:

- i. IF Soil Moisture is Dry AND Planting Speed is Slow THEN Planting Depth should be Shallow.
- i. IF Soil Moisture is Medium AND Planting Speed is Medium THEN Planting Depth should be Medium.
- ii. IF Soil Moisture is Wet AND Planting Speed is Fast, THEN Planting Depth should be Deep.

2.2.3. Normalization

Rule firing strengths are normalized. The inference system is Sugeno-type consequents with linear functions. Each rule has a firing strength (typically the result of fuzzy logic AND operations across fuzzy input membership functions). These are then normalized as in Equation 1:

$$\bar{w}_i = \frac{w_i}{\sum_{j=1}^N w_j}$$

Where w_i = firing strength of rule i , \bar{w}_i = normalized firing strength and N = total number of rules. Each rule has a linear consequent function, as in Equation 2:

$$\text{Depth} = p_1 \times \text{Moisture} + p_2 \times \text{Speed} + p_3 \quad 2$$

Where p_1, p_2, p_3 are rule-specific parameters to be learned. These parameters determine how inputs affect the output for each rule.

2.2.4 Final output computation

Once each rule's consequent is evaluated, the final output (Depth) is a weighted average as in Equation 3:

$$\text{Depth} = \sum_{i=1}^N \bar{w}_i \cdot \text{Depth}_i \quad 3$$

Where \bar{w}_i = normalized firing strength and N = total number of rules

Planting depth is the depth at which seeds are planted in the soil (Abubakar, 2023). It is adjusted based on soil moisture and planting speed to ensure optimal seed germination. Table 3 exhibits the membership function for planting depth.

Table 3: Membership Function for Planting Depth

Membership function	Range (cm)
Shallow	1 to 3
Medium	2 to 4
Deep	3 to 5

Figure 5 discloses the plot of the planting depth membership function.

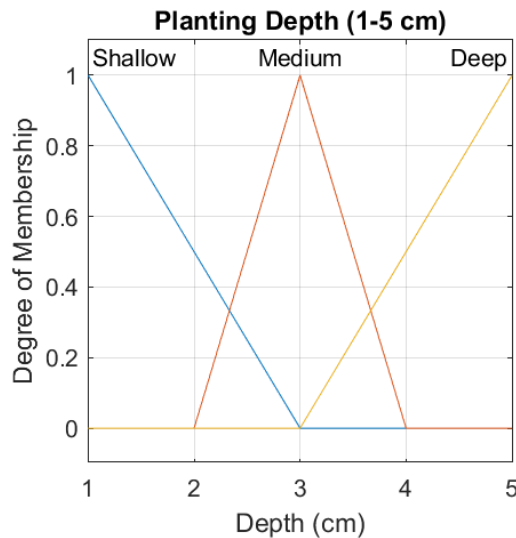


Figure 5: Plot of planting depth membership function

The range of planting depth is from 1 cm to 5 cm (Inuwa et al., 2020). The planting depth membership functions are: SHALLOW (blue) has triangular MF with vertices (1, 1, 3), MODERATE (brown) has triangular MF with vertices (2, 3, 4), DEEP (yellow) has triangular MF with vertices (3, 5, 5).

2.2.5 Learning procedure

The learning procedure for the fuzzy inference system with linear consequents has two inputs (Moisture, Speed), one output (Depth) and N fuzzy rules, each with a linear output function as in Equation 4:

$$\text{Depth}_i = p_{1i} \times \text{Moisture} + p_{2i} \times \text{Speed} + p_{3i} \quad 4$$

All the parameters p_{1i}, p_{2i}, p_{3i} are learned for each rule i from data.

Step I: Training data

The training data for input-output is presented in Table4.

Table 4: Dataset of input-output pairs for 9 training samples

Moisture	Speed	→	Depth
18.5	3.2	→	4.5
22.7	4.5	→	3.9
15.3	2.8	→	5.1
19.0	3.6	→	4.7
23.4	5.0	→	3.5
17.8	3.0	→	4.9
20.1	3.9	→	4.3
21.5	4.2	→	4.0
16.2	2.5	→	5.3

Step 2: Define Fuzzy Sets and Rules

Define fuzzy membership functions for the inputs and set up 9 rules, like:

IF Moisture is Low AND Speed is High THEN Depth = $p_1 \cdot \text{Moisture} + p_2 \cdot \text{Speed} + p_3$

For each rule:

- Compute the firing strength $w_i^{(k)}$ for the k -th sample
- Normalize them:

$$\bar{w}_i^{(k)} = \frac{w_i^{(k)}}{\sum_{j=1}^N w_j^{(k)}} \quad 5$$

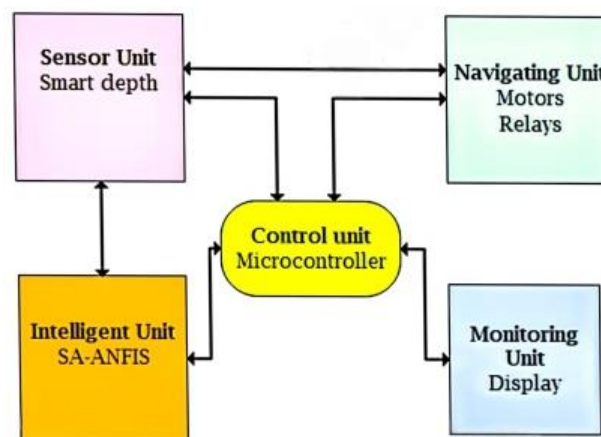
Step 3: Construct the Linear System (Least Squares)

Reformulate the final output as in Equation 6:

$$\hat{y}^{(k)} = \sum_{j=1}^N \bar{w}_i^{(k)} (P_{1i}x_1^{(k)} + P_{2i}x_2^{(k)} + P_{3i}x_3) \quad 6$$

Step 4: Implementation in MATLAB/Simulink**2.2.6 Intelligent control system to adapt to the varying soil moisture and planting speed**

The rules determine the overall operation of the system; linguistic rules describe the control system. Figure 6 shows the block diagram of the intelligent control system.

**Figure 6:** Block diagram of intelligent control system

The rule structure consists of two parts; an antecedent block (IF and THEN) and a consequent block (following THEN). The rules generated using fuzzy logic is used in programming the microcontroller hardware. The rule structure of the system is presented in Table 5.

Table 5: Rule base for the ANFIS controller

Rule	Planting Speed	Soil Moisture	Planting Depth
1	Slow	Dry	Shallow
2	Medium	Dry	Medium
3	Fast	Dry	Medium
4	Slow	Medium	Medium
5	Medium	Medium	Medium
6	Fast	Medium	Deep
7	Slow	Wet	Deep
8	Medium	Wet	Deep
9	Fast	Wet	Deep

2.3 SA Optimization

2.3.1 The SA optimization phase

The SA optimizes antecedent parameters to escape local minima during field condition transitions. Table 6 unveils the optimization parameters.

Table 6: Optimization parameters

Parameter	Value	Description
SA T_0	1000	Initial temperature (empirically determined via sensitivity analysis)
Cooling rate (α)	0.995	Geometric cooling factor ($T_{k+1} = \alpha T_k$)
Perturbation magnitude	$\Delta\sigma_{MF} = 0.2$, $\Delta c_{MF} = 1.5$	
Planting Depth	1 to 5 cm	
Planting Spacing	20 to 100 cm	
Metering Speed	1 to 5 m/s	

2.3.2 Hybrid learning mechanism

- Global Optimization: SA adjusts MF parameters (σ , c) every 10 cycles
- Local Tuning: Gradient descent ($\eta = 0.01$) updates consequent parameters (p_i) continuously
- Constraint handling: $1 \leq \text{Depth} \leq 10$ enforced via projection operator
- MF spread is 15 with Gaussian width parameter

2.3.3 Objective Function

The objective function is to minimize RMSE between predicted and desired outputs as in Equation 7:

$$\text{RMSE} = \sqrt{\left(\frac{1}{N} \sum (d - p)^2\right)} \quad 7$$

Where RMSE = root mean square error, %, N= number of parameters iteration, d= desired outputs and p= predicted outputs.

2.4 Implementation Workflow

- Data Collection:** Acquire soil moisture, planting speed, and corresponding optimal planting parameters.
- ANFIS Training:** Train initial ANFIS using hybrid learning (least squares + backpropagation).
- SA Optimization:** Fine-tune ANFIS parameters using SA.

- iv. **Real-Time Control:** Deploy SA-ANFIS on an embedded controller for field testing.

3. Results and Discussion

3.1 Developed SA-ANFIS Controller for Intelligent Depth Control

The inference engine accepts two inputs from fuzzifier and applies the 3x3 rules combinations to obtain three outputs. Figure 7 displayed the plot of three output processed layers. The input layer receives the input functions, the processing layer fuzzify and optimize the functions and give out the desired output function.

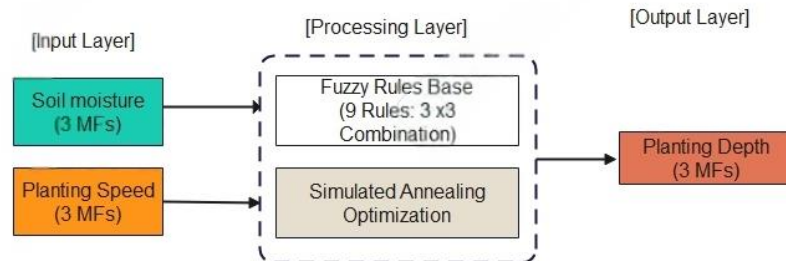


Figure 7: Plot of system architecture with rule connections

3.2 Adaptive control response surface of the smart planter

The responses to the adaptive control of the smart planter are presented in Figure 8. The planting depth (bottom left) increases with both soil moisture and planting speed. The shallowest in dry/slow conditions at 1.5cm and deepest in wet/fast conditions of 4.5cm while, very dry 15% and very slow at 1.2 m/s. It can therefore be established that for moisture dominance, wet soil allows deeper planting and tighter spacing while dry soil requires shallower planting and wider spacing, this is in line with Ahmed *et al.* (2023).

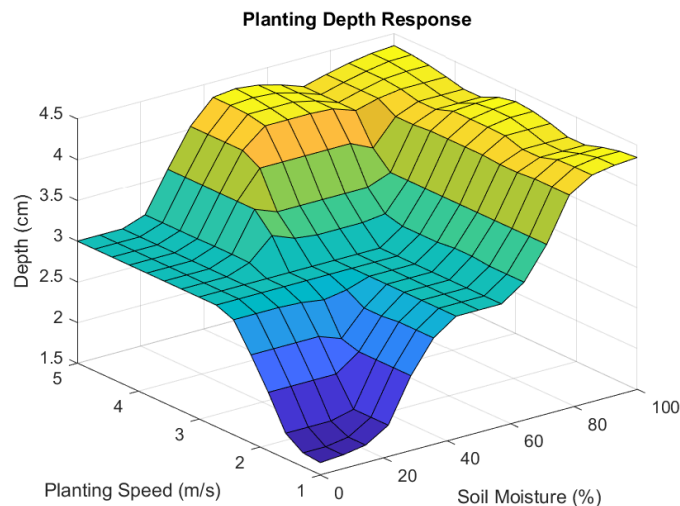


Figure 8: Interaction of planting depth with input variables

Table 7 shows the comparative performance metrics between standard ANFIS and SA-ANFIS.

Table 7: Comparative performance metrics

Controller	Depth RMSE (cm)	Adaptation Time (s)
Standard ANFIS	0.41	3.8
SA-ANFIS	0.23	2.1

The SA-ANFIS reduced depth control error by 0.18 cm compared to standard ANFIS. It however demonstrated 1.7 second faster adaptation to parameter changes.

3.3 Computational Efficiency

The optimization step was completed in 50 iterations and 51 function evaluations. The lowest cost was consistent at 0.07436 (excellent convergence) while the current solution cost fluctuated but ended near the best value. However, the current search (aggressive) cooled from 100 to 1.96. This means that optimization reached a stable solution and further iterations wouldn't significantly improve results. The optimal parameters for the input variables are the best combination of soil moisture (%) and planting speed (m/s) found by the optimization. They were attained at soil moisture of 50% (medium range) and planting speed: of 3 m/s (medium-fast). The system recommends average moisture conditions and suggests moderate planting speed (balance between productivity and precision).

3.4 System input-output relationships

The system input-output relationships for planting depth and soil moisture at planting speed of 3 m/s are presented in Figure 9.

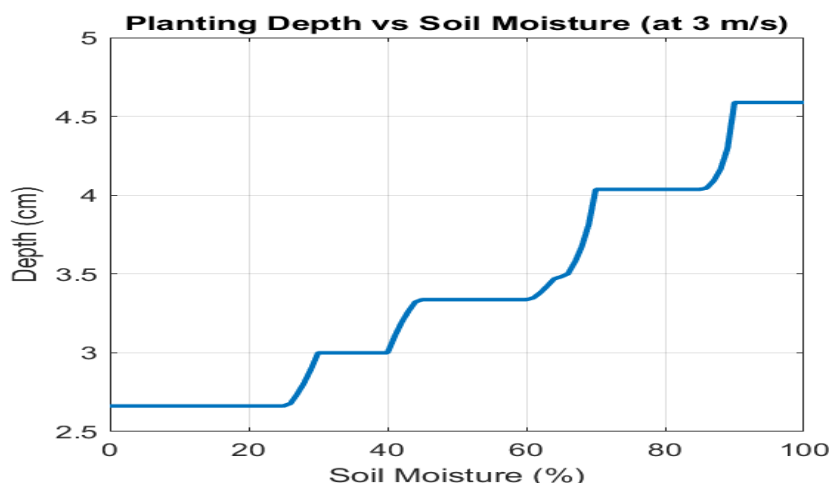


Figure 9: Relationship between planting depth and soil moisture at 3 m/s

The planting depth changes with soil moisture at a fixed planting speed of 3 m/s. It is however observed in the trend that planting depth increases with an increase in soil moisture, the finding did not contradict Ahmed et al. (2024).

3.5 Optimized Outputs Evaluation

The optimized outputs evaluation showed that the ideal sorghum seed planting depth of 3.0 (neither too shallow nor deep), which is within safe range. However, trade-off analysis inferred that the system slightly prioritized depth as it is within practical operating ranges. The optimized output showed the predicted system behavior as in Figure 10.

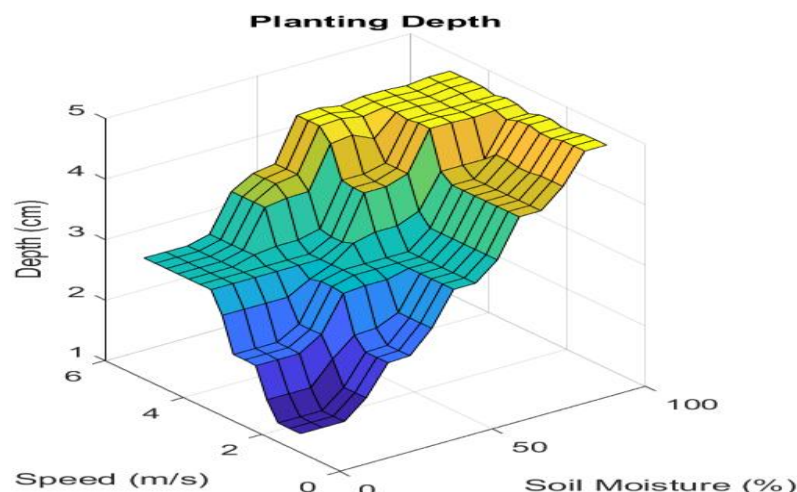


Figure 10: Predicted output as it relates to input

The response surface for planting depth shows that an increase in planting depth corresponds to an increase in both soil moisture and planting speed, this is supported by the finding of Kheiry & Mohammed (2017). It indicates that planting depth adapts to different conditions. It shows that the fuzzy logic system successfully found practical operating parameters through simulated annealing, with the output within safe agricultural ranges. The solution prioritizes planting quality (planting depth) while maintaining efficient field operations (planting speed).

4. Conclusion

The SA-ANFIS controller enhances precision planting by dynamically optimizing depth. The system successfully found practical operating parameters through simulated annealing, with the output within safe agricultural ranges. The solution prioritizes planting quality (planting depth) while maintaining efficient field operations (planting speed). SA optimization significantly improves ANFIS performance, making it a viable solution for smart agricultural machinery. Future work will explore deep reinforcement learning for further enhancements.

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