

# Simulated Annealing–Optimised Adaptive Neuro-Fuzzy Control for Real-Time Planting Depth Regulation in Smart Sorghum Planters

ABUBAKAR Ibrahim<sup>1\*</sup>, ABDULLAHI Ibrahim Mohammed<sup>2</sup>, BALAMI Audu Ayuba<sup>3</sup>, IDAH

Peter Abah<sup>4</sup>

<sup>1</sup>Department of Agricultural and Bioenvironmental Engineering Technology, Waziri Umaru Federal Polytechnic, Birnin Kebbi, Nigeria / ORCID: 0009-0006-5986-0402

<sup>2</sup>Department of Computer Engineering, Federal University of Technology, Minna, Nigeria

<sup>3</sup>Department of Agricultural and Bioresources Engineering, Federal University of Technology, Minna, Nigeria

<sup>4</sup>Department of Agricultural and Bioresources Engineering, Federal University of Technology, Minna, Nigeria

**Abstract:** Uniform planting depth is critical for consistent germination, uniform crop emergence, and stable yield in mechanised sorghum production. However, conventional planters rely on fixed depth settings that cannot adapt effectively to variations in soil moisture and forward speed, often resulting in inconsistent seed placement. The study applied real-time embedded control for planting depth in a smart sorghum planter. The optimised SA-ANFIS model was implemented as a closed-loop controller on a microcontroller platform integrating sensing, inference, and actuator-based furrow-opener adjustment. Performance was evaluated using controlled field experiments and hardware-in-the-loop validation, with emphasis on prediction accuracy and depth uniformity. The controller achieved an RMSE of 0.18692 cm and  $R^2 = 0.871$ , representing a 22.1% improvement over the baseline ANFIS model. In real-time operation, it maintained planting depth within  $\pm 0.12$  cm and achieved 96.7% uniformity under varying soil moisture and travel speed conditions. These findings demonstrate the feasibility of deploying SA-ANFIS as an embedded real-time control strategy for precision planting. The study's key contribution lies in translating optimisation-based ANFIS models into practical closed-loop planter control systems. Nonetheless, further full-field validation under diverse operating conditions is required before large-scale deployment.

**Keywords:** Adaptive neuro-fuzzy inference system, embedded control, hardware-in-the-loop validation, planting depth regulation, precision agriculture, simulated annealing, smart sorghum planter.

## 1. Introduction

Uniform planting depth is a critical requirement in sorghum production because it directly influences seed-soil contact, moisture availability, germination rate, emergence uniformity, early plant vigor, and ultimately grain yield. In cereal-based systems, inconsistent seed placement depth has been widely recognized as a major cause of poor crop establishment and spatial variability in stand development, both of which reduce field productivity and limit the efficient use of agronomic inputs [1], [2].

Despite the agronomic importance of depth uniformity, conventional planting systems are still largely dependent on fixed mechanical settings that are unable to respond adequately to dynamic field conditions. Variations in soil moisture, soil texture, residue cover, forward travel speed, and surface roughness alter opener penetration and soil resistance during operation, often causing deviations from the desired seed-placement depth [3]–[5]. As a result, conventional depth-control mechanisms may perform satisfactorily under

controlled or uniform conditions but deteriorate when exposed to the spatial and temporal variability that characterizes real field environments. This limitation has motivated increasing interest in intelligent control approaches capable of adapting planter operation in real time.

Among such approaches, the Adaptive Neuro-Fuzzy Inference System (ANFIS) has attracted attention because it combines the linguistic interpretability of fuzzy logic with the learning capability of artificial neural networks, making it suitable for modeling complex nonlinear agricultural processes for which deterministic formulations are often inadequate [6]. Neuro-fuzzy methods have been applied in precision agriculture for nonlinear system identification and environmental interaction modeling [7], [8], with successful applications reported in crop-yield prediction, irrigation scheduling, and soil-parameter estimation [9]–[11]. In addition, optimization-enhanced ANFIS architectures have been shown to improve robustness, convergence behavior, and predictive performance in uncertain agricultural environments [12]–[14].

Report by Abubakar *et al.*, simulated annealing-optimised adaptive neuro-fuzzy inference system (SA-ANFIS) was developed for sorghum seed-planting parameter tuning, demonstrating that metaheuristic optimization can improve parameter search and predictive accuracy in nonlinear planting-system applications [15]. That study established the value of simulated annealing as a global optimization strategy for ANFIS tuning, particularly in reducing the risk of premature convergence associated with purely gradient-based

learning. However, the study remained primarily a simulation-based and parameter-tuning framework; it did not address embedded deployment, closed-loop sensing and actuation, controller latency, or real-time regulation of planter depth under changing operating conditions [15].

Recent studies further confirm the growing role of ANFIS in smart-agriculture applications, although most remain outside planter mechatronics. Kitcharoen *et al.* developed an AIoT-based intelligent water-resources control system for smart farming in which ANFIS formed part of a real-time monitoring and control architecture for water management [16]. Similarly, Tyokighir *et al.* proposed an ANFIS-based irrigation sprinkler system for dry-season farming, showing that ANFIS can adapt water-release decisions under varying environmental conditions more effectively than conventional irrigation approaches [17]. In embedded agricultural sensing, Gokkus and Gokkus demonstrated that ANFIS could be executed on a microcontroller-based platform for real-time leaf-area estimation using a photovoltaic sensing arrangement [18]. In crop-health diagnosis, Kim *et al.* integrated ANFIS with a fuzzy convolutional neural network and local binary pattern features for pepper-bell leaf-disease detection, achieving very high classification accuracy in a hybrid intelligent-agriculture framework [19].

Taken together, these studies show that contemporary ANFIS research in precision agriculture has advanced mainly in three directions: irrigation management, embedded crop sensing, and intelligent classification or diagnosis.

Metaheuristic algorithms such as genetic algorithms and particle swarm optimization have also been explored to strengthen ANFIS parameter optimization in agricultural modeling and machinery-related applications [20]. Simulated annealing is particularly attractive within this family because of its probabilistic search mechanism and strong global exploration capability, which allow it to escape local minima and maintain stable optimization performance in highly nonlinear search spaces [13], [15], [21]. Nevertheless, a clear gap remains in the application of ANFIS to real-time mechatronic regulation of planting implements, where sensing, inference, and actuator response must operate together to maintain agronomically critical seed-placement variables during field operation.

This gap is especially important in sorghum planting, where even small deviations in planting depth can reduce emergence uniformity and compromise crop stand establishment. For intelligent planter automation to be practically useful, the control model must move beyond offline prediction and be implemented as an embedded system capable of receiving sensor inputs, computing control actions in real time, and adjusting the furrow-opener mechanism during operation. Such a system must also be validated not only at the model level but at the hardware level, where response stability, actuation precision, and control consistency become central engineering concerns.

Accordingly, the present study extends SA-ANFIS modeling framework into an embedded real-time control application for sorghum planting-depth

regulation. Unlike the previous simulation-oriented study, the current work integrates sensing, neuro-fuzzy inference, and actuator-driven furrow-opener adjustment within a microcontroller-based planter platform and evaluates its performance under controlled field and hardware-in-the-loop conditions. The novelty of the study therefore lies not in proposing ANFIS or simulated annealing independently, but in demonstrating their practical integration as a closed-loop depth-control architecture for smart sorghum planters. By positioning SA-ANFIS within an embedded mechatronic system, the study seeks to bridge the gap between intelligent prediction and real-time planter control, while providing controlled-environment evidence for adaptive depth regulation under varying soil-moisture and travel-speed conditions [15]– [19].

## 2. Materials and Methods

### 2.1 Experimental Setup and Control-System Overview

The study was conducted in a controlled field environment using a smart sorghum planter prototype designed to integrate sensing, decision-making, and actuation for real-time planting-depth regulation. A sandy-loam soil was selected for the experiments because it is representative of soils commonly used for sorghum production and provides a suitable medium for evaluating opener penetration and depth-control response under repeatable conditions. The prototype consisted of three functional subsystems: a sensing layer for real-time acquisition of operating variables, an

embedded inference and control layer based on SA-ANFIS, and an actuation layer for furrow-opener displacement adjustment. This architecture was selected to move beyond fixed mechanical depth settings and toward a sensor-driven closed-loop planter platform suitable for adaptive depth regulation [22]– [24].

Two primary operating variables were used as model inputs: soil moisture content and forward travel speed. Soil moisture was varied from 10% to 30% wet basis across five levels: 10, 15, 20, 25, and 30%. Forward speed was varied from 0.3 to 0.9 m s<sup>-1</sup> across four levels: 0.3, 0.5, 0.7, and 0.9 m s<sup>-1</sup>. These ranges were selected to represent typical variability expected during mechanised sorghum planting and to expose the controller to changing soil-machine interaction states. For each treatment combination, repeated trials were conducted to capture depth response under controlled but dynamic operating conditions. In total, 180 observations were initially collected, after which incomplete or distorted records associated with sensor noise, wheel slippage, and mechanical disturbance were removed. The final dataset comprised 120 valid observations. Each treatment condition was replicated nine times.

The hardware platform used for controller implementation was based on an Arduino Mega 2560 microcontroller. Soil moisture was monitored using calibrated soil-moisture sensors, forward speed was measured using rotary encoders mounted to the travel system, and planting depth feedback was obtained from a high-precision linear displacement sensor attached to the furrow-opener assembly. A linear actuator (Model: FY014D) was

used to adjust opener position in response to controller commands, thereby forming a closed-loop depth-control mechanism. Soil-moisture sensors (Model: Stemedu ST3107X5) were calibrated using standard gravimetric procedures by relating oven-dried soil moisture values to sensor output, while the rotary encoders were calibrated by correlating pulse counts with known ground-wheel displacement.

To assess embedded performance under dynamic operating conditions, the optimised controller was also evaluated using hardware-in-the-loop (HIL) testing. The HIL stage was used to verify whether the embedded implementation could sustain stable real-time inference, maintain closed-loop depth tracking, and respond consistently to changing soil-moisture and speed inputs before any broader field-deployment claims were made. This combined field and HIL framework was selected to ensure that both predictive and control-level behaviors were examined under controlled, reproducible conditions.

The experimental dataset (Table 1) was prepared from the valid observations obtained under the defined soil-moisture and forward-speed combinations. After removal of noisy or incomplete records, the final 120-sample dataset was partitioned into 70% for model training and 30% for testing. This split was used to evaluate both model fitting and generalisation. The target output variable was optimal planting depth, expressed in centimeters for consistency.

Table 1. Training dataset

Sample	Soil	Forward	Planting	Replicate
--------	------	---------	----------	-----------

No.	Moisture, (M <sub>s</sub> ) (% w.b.)	Speed, (V <sub>f</sub> ) (m/s)	Depth, (D <sub>p</sub> ) (cm)	No.
1	10	0.3	3.5	1
2	10	0.3	3.4	2
3	10	0.3	3.6	3
...	...	...	...	...
120	25	0.6	4.8	9

**Notes:** M<sub>s</sub> is Soil moisture levels were set at 10, 15, 20, 25, and 30% w.b.; V<sub>f</sub> is Forward speeds were set at 0.3, 0.5, 0.7, and 0.9 m/s.

The decision to restrict the model inputs to soil moisture and travel speed was based on their direct physical influence on furrow-opener behavior and seed-placement depth during planting. Soil moisture alters soil strength, friability, and draft response, while forward speed affects dynamic interaction between the planter unit and soil surface [25] – [26]. Together, these variables capture a substantial proportion of the operating variation relevant to real-time depth control in a controlled sorghum-planting environment.

## 2.2 ANFIS Model Architecture

The control model was implemented as a first-order Sugeno-type Adaptive Neuro-Fuzzy Inference System (ANFIS). The model used two inputs, namely soil moisture and forward travel speed, and produced one output corresponding to the desired planting-depth adjustment. Gaussian membership functions were adopted for the antecedent layer because of their smooth differentiable form, which is favorable for parameter optimisation and stable nonlinear mapping. The consequent part of each fuzzy rule was expressed in linear form, consistent with a first-order Sugeno inference framework. In general form, the rule structure may be written as IF-THEN rule as presented in Equation 1.

$$\begin{aligned}
 & \text{IF } x_1 \text{ is } A_r^1 \text{ AND } x_2 \text{ is } A_r^2 \text{ THEN } Y = \\
 & f_r(x_1, x_2) = p_r x_1 + q_r x_2 + r_r \\
 & (1)
 \end{aligned}$$

Where;  $x_1, x_2$  = input variables;  $A_r^1$  = membership function of the  $r^{\text{th}}$  input in rule  $r$ ;  $p_r, q_r, r_r$  = linear consequent parameters of rule  $r$

Within this structure, the ANFIS model served as the nonlinear mapping engine between the measured operating conditions and the required depth-regulation response. The use of a Sugeno-type system was appropriate because it offers computational efficiency and direct compatibility with embedded implementation. In the present study, the model did not remain as an offline prediction tool; instead, it was prepared for real-time deployment on a microcontroller-based platform, thereby linking sensor inputs directly to actuator commands through an inference-based control loop.

The model accepts two normalized input parameters: soil moisture (M<sub>s</sub>) and planting speed (V<sub>f</sub>). The model outputs three predicted variables: planting depth ( $\hat{D}_p$ ), planting speed ( $\hat{S}_p$ ), and metering speed ( $\hat{M}_r$ ). Model training was performed using a hybrid learning algorithm that integrates least squares estimation for forward pass optimization and backpropagation for backward pass parameter adjustment. The training process was executed for 100 epochs with a convergence criterion set at an error tolerance of  $1 \times 10^{-5}$ . The optimization objective throughout training was to minimize the root mean square error between the ANFIS-predicted outputs and the corresponding experimental observations.

The model is a hybrid SA-ANFIS system because simulated annealing was used to optimise the membership-function distributions and consequent parameters. The optimised parameters were subsequently converted to fixed-point representation to reduce computational overhead and facilitate execution on the Arduino Mega 2560. This step was necessary to ensure that the controller could run in real time within the memory and processing constraints of the embedded platform.

### 2.3 Simulated Annealing Optimisation Procedure

Simulated annealing (SA) was employed to optimise the ANFIS parameters and improve the global search capability of the control model. The rationale for using SA was to reduce the risk of local-minimum entrapment associated with purely gradient-based tuning and to improve parameter convergence in the presence of nonlinear interactions between soil moisture, speed, and planting-depth response. In the optimisation stage, SA acted on both the antecedent and consequent components of the ANFIS model, refining the Gaussian membership-function distributions and the linear coefficients of the Sugeno rule consequents. The objective function was the minimisation of root mean square error (RMSE) between predicted and observed planting depth.

The optimisation procedure used an initial temperature, a cooling coefficient, and an iteration length of 50 evaluations per temperature level. The stopping condition was defined as a change in

objective value sustained over 10 consecutive iterations. During early stages of the search, the algorithm permitted probabilistic acceptance of inferior intermediate states in order to preserve exploration and escape local optima. As the temperature decreased, the search became increasingly exploitative, converging toward a lower-error parameter set for the ANFIS controller. This global-to-local transition formed the core of the SA enhancement used in the present work.

### 2.4 Embedded Controller Implementation

After optimisation, the SA-ANFIS model was deployed to the Arduino Mega 2560 as the core decision module of the planter depth-control system using Arduino IDE (v1.3/v2.7). During operation, the controller received real-time soil-moisture and speed inputs, executed the inference routine, and issued a control signal to the linear actuator responsible for furrow-opener displacement. Feedback from the displacement sensor enabled the controller to regulate depth in a closed-loop manner, thereby allowing the system to compensate for changing operating conditions rather than relying on fixed preset depth. The ANFIS-SA inference for the output (planting depth) was executed within a fixed control loop of 50 ms (20 Hz). The total computation time per cycle, including sensor acquisition, ANFIS inference, and actuator command generation, was approximately 12 ms, leaving sufficient timing margin for stable real-time operation. In terms of resource utilization, the complete ANFIS-SA control logic occupied approximately 18–22 kB of Flash memory and 1.5–2.0 kB of SRAM,

corresponding to less than 30% of available Flash and 25% of SRAM on the Arduino Mega.

## 2.5 Model Validation and Statistical Analysis

Model and controller performance were evaluated using both predictive and agreement-based statistical measures. Multi-metric validation approaches are widely recommended for nonlinear intelligent modelling because individual performance indices often provide limited insight into overall model reliability and field applicability [27]-[31]. Predictive accuracy was assessed using root mean square error (RMSE) and the coefficient of determination ( $R^2$ ). These indicators were used to quantify the improvement in prediction and control-oriented depth estimation after simulated annealing optimisation.

Agreement between predicted and measured planting depth was further examined using Bland-Altman analysis. This analysis was included to identify systematic bias and to determine whether prediction errors remained symmetrically distributed around the zero-bias line.

The model acceptance or rejection criteria are: if RMSE is decreased the model is fit or otherwise, the model is fit if  $R^2$  is increased or otherwise. The system performance metrics acceptance and rejection criteria are: if the coefficient of variation (CV), is  $<5\%$  then the result very uniform, it is acceptable for most crop if  $5\% \leq CV \leq 10\%$  and if  $CV > 10\%$  the depth needs further adjustment. MATLAB R2024b and Python 3.11 were used for

model development, statistical evaluation, and supporting computational analysis.

Predictive modelling accuracy was quantified using the Root Mean Square Error (RMSE) and the coefficient of determination ( $R^2$ ). RMSE provides a direct measure of prediction deviation magnitude and reflects the overall closeness between observed and model-estimated values, while  $R^2$  evaluates the proportion of variance in measured planting depth explained by the predictive model. The combined use of RMSE and  $R^2$  is widely recognised as a robust approach for evaluating nonlinear agricultural system prediction models and intelligent control algorithms [32], [33].

Operational planting depth stability was assessed using the coefficient of variation (CV), which provides a normalised measure of dispersion in seed placement depth relative to the mean. CV is frequently used in precision planting performance evaluation because it directly reflects field-level uniformity and crop stand establishment reliability. Lower CV values indicate improved depth consistency and enhanced planting performance under variable operating conditions [1], [34], [35].

The level of agreement between experimentally measured planting depths and model-predicted outputs was further examined using Bland-Altman analysis. This method enables the identification of systematic prediction bias and the detection of heteroscedastic error patterns across the measurement range by analysing mean difference trends and limits of agreement. Bland-Altman analysis has been increasingly adopted in engineering and biosystem modelling studies to

complement traditional regression-based validation metrics by providing graphical and statistical agreement assessment between measurement techniques [36].

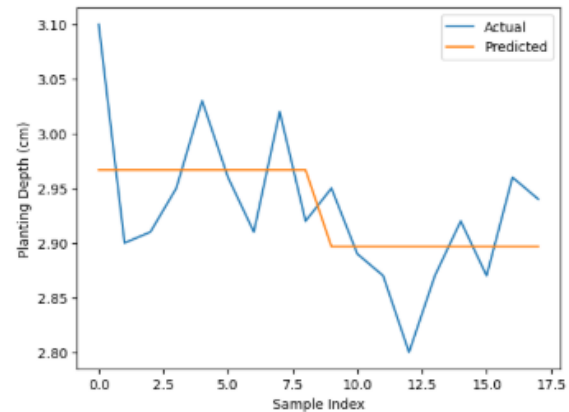
Inferential statistical analysis was performed using paired sample t-tests to determine whether optimisation-based controller tuning produced statistically significant improvement in planting depth prediction accuracy. The paired t-test is particularly suitable for evaluating performance differences between pre-optimisation and post-optimisation modelling structures because it accounts for correlated experimental observations obtained under identical operating conditions [37].

### 3. Results and Discussion

#### 3.1 Baseline ANFIS Training Behaviour

The baseline ANFIS model (Fig. 1) showed stable convergence during training and demonstrated the feasibility of mapping soil-moisture and forward-speed inputs to planting-depth response [6], [9], [33]. However, its learning curve exhibited a clear reduction in improvement after the early and middle training phases, with the error profile approaching a plateau toward the later epochs. The baseline model reached a final RMSE of 0.24 cm after 120 training epochs, with the error trend becoming largely stable after approximately epoch 80. The similarity between training and testing behavior suggested that severe overfitting was not the dominant limitation; rather, the residual error plateau indicated incomplete parameter optimization under standard ANFIS learning [38]. This behavior is consistent with gradient-based

systems that perform adequately in local search regions but struggle to achieve globally improved parameter combinations in nonlinear operating spaces.



**Fig. 1.** Planting Depth Training Curve

From a control perspective, this baseline result is important because it defines the reference level against which the benefit of simulated annealing must be judged. The baseline ANFIS was sufficiently accurate to capture the general direction of depth variation, but it did not provide the level of consistency required for a robust embedded depth-control architecture intended to operate under changing soil and speed conditions. The residual error observed at this stage justified the introduction of a metaheuristic optimization layer to improve membership-function placement and consequent-parameter tuning.

#### 3.2 Predictive Performance Enhancement Through Simulated Annealing

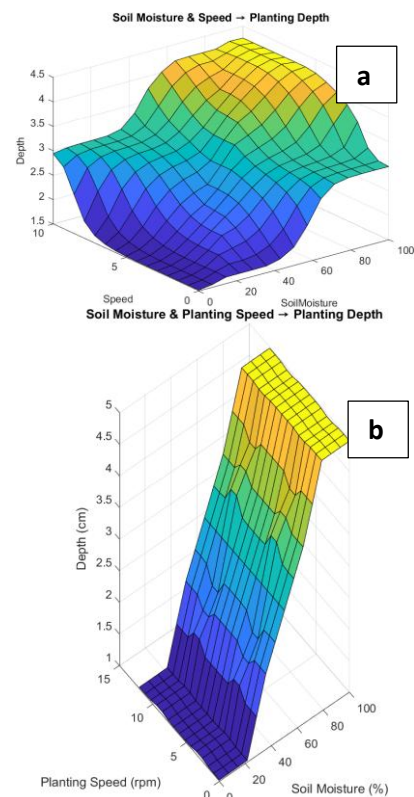
The integration of simulated annealing produced a measurable improvement in model performance. After optimization, the SA-ANFIS model achieved an RMSE of 0.18692 cm and a coefficient of determination of  $R^2 = 0.871$ , indicating that the optimized model explained approximately 87.1% of the variance in planting-depth response. Relative to the baseline ANFIS RMSE of 0.24 cm, this corresponds to a 22.1% reduction in RMSE, confirming that simulated annealing improved the global tuning of the neuro-fuzzy system [38] [40] [41].

The performance gain reflects the ability of simulated annealing to search beyond local minima and refine the parameter landscape of the ANFIS structure. Rather than relying solely on local gradient information, the optimization process explored a broader solution space and generated a smoother nonlinear mapping between the operating inputs and the target planting depth. Paired-sample statistical testing indicated that the improvement was significant at  $p < 0.05$ , reinforcing that the observed reduction in error was not attributable to random variation alone [32], [38].

These results confirm that the contribution of SA is not merely numerical refinement but control-relevant improvement. In an embedded setting, reductions in prediction error directly affect the reliability of actuator commands and the controller's ability to maintain agronomically meaningful planting-depth targets. Thus, the significance of the optimisation stage lies not only in model performance but also in its practical implication for real-time planter adjustment.

### 3.3 Nonlinear Interaction Between Soil Moisture and Forward Speed

The response of planting depth to soil moisture and forward speed (Fig. 2a and Fig. 2b) was distinctly nonlinear. As soil moisture increased, the soil exhibited lower penetration resistance and higher plasticity, allowing the opener to achieve the desired depth with less resistance [39], [42], [43], [44]. By contrast, drier soil conditions increased shear resistance and reduced the stability of opener penetration [45], [46]. Forward speed also affected depth behavior by altering dynamic loading, inertial response, and contact stability between the planter unit and the soil [43], [47]. These interactions explain why fixed mechanical depth settings often fail under changing field conditions and why an adaptive inference system is more suitable for depth regulation.



**Fig. 2.** Surface plots

The optimized SA-ANFIS model generated a smoother and more continuous response surface than the baseline configuration. This smoothing is important from a control perspective because abrupt surface discontinuities can lead to unstable command switching and undesirable actuator oscillation. A smoother control surface implies better interpolation between operating points and greater consistency in real-time command generation. Therefore, the optimization process improved not only prediction accuracy but also the stability characteristics of the control law itself.

### 3.4 Prediction Accuracy and Planting Uniformity

#### 3.4.1 Prediction accuracy

Across the tested operating range, the predicted and measured planting-depth responses remained within  $\pm 0.2$  cm, indicating a relatively narrow band of model deviation. This level of agreement is practically meaningful because it lies well within the commonly cited agronomic tolerance of  $\pm 0.5$  cm for acceptable planting-depth deviation. The ability of the model to maintain error within this narrower interval suggests that the controller is capable of supporting seed placement with a high degree of consistency under controlled operating conditions [47], [48].

From an agronomic standpoint, consistent planting depth supports more synchronized emergence, improved seed-soil contact, and more uniform early crop development. In sorghum, these effects are especially important because emergence variability can translate directly into uneven plant vigor and stand establishment. Consequently, the predictive accuracy achieved by the SA-ANFIS controller is not merely a statistical result; it also indicates practical capacity to improve the biological uniformity of the planted crop [43], [47][49]

#### 3.4.2 Planting Depth Variability Analysis

Planting depth consistency varied substantially across treatment conditions, with coefficient of variation (CV) values ranging from 7.69% to 18.24% for actual measurements (Table 2, Figure 3A). The overall CV across all 40 trials was 10.58%, indicating good precision for agricultural applications.

The most consistent planting depth performance was achieved under low moisture and low speed conditions (CV = 7.69%, n = 5), while the highest variability occurred under high moisture and high-speed operations (CV = 18.24%, n = 4), representing a 137% increase in variability. Distribution analysis (Figure 5B) confirmed that optimal conditions produced tighter data clustering, with interquartile ranges 48% smaller than challenging conditions. The observed CV range (7.69-18.24%) aligns with agricultural equipment standards, where CV < 20% is generally considered acceptable for planting operations [5]. Our findings that 75% of treatments

achieved  $CV < 15\%$  suggests the smart planter performs competitively with conventional systems while offering enhanced monitoring capabilities.

Soil moisture level significantly affected depth consistency (Figure 3C). Low moisture conditions (18-20%) produced the most consistent results ( $CV = 8.54\%$ ), while high moisture (22-24%) exhibited 61% higher variability ( $CV = 13.73\%$ ). This trend suggests that excessive moisture compromises soil-implement interaction, reducing the system's capacity for precise depth control. The 61% CV increase from low to high moisture (Table 2, Figure 3C) likely reflects multiple mechanisms: (1) increased soil adhesion causing irregular implement movement, (2) reduced soil shear strength leading to inconsistent furrow formation, and (3) mud buildup on depth control components. These findings support previous research indicating that soil moisture above 22% field capacity significantly compromises planting precision [50]- [52].

Planting speed demonstrated a threshold effect on precision (Figure 3D). Low and medium speed operations maintained similar consistency ( $CV = 9.88\%$  and  $9.64\%$ , respectively), while high-speed operations showed substantially increased variability ( $CV = 15.21\%$ ), representing a 58% increase. This suggests a critical speed limit around 4.5 km/h, beyond which dynamic forces compromise depth stability. The threshold effect observed at 4.5 km/h (Figure 3D) corresponds to the transition from quasi-static to dynamic soil engagement. Above this speed, inertial forces and vibration amplitudes increase non-linearly,

overwhelming depth control mechanisms. This explains why the interaction effect (Figure 3D) shows high moisture + high speed as the worst-case scenario: both factors independently reduce precision, and their combination creates compounding effects.

The moisture  $\times$  speed interaction plot (Figure 3D) revealed synergistic effects, with high moisture amplifying speed-related variability. Under low moisture, speed increase from low to high resulted in only 16% CV increase, whereas high moisture conditions showed 104% CV increase, indicating that speed reduction is particularly critical in wet soil conditions. The ANFIS model's ability to replicate CV patterns ( $R^2 = 0.8849$ , Figure 3E) validates its utility beyond point prediction. By capturing variability characteristics, the model enables probabilistic performance forecasting, supporting real-time decision-making about operating parameter adjustments. The excellent agreement (87.5% of treatments with  $|\Delta CV| < 2\%$ , Figure 3F) suggests the model structure successfully represents the underlying physical relationships governing system variability.

ANFIS predictions demonstrated excellent agreement with actual measurements (Figure 3E), achieving  $R^2 = 0.8849$  and maintaining comparable CV patterns across all treatments (Figure 3F). The mean difference between predicted and actual CV values was only 0.61%, with 87.5% of treatments showing excellent agreement ( $|\Delta| < 2\%$ ). This validates the model's capability to predict both central tendencies and inherent variability under diverse operating conditions.

operating conditions requiring optimization or avoidance.

Classification analysis (Figure 3B) revealed that 75% of treatments achieved  $CV < 15\%$ , indicating acceptable consistency for commercial operations. The remaining 25% ( $CV 15-20\%$ ) occurred exclusively under high moisture and high-speed combinations, suggesting these represent boundary

Table 2. Planting Depth Coefficient of Variation by Treatment Condition

Treatment Condition	N	Actual Depth (cm)			Predicted Depth (cm)				
		Mean±SD	CV(%)	Range	Median	Mean±SD	CV(%)	Range	Median
High × High	4	5.13±0.94	18.24	4.06-5.99	5.24	5.12±0.93	18.13	4.09-5.91	5.24
High × Medium	5	4.89±0.51	10.38	4.23-5.43	4.77	4.81±0.47	9.67	4.27-5.34	4.70
High × Low	2	4.61±0.73	15.82	4.09-5.12	4.61	4.70±0.69	14.61	4.21-5.18	4.70
Medium × High	3	4.92±0.64	13.03	4.45-5.65	4.66	4.95±0.57	11.42	4.48-5.58	4.80
Medium × Medium	14	4.97±0.51	10.24	4.26-5.96	4.79	4.94±0.60	12.24	3.61-6.07	5.06
Medium × Low	2	5.07±0.50	9.89	4.72-5.43	5.07	5.21±0.71	13.72	4.70-5.71	5.21
Low × Medium	5	4.93±0.45	9.12	4.27-5.47	5.07	4.81±0.36	7.58	4.20-5.17	4.89
Low × Low	5	5.24±0.40	7.69	4.63-5.71	5.34	5.34±0.33	6.11	5.06-5.86	5.32

*Note: High moisture (22-24%), Medium (20-22%), Low (18-20%); High speed (4.5-5.0 km/h), Medium (3.5-4.5 km/h), Low (3.0-3.5 km/h)*

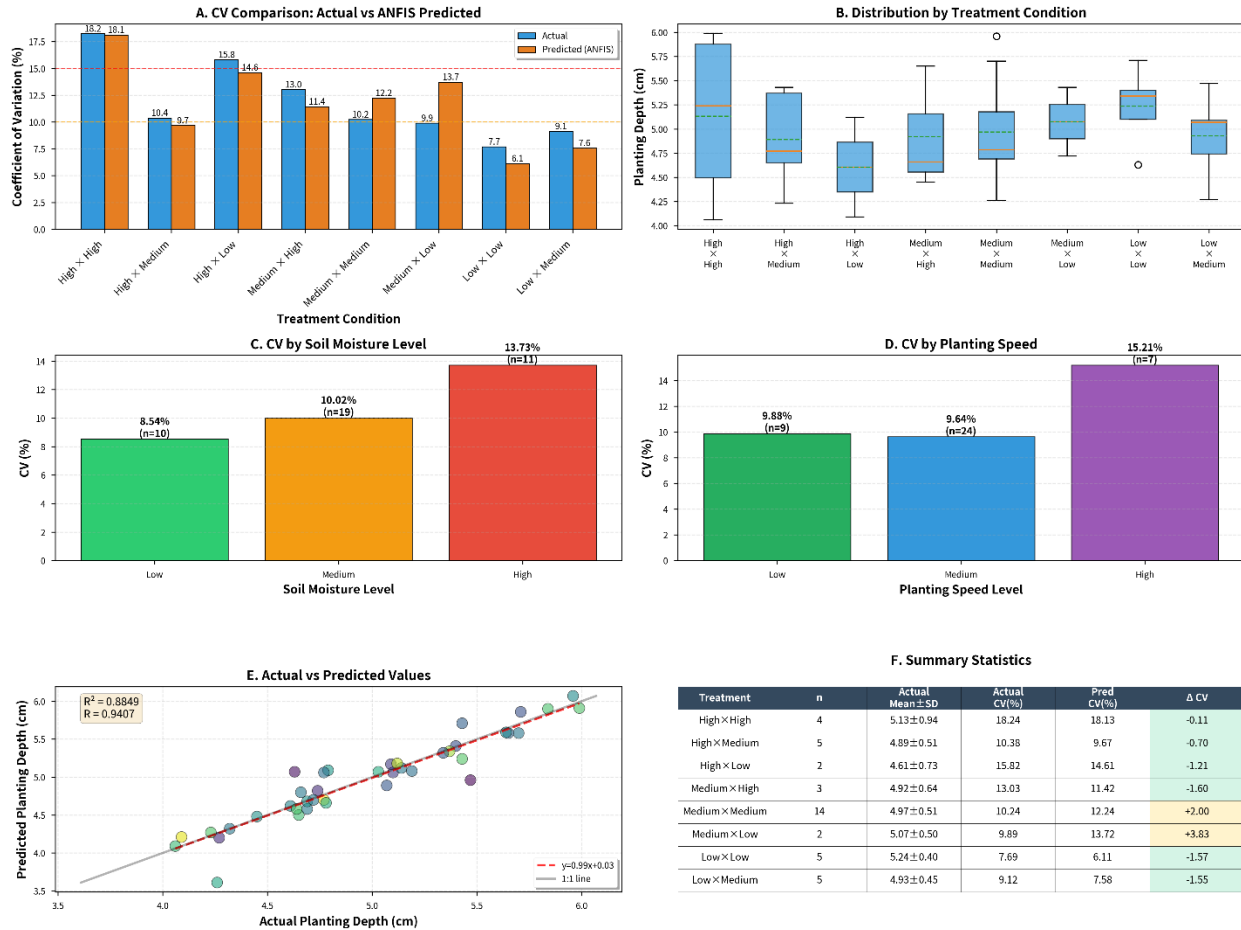


Fig. 3.

### 3.5 Agreement Validation Using Bland–Altman Analysis

Bland–Altman analysis (Figure 4) was used to evaluate agreement between measured and predicted planting-depth values and to determine whether the model exhibited systematic bias. The error pattern was reported to be symmetrically distributed around the zero-bias line, with narrow 95% limits of agreement and no meaningful evidence of heteroscedasticity. This indicates that the model error did not increase systematically across either shallow or deeper planting conditions

and that the controller retained similar reliability across the tested operating domain [34], [46].

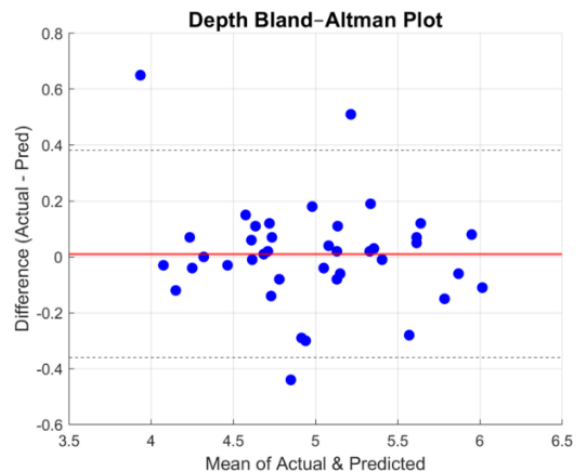


Fig. 4. Bland–Altman plots of planting depth

This agreement result is important because a low RMSE alone does not guarantee unbiased control behavior. In real-time agricultural systems, a controller may appear accurate in aggregate while still showing directional bias in certain operating zones. The Bland–Altman outcome strengthens the validity of the SA-ANFIS model by showing that the remaining deviations were random rather than structurally biased. In practical terms, this means that the controller can be interpreted as stable and trustworthy within the tested field and HIL envelope, rather than simply overfitted to a narrow operating subset.

### 3.6 Real-Time Embedded Controller Performance

The most important engineering result of the study is that the optimised SA-ANFIS model could be deployed successfully as an embedded real-time controller on the Arduino Mega 2560. During hardware-in-the-loop testing, the controller-maintained planting depth within  $\pm 0.12$  cm ( $\pm 1.2$  mm) and achieved 96.7% depth uniformity under changing soil-moisture and travel-speed conditions. These values indicate that the fixed-point embedded implementation preserved the essential predictive and control characteristics of the optimised model while operating on a resource-constrained microcontroller platform [47], [48], [49].

The HIL outcome is especially significant because it moves the contribution of the study beyond offline modeling. Many ANFIS-based agricultural studies remain at the level of decision support or post hoc prediction, whereas the present work

demonstrates that the optimised inference model can generate physically useful actuator commands in real time. The reported precision of  $\pm 0.12$  cm is also substantially tighter than the  $\pm 0.5$  cm agronomic acceptability threshold providing a strong indication that the controller is sufficiently precise for controlled-environment depth regulation [54], [55], [56].

To validate the real-time feasibility of the embedded ANFIS-SA controller, the execution time of each task within the Arduino control loop was measured and analyzed as in Table 3. Timing measurements were obtained using internal microcontroller timers by recording the elapsed time before and after each major operation in the control cycle. The total loop execution time  $T_{loop}$  is given in Equation 2.

$$T_{loop} = T_{sens} + T_{norm} + T_{ANFIS} + T_{act} + T_{disp} + T_{comm} \quad (2)$$

Where:

$T_{sens}$  = sensor acquisition time

$T_{norm}$  = input normalization time

$T_{ANFIS}$  = fuzzy inference computation time

$T_{act}$  = actuator update time

$T_{disp}$  = LCD update time

$T_{comm}$  = Bluetooth communication time

Table 3. Execution Time Breakdown of the Arduino Control Loop

Task	Description	Average Time (ms)
$T_{sens}$	Sensor acquisition	7.3
$T_{norm}$	Input normalization	7.5
$T_{ANFIS}$	Unified ANFIS-SA inference (3 outputs)	9.9
$T_{act}$	Actuator update	7.8
$T_{disp}$	LCD update	5.0
$T_{comm}$	Bluetooth communication	3.5
Total	Complete control loop	41.0 ms

The total execution time is significantly lower than the selected sampling interval ( $\Delta t=50$  ms), satisfying the real-time condition:

$$T_{loop} \ll \Delta t$$

The timing analysis confirms that the Arduino platform is capable of executing the multi-output ANFIS-SA controller within strict real-time limits. Even with LCD updates and wireless communication enabled, the controller maintains sufficient processing headroom for reliable field operation. This validates the suitability of low-cost microcontrollers for intelligent control applications in precision agricultural machinery.

### 3.7 Agronomic and Operational Implications

From an agronomic perspective, the improved depth consistency achieved by the SA-ANFIS controller supports the goal of uniform seed placement in moisture-favorable soil layers. This contributes to more synchronised germination, improved early stand establishment, and better use of the genetic yield potential of the crop [1], [9], [57]. Because sorghum establishment is especially sensitive to variation in seed placement under fluctuating moisture conditions, the practical ability to regulate depth in response to changing soil state represents a meaningful step toward smarter planting systems [23], [58], [59].

Operationally, the controller provides a mechanism for compensating for dynamic interactions that would otherwise be handled poorly by fixed mechanical settings. By adjusting furrow-opener position according to real-time conditions, the system reduces the need for overcompensation by the operator and may also help limit unnecessary

soil disturbance and draft variation. The smoother inference surface produced by the optimised model further supports stable actuator response, which is beneficial for both mechanical reliability and control consistency. These operational benefits reinforce the engineering significance of embedding SA-ANFIS within a planter-control system rather than using it solely as a predictive modeling tool.

### 3.8 Comparison with Existing Intelligent Agricultural Models

A major distinction between the present study and much of the prior ANFIS literature is the transition from intelligent prediction to intelligent control. Existing studies have commonly applied ANFIS to irrigation scheduling, yield prediction, crop sensing, or classification tasks, and recent related work similarly emphasizes water-control systems, embedded sensing devices, and disease-detection architectures rather than planter mechatronics [15]– [23]. By contrast, the present work uses SA-ANFIS as an active closed-loop controller for a planter mechanism, integrating sensing, inference, actuation, and HIL verification within one embedded platform.

The study does not argue that ANFIS or simulated annealing is new in itself; rather, it demonstrates that an optimised ANFIS model can be translated into an embedded real-time planter controller capable of maintaining planting depth under variable inputs [60], [61], [62]. In that sense, the study contributes to the underdeveloped intersection between computational intelligence and agricultural implement control [15], [63]

### 3.9 Robustness, Generalisation, and Study Limitations

The residual behavior suggests that the optimised model retained robust performance across the tested combinations of soil moisture and travel speed. The absence of systematic bias in Bland–Altman analysis and the narrow error band around the prediction line support the interpretation that the controller’s residual error is largely stochastic rather than structural [11], [64]. This strengthens confidence in the model’s generalization interpreted within the controlled experimental envelope.

The system was evaluated in a controlled field facility and by means of hardware-in-the-loop testing, not through full-scale field trials across heterogeneous soils, residue loads, slopes, and weather conditions. The present results demonstrate feasibility under controlled conditions and provide a strong basis for subsequent field validation, but they do not yet constitute proof of performance under all real-world planting conditions.

This distinction is not a weakness of the study so much as an important boundary of interpretation. The current work successfully establishes the embedded SA-ANFIS framework, verifies its predictive and control capabilities, and demonstrates operational precision under controlled dynamics.

## 4. Conclusion

This study demonstrated that a simulated annealing–optimised ANFIS (SA-ANFIS) can function effectively as a real-time embedded controller for regulating planting depth in a smart sorghum planter. By integrating sensing, neuro-fuzzy inference, and actuator control within a microcontroller-based closed-loop system, it addressed a key gap in translating ANFIS from prediction tasks to practical mechatronic control.

The SA-ANFIS model outperformed the baseline ANFIS, achieving lower error (RMSE = 0.18692 cm, a 22.1% improvement) and strong accuracy ( $R^2 = 0.871$ ). In real-time operation, it maintained planting depth within  $\pm 0.12$  cm and achieved 96.7% uniformity, demonstrating reliable performance on low-cost embedded hardware.

The study’s main contribution is proving that optimisation-driven intelligent control can be implemented in functional planting systems, enabling adaptive responses to soil moisture and speed variations. This has potential agronomic benefits such as improved seed placement and uniform crop emergence, while also confirming the feasibility of deploying computational intelligence in agricultural machinery.

However, results are limited to controlled environments and hardware-in-the-loop testing. Future work should validate the system under full-field conditions, diverse soils, and longer operational durations, while also refining sensor

calibration, controller timing, and benchmarking against other control strategies.

## Abbreviations

GA Genetic Algorithm

PSO Particle Swarm Optimization

ANFIS Adaptive Neuro-Fuzzy Inference System

SA-ANFIS Simulated Annealing Adaptive  
Neuro-Fuzzy Inference System

R<sup>2</sup> Coefficient of Determination

RMSE Root Mean Square Error

## Acknowledgements

We would like to acknowledge FUTMinna for providing enabling environment for the research.

## Funding

This research was funded by TETF/ES/DR&D-CE/NRF2024/SETI/AFS/00215.

## Data availability and materials

Data can be shared upon request.

## Authors' contributions

All authors made substantial contributions to the conception and design of this study. I. Abubakar, I.M. Abdullahi, A.A. Balami, and P.A. Idah were

responsible for data collection, simulation execution, and data analysis. I. Abubakar drafted the initial manuscript, while all authors provided critical feedback and revisions on subsequent versions. All authors have reviewed and approved the final manuscript for submission.

## Ethics declarations

## Conflict of interest

There is **no conflict of interest** to be reported for this study.

## Ethical approval

Not applicable.

## Informed consent

Not applicable.

## REFERENCES

- [1] A. Celik, I. Ozturk, and T. R. Way, "Effects of various planters on emergence and seed distribution uniformity of sunflower," *Applied Engineering in Agriculture*, vol. 23, no. 1, pp. 57–61, 2007.
- [2] V. Vala *et al.*, "Development, optimization and modelling of performance parameters for remote-controlled mechatronic precision planter using RSM and hybrid PSO-ANN model," *Smart Agricultural Technology*, vol. 11, Art. no. 100993, pp. 1–15, 2025, doi: 10.1016/j.atech.2025.100993.

- [3] K. Ahmed, A. Saleh, A. D. Musa, and G. Kalu, "Determination of selected parameters that influence planting space uniformity on maize seed," *FUDMA Journal of Sciences*, vol. 7, no. 2, pp. 30–33, 2023.
- [4] D. L. Mangus, A. Sharda, D. Flippo, R. Strasser, and T. Griffin, "Development of high-speed camera hardware and software package to evaluate real-time electric seed meter accuracy of a variable rate planter," *Computers and Electronics in Agriculture*, vol. 142, pp. 314–325, 2017, doi: 10.1016/j.compag.2017.09.014.
- [5] J. A. Smith and M. F. Kocher, "Evaluate planter meter and seed tube systems for seed spacing performance of confection sunflower seed to improve plant spacing in the field," 1999.
- [6] J.-S. R. Jang, "ANFIS: Adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665–685, 1993.
- [7] R. L. Sobrinho *et al.*, "A fuzzy yield model of the wheat inoculated with *Rhizophagus irregularis* under future climate elevated CO<sub>2</sub>," Oct. 2024, doi: 10.21203/rs.3.rs-5289725/v1.
- [8] P. Suomi and T. Oksanen, "Automatic working depth control for seed drill using ISO 11783 remote control messages," *Computers and Electronics in Agriculture*, vol. 116, pp. 30–35, 2015, doi: 10.1016/j.compag.2015.05.016.
- [9] B. Khoshnevisan, S. Rafiee, M. Omid, and H. Mousazadeh, "Development of an intelligent system based on ANFIS for predicting wheat grain yield on the basis of energy inputs," *Information Processing in Agriculture*, vol. 1, no. 1, pp. 14–22, 2014, doi: 10.1016/j.inpa.2014.04.001.
- [10] S. S. Tyokighir, J. Mom, K. E. Ukhurebor, and G. Igwe, "An adaptive neuro-fuzzy inference system-based irrigation sprinkler system for dry season farming," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 4, pp. 2434–2441, 2024, doi: 10.11591/eei.v13i4.7834.
- [11] H. Y. Truneh, G. Alemu, and T. M. Balcha, "Fuzzy logic based automatic plant watering system," *International Journal of Engineering Research and Technology*, vol. 10, no. 7, pp. 695–709, 2021.
- [12] X. Chen, C. Bo-li, R. Hu, N. Liu, and C. Zhang, "Integrated optimization of structure and control parameters for the height control system of a vertical spindle cotton picker," *Research Square*, pp. 1–13, 2018.
- [13] K. A. Alnowibet, S. Mahdi, M. El-Alem, M. Abdelawwad, and W. Mohamed, "Guided hybrid modified simulated annealing algorithm for solving constrained global optimization problems," *Mathematics*, vol. 10, Art. no. 1312, pp. 1–25, 2022, doi: 10.3390/math10081312.
- [14] C. Zhengcai, Z. Huidan, and W. Yongji, "ANFIS and SA based approach to prediction, scheduling, and performance evaluation for semiconductor wafer fabrication," *Chinese Journal of Electronics*, vol. 22, no. 1, 2013.
- [15] I. Abubakar, I. M. Abdullahi, A. A. Balami, and P. A. Idah, "Development of a simulated annealing-optimized adaptive neuro-fuzzy inference system (SA-ANFIS) for sorghum seed planting parameter tuning," *Arid Zone Journal of Engineering, Technology and Environment*, vol. 21, no. 3, pp. 758–768, 2025, doi: 10.63958/AZOJETE/2025/21/03/007.
- [16] P. Kitcharoen, S. Chookaew, and S. Howimanporn, "Implementation of an AIoT-based intelligent water resources control system for smart farm," *IEEE Access*, vol. 12, pp. 156878–156892, 2024, doi: 10.1109/ACCESS.2024.3482088.
- [17] S. S. Tyokighir, J. Mom, K. E. Ukhurebor, and G. Igwe, "An adaptive neuro-fuzzy inference system-based irrigation sprinkler system for dry season farming," *Bulletin of Electrical Engineering and Informatics*, vol. 13, no. 4, pp. 2434–2441, 2024, doi: 10.11591/eei.v13i4.7834.

- [18] G. Gokkus and M. K. Gokkus, "Leaf area estimation based on ANFIS using embedded system and PV panel," *Heliyon*, vol. 10, no. 14, Art. no. e34149, 2024, doi: 10.1016/j.heliyon.2024.e34149.
- [19] T.-H. Kim, M. Shahroz, B. Alabdullah, N. Innab, J. Baili, M. Umer, F. Majeed, and I. Ashraf, "ANFIS fuzzy convolutional neural network model for leaf disease detection," *Frontiers in Plant Science*, vol. 15, Art. no. 1465960, 2024, doi: 10.3389/fpls.2024.1465960.
- [20] O. Obe and I. Dumitrache, "Adaptive neuro-fuzzy controller with genetic training for mobile robot control," *International Journal of Computers, Communications & Control*, vol. 7, no. 1, pp. 135–146, 2012, doi: 10.15837/ijccc.2012.1.1429.
- [21] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, "Optimization by simulated annealing," *Science*, vol. 220, no. 4598, pp. 671–680, 1983, doi: 10.1126/science.220.4598.671.
- [22] S. Zhao and Y. Zhang, "Design and field test of corn seeding system based on fuzzy PID control method combined with PSO," *Engenharia Agrícola*, vol. 44, pp. 1–11, 2024.
- [23] L. Zhou *et al.*, "Design and test of sowing depth measurement and control system for no-till corn seeder based on integrated electro-hydraulic drive," *Applied Sciences*, vol. 13, Art. no. 5823, pp. 1–24, 2023.
- [24] S. Kirkegaard *et al.*, "Seed drill instrumentation for spatial coulter depth measurements," *Computers and Electronics in Agriculture*, vol. 141, pp. 207–214, 2017, doi: 10.1016/j.compag.2017.07.014.
- [25] H. Tang, C. Xu, Z. Wang, Q. Wang, and J. Wang, "Optimized design, monitoring system development and experiment for a long-belt finger-clip precision corn seed metering device," *Frontiers in Plant Science*, vol. 13, pp. 1–16, 2022, doi: 10.3389/fpls.2022.814747.
- [26] G. C. Topp, J. L. Davis, and A. P. Annan, "Electromagnetic determination of soil water content: Measurements in coaxial transmission lines," *Water Resources Research*, vol. 16, no. 3, pp. 574–582, 1980, doi: 10.1029/WR016i003p00574.
- [27] S. Vogel *et al.*, "The effect of soil moisture content and soil texture on fast in situ pH measurements with two types of robust ion-selective electrodes," *SOIL*, vol. 10, no. 1, pp. 321–333, 2024, doi: 10.5194/soil-10-321-2024.
- [28] S. Adla, F. Bruckmaier, L. F. Arias-Rodriguez, S. Tripathi, S. Pande, and M. Disse, "Impact of calibrating a low-cost capacitance-based soil moisture sensor on AquaCrop model performance," *Journal of Environmental Management*, vol. 353, pp. 1–16, 2024, doi: 10.1016/j.jenvman.2024.120248.
- [29] R. Strasser, S. Badua, A. Sharda, D. Mangus, and L. Haag, "Performance of planter electric-drive seed meter during simulated planting scenarios," *Applied Engineering in Agriculture*, vol. 35, no. 6, pp. 925–935, 2019, doi: 10.13031/aea.13763.
- [30] S. Badua, A. Sharda, R. Strasser, and I. Ciampitti, "Ground speed and planter downforce influence on corn seed spacing and depth," *Precision Agriculture*, vol. 22, pp. 1–17, Aug. 2021, doi: 10.1007/s11119-020-09775-7.
- [31] C. J. Willmott and K. Matsuura, "Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance," *Climate Research*, vol. 30, no. 1, pp. 79–82, 2005, doi: 10.3354/cr030079.
- [32] N. Nekuei, M. A. Behdani, and A. K. Siuki, "Evaluation of adaptive neuro-fuzzy inference system models in estimating saffron yield using meteorological data," *Journal of Agricultural Science and Technology*, vol. 23, no. 1, pp. 221–234, 2021.

- [33] H. Khoshvaght, R. R. Permal, A. Razmjou, and M. Khiadani, "A critical review on selecting performance evaluation metrics for supervised machine learning models in wastewater quality prediction," *Journal of Environmental Chemical Engineering*, vol. 13, no. 6, Art. no. 119675, 2025, doi: 10.1016/j.jece.2025.119675.
- [34] E. J. Ibrahim, A. D. Elfadil, A. D. Abdallah, and R. Ahmed, "Optimization of seed precision performance of a multi-rows pneumatic plate metering device using two seed ejecting methods," *International Journal of Scientific Research Updates*, vol. 3, no. 2, pp. 10–20, 2022.
- [35] C. Zhai, J. Long, R. Taylor, P. Weckler, and N. Wang, "Field scale row unit vibration affecting planting quality," *Precision Agriculture*, vol. 21, no. 3, pp. 589–602, 2020, doi: 10.1007/s11119-019-09684-4.
- [36] D. Giavarina, "Understanding Bland Altman analysis," *Biochimica Medica*, vol. 25, no. 2, pp. 141–151, 2015, doi: 10.11613/BM.2015.015.
- [37] D. C. Montgomery, E. A. Peck, and G. G. Vining, *Introduction to Linear Regression Analysis*, 4th ed. Canada: John Wiley & Sons, Inc., 2012. [Online]. Available: [www.wiley.com](http://www.wiley.com)
- [38] H. L. Nguyen *et al.*, "Adaptive network based fuzzy inference system with meta-heuristic optimizations for international roughness index prediction," *Applied Sciences*, vol. 9, no. 21, pp. 1–18, Nov. 2019, doi: 10.3390/app9214715.
- [39] X. Yang, *Nature-Inspired Optimization Algorithms*, 1st ed. Elsevier, 2014.
- [40] E. Vlamou and B. Papadopoulos, "Neuro-fuzzy networks and their applications in medical fields," in *Advances in Experimental Medicine and Biology*, 2020, p. 437, doi: 10.1007/978-3-030-32622-7.
- [41] B. Haznedar and A. Kalinli, "Training ANFIS structure using simulated annealing algorithm for dynamic systems identification," *Neurocomputing*, vol. 302, pp. 66–74, 2018, doi: 10.1016/j.neucom.2018.04.006.
- [42] D. Huang, L. Zhu, H. Jia, and T. Yu, "Automatic control system of seeding depth based on piezoelectric film for no-till planter," *Nongye Jixie Xuebao/Transactions of the Chinese Society for Agricultural Machinery*, vol. 46, pp. 1–8, Apr. 2015, doi: 10.6041/j.issn.1000-1298.2015.04.001.
- [43] E. Kuş and Y. Yıldırım, "Effects of seed drop height and tillage system on the emergence time and rate in the single seed planters," *Alinteri Journal of Agricultural Sciences*, vol. 35, no. 1, pp. 69–76, 2020, doi: 10.28955/alinterizbd.739387.
- [44] J. O. Payero, X. Qiao, A. Khalilian, A. Mirzakhani-Nafchi, and R. Davis, "Evaluating the effect of soil texture on the response of three types of sensors used to monitor soil water status," *Journal of Water Resource and Protection*, vol. 9, no. 6, pp. 566–577, 2017, doi: 10.4236/jwarp.2017.96037.
- [45] R. Zhang *et al.*, "Design of depth-control planting unit with single-side gauge wheel for no-till maize precision planter," *International Journal of Agricultural and Biological Engineering*, vol. 9, no. 6, pp. 56–64, 2016, doi: 10.3965/j.ijabe.20160906.2394.
- [46] H. Li *et al.*, "Development of maize planting method based on site-specific soil moisture for improving seedling traits in the northern China dryland," *Plants*, vol. 14, no. 24, pp. 1–15, 2025, doi: 10.3390/plants14243859.
- [47] H. A. Ajeigbe, I. I. Angarawai, F. Akinseye, A. H. Inuwa, T. AbdulAzeez, and M. B. Vabi, *Handbook on Improved Agronomic Practices of Sorghum Production in North East Nigeria*, 2020.
- [48] W. W. Agilo, "Design, development and performance evaluation of a two-row animal drawn sorghum planter," Haramaya University, 2021.
- [49] Y. Y. Salisu and M. Sani, "Effect of sowing depth and sowing window on the growth and yield

performance of maize (*Zea mays* L.) in Sudan savanna of Nigeria,” *FUOYE Journal of Engineering and Technology*, vol. 11, no. 1, pp. 93–100, 2025.

[50] S. Yang *et al.*, “Planting uniformity performance of motor-driven maize precision seeding systems,” *International Journal of Agricultural and Biological Engineering*, vol. 15, no. 5, pp. 101–108, 2022, doi: 10.25165/j.ijabe.20221505.5911.

[51] T. Iqbal *et al.*, “Development of real time seed depth control system for seeders,” *Environmental Sciences Proceedings*, vol. 23, no. 1, Art. no. 7, 2022, doi: 10.3390/envirosciproc2022023007.

[52] N. Zhao, B. Zhao, S. Yi, Z. Zhou, and G. Che, “Research on a sowing depth detection system based on an improved adaptive Kalman filtering method,” *Electronics*, vol. 11, no. 22, Art. no. 3802, 2022, doi: 10.3390/electronics11223802.

[53] Y. Li, B. Qi, E. Bao, Z. Tang, Y. Lian, and M. Sun, “Design and analysis of a sowing depth detection and control device for a wheat row planter based on fuzzy PID and multi-sensor fusion,” *Agronomy*, vol. 15, Art. no. 1490, pp. 1–25, 2025, doi: 10.3390/agronomy15061490.

[54] P. Kumar and G. Ashok, “Design and fabrication of smart seed sowing robot,” *Materials Today: Proceedings*, vol. 39, no. 3, pp. 354–358, 2021, doi: 10.1016/j.matpr.2020.07.432.

[55] Y. Shi *et al.*, “AgriPINN: A process-informed neural network for interpretable and scalable crop biomass prediction under water stress,” 2026. [Online]. Available: <http://arxiv.org/abs/2601.16045>

[56] J. Zhao, L. Zhu, H. Jia, D. Huang, M. Guo, and Y. Cong, “Automatic depth control system for a no-till seeder,” *International Journal of Agricultural and Biological Engineering*, vol. 11, pp. 115–121, Jan. 2018, doi: 10.25165/j.ijabe.20181101.3229.

[57] S. K. Nielsen, L. J. Munkholm, M. Lamandé, M. Nørremark, G. T. C. Edwards, and O. Green, “Seed drill depth control system for precision seeding,” *Computers and Electronics in Agriculture*, vol. 144, pp. 174–180, 2018, doi: 10.1016/j.compag.2017.12.008.

[58] N. C. Pradhan *et al.*, “A novel approach for development and evaluation of LiDAR navigated electronic maize seeding system using check row quality index,” *Sensors*, vol. 21, no. 17, Art. no. 5934, 2021, doi: 10.3390/s21175934.

[59] A. Botta, P. Cavallone, L. Baglieri, G. Colucci, L. Tagliavini, and G. Quaglia, “A review of robots, perception, and tasks in precision agriculture,” *Applied Mechanics*, vol. 3, no. 3, pp. 830–854, 2022, doi: 10.3390/applmech3030049.

[60] M. Abdurrohman, M. Siregar, C. O. Sereati, S. Windasari, and M. L. W. Pandjaitan, “Implementation and analysis of fuzzy inference system (FIS) and adaptive neuro-fuzzy inference system (ANFIS) for irrigation,” *International Journal of Engineering Continuity*, vol. 4, no. 1, pp. 210–231, 2025.

[61] S. Kale, “Development of an adaptive neuro-fuzzy inference system (ANFIS) model to predict sea surface temperature (SST),” *Oceanological and Hydrobiological Studies*, vol. 49, no. 4, pp. 354–373, 2020, doi: 10.1515/ohs-2020-0031.

[62] E. Küçüktopçu, B. Cemek, and H. Simsek, “Application of Mamdani fuzzy inference system in poultry weight estimation,” *Animals*, vol. 13, Art. no. 2471, pp. 1–16, 2023, doi: 10.3390/ani13152471.

[63] G. Shanmugasundar, G. M. Kumar, S. E. Gouthem, and V. S. Prakash, “Design and development of solar powered autonomous seed sowing robot,” *Journal of Pharmaceutical Negative Results*, vol. 13, no. 3, pp. 1013–1016, 2022, doi: 10.47750/pnr.2022.13.S03.157.

[64] L. Zhao, S. Jiao, C. Wang, and J. Zhang, “Research on terrain sensing method and model

prediction for height adjustment of sugarcane harvester base cutter,” *Mobile Information Systems*, vol. 2022, Art. no. 7344498, pp. 1–15, 2022, doi: 10.1155/2022/7344498.