

Optimization of seeding performance of a mechatronic seed metering mechanism using integrated CANFIS-MOGA

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Abstract: In row crop cultivation, uniform plant spacing is crucial for maximizing grain yield. The seed spacing uniformity of a mechatronic seed metering mechanism is influenced by its operational parameters i.e., forward speed, cell size and seed metering plate inclination. To achieve uniform seed spacing, optimization of these parameters is crucial. In this study, hybrid Coactive Neuro-Fuzzy Inference System (CANFIS) and Multi-Objective Genetic Algorithm (MOGA) was developed to optimize operational parameters. The developed mechatronic seed metering mechanism was tested in the laboratory using sticky belt test setup with selected variables. The forward speed, cell size and metering plate inclination were considered as independent parameters and miss index (M_i), multiple index (M_{ui}) and precision index (P_i) were considered as response variables to develop the CANFIS model. The CANFIS predicted the response variables with R^2 value of 0.99 during testing phase and 0.94 to 0.98 during training phase. Sensitive analysis of the independent parameters revealed that the forward speed is the most sensitive parameter, followed by cell size and seed metering plate inclination. The predicted results of the CANFIS were utilized as a fitness function in the genetic algorithm to obtain the optimal operational parameters of the mechatronic seed metering device corresponding to minimum M_i , M_{ui} and P_i . The optimum parameters of seed metering device were found to be 3.24 kmh⁻¹ forward speed, 14 mm cell size and 50 degree seed metering plate inclination with M_i of 5.04%, M_{ui} of 6.60% and P_i of 11.06%. To verify the reliability of the simulated results of hybrid CANFIS-MOGA, the validation test was conducted and found relative error of 1.30%, -3.12% and 0.80%, respectively between predicted and actual values of M_i , M_{ui} , and P_i , respectively, thus demonstrating robustness and reliability of the developed hybrid model.

Keywords: CANFIS, MOGA, Pareto front, sensitivity

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1 Introduction

In row crop cultivation, uniform plant spacing is

crucial for maximizing grain yield. Seeds planted at consistent intervals within a row, reduces intra-specific competition, allowing for more effective utilization of

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soil moisture, nutrients, and sunlight (Tao et al., 2019). This uniformity in seed spacing results in better germination, more even crop emergence, and improved root development, all of which contribute to higher crop quality and productivity (Pareek et al., 2023a). In contrast, uneven plant distribution can lead to a grain yield reduction of up to 30% (Xu et al., 2021) emphasizing the importance of precise seed placement for maximizing crop yields.

In Indian agriculture, mechanical planters, fitted with inclined plate seed metering mechanism, are widely employed for sowing bold seeds such as maize, sunflower, gram, soybean, cotton, chickpea and groundnut (Pareek et al., 2021). These planters are preferred for their ability to provide higher seeding performance with lower seed damage compared to horizontal and vertical plate planters. The conventional mechanical planters utilize a ground wheel to drive the seed metering unit (Anantachar et al., 2010). In such systems, the movement of the ground wheel, which is in direct contact with the soil, controlling the timing and spacing of seed drops. However, these wheels are prone to slippage, skidding, jerking due to uneven or loose soil, which leads to inconsistent seed spacing (Rajaiah et al., 2016). Further, power transmission system induces vibration to seed metering units especially during higher planting speed. Despite the widespread use of mechanical planters, these limitations underscore the need for improvements in existing planter to enhance the uniformity of seed spacing and overall planting performance. To improve seeding uniformity, advancements in planting technology such as pneumatic, vacuum and belt type seed metering devices, have been made over last few decades. The precision planter utilizing a pneumatic and vacuum type metering unit necessitates a blower powered by high capacity engine or tractor. This results in higher operating cost, increased machine weight and environmental pollution (Abhyankar et al., 2023). While, belt type seed metering mechanism requires larger width of machine and higher cost. Hence, researcher and manufacturers are exploring cost effective, simple, environmental friendly

alternative that can be retrofitted into existing planter. The adoption of sensors, actuators and control circuits enhanced farm machinery control and improved functional precision. Therefore, to address the limitation of the existing planter, mechatronic seed metering presents a promising solution.

Several research studies were undertaken to develop electronic or mechatronic seed metering control system retrofittable for existing mechanical planter in recent years (Leela and Saravanakumar, 2019; Rajaiah et al., 2016; Pareek et al., 2023b). The results of these studies indicated improved seed uniformity than the ground wheel driven seed metering. Further, planter can be operated at higher operating speed (Gautam, 2017; Modi et al., 2020). The seeding performance of seed metering is described by miss index, multiple index, quality of feed index and precision index (ISO standard 7256/1–1984(E)). The miss, multiple and quality of feed index indicates frequency of skips, multiple seeds and occurrence of single seed. While precision index represents the variability in the spacings that are classified as singles. Lower value of miss, multiple and precision index and higher value of quality feed index indicates better seeding performance. Since the quality of feed index is a product of miss and multiple index, only miss, multiple and precision index can be used to describe the seeding uniformity of a seed metering unit. These indicators often conflict, rendering it challenging to achieve optimal seeding results. Several studies have identified speed of operation (Pareek et al., 2021), cell size (Gautam, 2017), inclination of seed metering plate (Rajaiah et al., 2016) are most significant factors influencing seeding performance of a mechatronic seed metering system. To achieve uniform seed spacing, these parameters corresponding to minimum miss, multiple and precision index need to be optimized. Most of the aforementioned studies evaluated the developed electronic or mechatronic system in the laboratory as well in the field and compared results with mechanical ground wheel drive system. Yet, no study employed the optimization technique to optimize operational parameters of a

mechatronic seed driving unit which is essential for improving seeding uniformity.

The relationship between operational parameters and three seeding performance indicators are complex and non linear. Traditional methods may not sufficient to approximate underlying relationships. In recent years, Artificial intelligence approaches like artificial neural network (ANN) and Fuzzy logic have been employed to approximate the underlying input-output relationship (Alaneme et al., 2023; Pareek et al., 2021). ANN is widely used in modelling intricate nonlinear relationships and its capacity to learn from data (Pareek et al., 2023a). However, it needs large dataset for effective training and can experience challenges like over fitting and lengthy computational time. Fuzzy logic has been applied to address uncertainty and imprecision. Though, fuzzy logic is flexible and effective in dealing vague information, it struggles with high-dimensional data and lacks the adaptive learning capabilities (Tripura et al., 2021). To improve predictive modelling of nonlinear and intricate relationship in data effectively, Coactive Neuro-Fuzzy Inference System (CANFIS) which is a hybrid model integrates the capabilities of FL and ANN (Olatunji et al., 2022) has been developed. CANFIS is the extended class of its predecessor ANFIS. Unlike ANFIS which is limited to single output, CANFIS is for multi outputs. It is used to model energy consumption (Chiroma et al., 2014), groundwater level (Boo et al., 2024), pattern recognition and optimization of materials in manufacturing industries (Azhar et al., 2022).

Traditionally, researchers have employed statistical methods such as Taguchi Method and Response surface method to optimize operational and design parameters of agricultural machines (Du et al., 2023; Kumar et al., 2024). These techniques have proven effective, they often face limitations in handling complex, nonlinear problems (Kumar et al., 2015). Over the past few decades, evolutionary algorithms (EAs) have become increasingly popular for addressing optimization problems. Among the most widely used EA technique is the genetic algorithm (GA) due to relatively easy to implement.

GA is inspired by population genetics and evolutionary process at the population level. It is particularly effective at solving multi-objective optimization problems by identifying a set of optimal solutions, known as Pareto-optimal solutions. Because of this, it has been integrated with techniques like ANN (Pavan et al., 2024), ANFIS (Sabry et al., 2021) and Fuzzy logic to retrieve optimal solutions more efficiently.

By considering all the above factors, the present study was conducted to optimize the operational parameters of a mechatronic seed metering device of the planter using hybrid CANFIS-MOGA. Initially CANFIS was developed for predicting the seeding parameters of a mechatronic seed metering unit considering three independent parameters like forward speed, cell size and angle of inclination of seed metering plate and three response variables like miss, multiple and precision index. Further, perturbation method of sensitive analysis was carried out to observe the sensitive independent parameters. Then Multi-objective genetic algorithm was used to retrieve the Pareto-optimal solutions for a mechatronic seed metering unit. Subsequently, simulated results were verified by conducting experiments.

2 Materials and methods

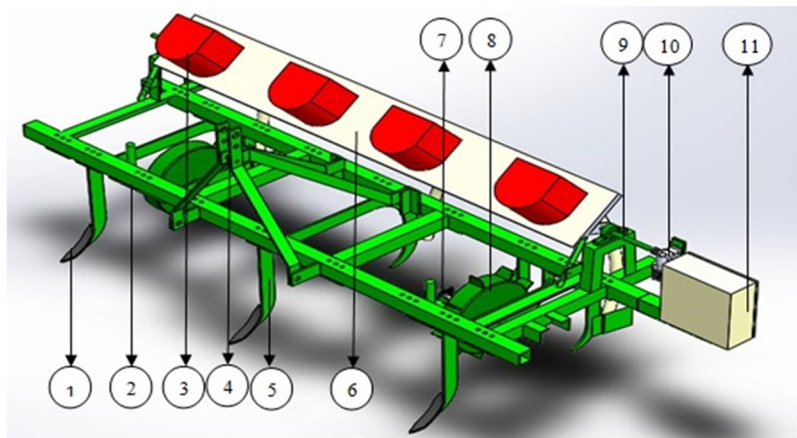
2.1 Description of a mechatronic based precision planter

The planter consists of main frame, seed box, ground wheel, furrow opener and embedded system (Figure 1). The main frame consist of two main parallel MS hollow rectangular bar section of 250 cm × 6.5 cm × 6.5 cm with thickness of 0.5 cm, two MS angular bar of size 50 cm × 5cm attached connecting two main parallel MS hollow rectangular bar at a distance of 212 cm from both the ends. Three point linkage of category-II attached to the main frame at the front side to hitch the planter to the tractor. Four seeds box having a shape of rectangular at the bottom side and semi-circular at the top side of which the rectangular section size of 20 cm × 12 cm and the semi-circular size of radius 10.2 cm ± 0.50 cm and height of the seeds box 20.4 cm. Planter consists of shovel type of furrow

openers and seed tube made up of PVC pipe and the diameter of the pipe was 4.0 cm with 0.1 cm of thickness. The planter has adjustment to change row to row spacing from 60 cm to 90 cm.

The embedded system was developed to drive seed metering mechanism instead of ground wheel drive. The embedded system comprised of microcontroller (ATmega328), stepper motor ((BH57 SH 56-2804 AK), motor driver module, incremental rotary encoder (E50S8-2-2-T-24 - 50 mm), 20x4LCD with I2C module, step down converter and battery (24 V battery). The rotary encoder having 2000 pulse per revolution was mounted at the hub of ground wheel frame using bracket. The shaft of optical rotary encoder was attached by coupling with the ground

wheel shaft. As the ground wheel rotates, the rotary encoder sends the signals to the microcontroller in the form of pulse per revolution. The microcontroller controls the stepper motor attached to the seed metering plate shaft through series of micro stepping drive (BH-SMART-4.5A). LCD20x4 was used to display planter rpm, pulses, and seed rate. The I2C module is used to make a serial communication between LCD display and microcontroller. The entire working mechanism was controlled by Arduino Nano microcontroller. The program code was written using Arduino IDE software and uploaded to the Arduino Nano. The circuit diagram of the embedded system is shown in Figure 2.



1. Furrow opener
2. Main frame
3. Seed box
4. Three point linkage
5. Tyne
6. Seed box frame
7. Rotary encoder
8. Ground wheel
9. Main shaft
10. Stepper motor
11. Control box

Figure1 Isometric view of the developed mechatronic based precision planter

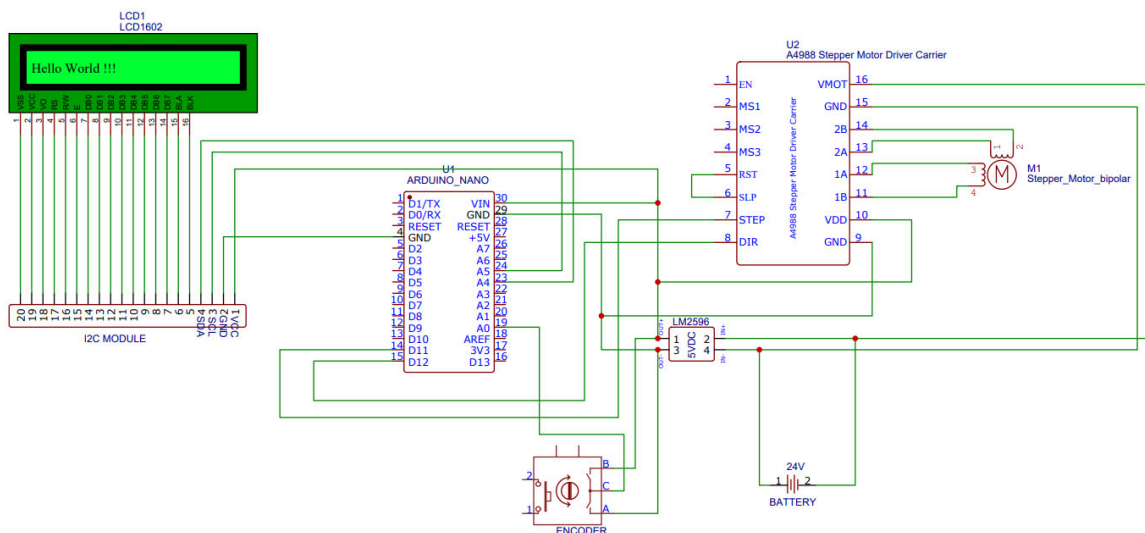


Figure 2 Circuit diagram of embedded system (Software used: EasyEDA)

2.2 Experimental setup

The laboratory experiments were conducted to assess the seeding performance of the mechatronic seed metering device of a planter using sticky belt test setup at Farm Machinery testing centre, Department of Farm Machinery and Power Engineering, UAS, Raichur, Karnataka (17° 21' 32" N latitude and 76° 48' 10" E longitude), India. The entire planter was mounted on sticky belt using a hydraulic jack equipped with suitable holding frame (Figure 3). Among four seed metering unit, only two seed metering unit with seeds in the hopper are operated. The sticky belt type seeding test bed composed of endless belt moving on two rollers of 130 cm length and 11 cm diameter provided at a distance of 1000 cm and driven by 1.5 kW electric motor. The linear speed of the belt was controlled through motor controller. One revolution of

the driving roller, the belt moves at 73 cm which was recommended plant to plant spacing of 75 cm. Using another 1.5 kW electric motor, rpm of the planter was synchronized with the corresponding operational speed. Both motors are controlled through motor speed controller with AC to DC converter. Sufficient grease was smeared on the belt to capture the dropped seeds devoid of rolling or bouncing. The forward speed of planter or belt speed was calculated using the following formula (Abhyankar et al., 2023)

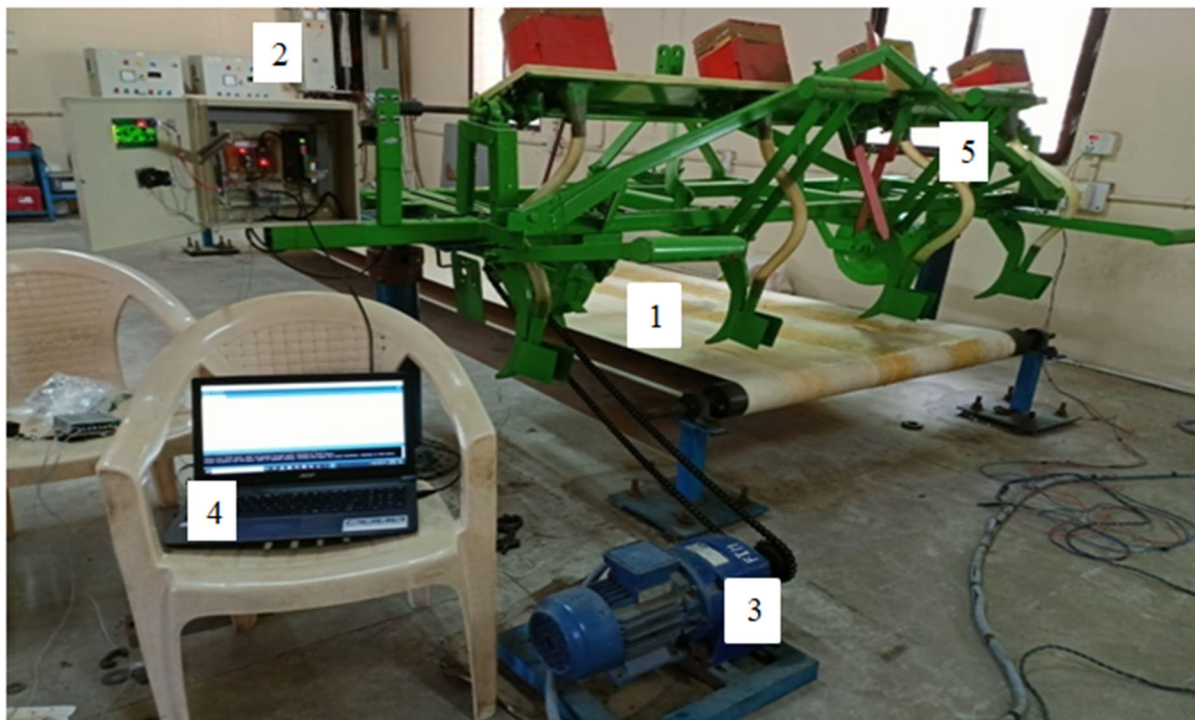
$$V = \frac{\pi \times D \times N}{60} \times 3.6 \quad (1)$$

Where:

V is the belt speed or forward speed, kmh^{-1} ;

D is the diameter of the driving roller, m;

N is the rpm of the driving roller of the sticky belt.



1. Stickybelt; 2. Controlpanel; 3. Electric motor; 4. laptop 5. Planter

Figure 3 Laboratory test setup for evaluation of seeding performance

2.3 Experimental design and data collection

In this study, the operating parameters of the mechatronic seed metering device i.e., speed of operation, cell size and seed metering plate inclination were considered as independent parameters and miss index (M_i), multiple index (M_{ui}) and precision index (P_i) were considered as response variables. The levels of

independent variables were selected based on the previous studies and preliminary trails. Furthermore, the operational parameters of the mechatronic based seed metering device were significantly influenced by the physical properties of the seeds being used. In this study, SRCH-BG II varieties of hybrid Bt-cotton seeds were used and their physical properties of the seeds are

reported by Yadav et al. (2023). In Indian conditions, mechatronic seed metering can be operated at forward speed of 1.6 to 4.8 kmh⁻¹ (Pareek et al., 2023b). Preliminary trials of the developed mechatronic seed metering device revealed that at forward speeds exceeding 4.5 kmh⁻¹, a significant increase in missed seeds and multiple seed indices was observed. Therefore, in this study, the forward speed was varied from 2 to 4.5 kmh⁻¹. The cell size was varied from 10 to 14 mm. seed metering plate inclination is the angle between the metering plate and the horizontal axis. The developed system includes a mechanism that allows the seed metering plate to be adjusted by tilting the seed hopper upwards or downwards. The laboratory experiments were conducted at six levels of the forward speed, three levels of cell size and metering plate inclination. The randomized block experimental design was employed and 54 sets of the trails were conducted with three replications. Before performing each trail, seed hopper was filled 75% its volume by cotton seeds. Initially, the belt speed and planter speed were set to match the forward operational speed and then adjusted while keeping other parameters constant. Similarly, seed spacing observations were made by varying each independent parameter one at a time, while keeping the remaining parameters constant. These seed spacing values further analysed using following formula for miss index (Abhyankar et al., 2023), multiple index (Abhyankar et al., 2023) and precision index (Pareek et al., 2023b).

$$M_i = \frac{n_1}{N} \times 100 \quad (2)$$

$$M_{ui} = \frac{n_2}{N} \times 100 \quad (3)$$

$$P_i = \frac{\sigma}{S_d} \times 100 \quad (4)$$

Where:

S_d is the desired seed spacing;

n_1 is number of spacing $\geq 1.5 S_d$;

n_2 is the number of spacing $\leq 0.5 S_d$;

N is the number of observations;

σ is the standard deviation of seed spacing classified as singles.

2.4 CANFIS

CANFIS is a hybrid computational framework that combines the advantages of artificial neural networks (ANN) and fuzzy inference systems (FIS). Coactive neuro-fuzzy inference system used in this study belongs to general class of Adaptive neuro-fuzzy system (ANFIS). It is favored over other ANFIS structures for its ability to generate multiple input-outputs using nonlinear fuzzy rules, with both ANN and FIS playing key roles in enhancing estimation accuracy (Tahmasebi and Hezarkhani, 2012). The CANFIS comprises of input layer, fuzzification layer, rule layer, normalization layer, consequent layer (neuro layer) and output layer. The CANFIS model performs following layer tasks.

Input layer: in this layer, input variables u_i are processed the sum of the weight strengths is normalized to equal one

$$u_i (i = 1, 2, \dots, n) \quad (5)$$

Fuzzification layer: in this layer, the input variables (u_i) are fuzzified using fuzzy membership functions. This layer entails the use of membership functions on the input data, enabling a more flexible and nuanced representation of the information (Tahmasebi and Hezarkhani, 2012).

$$O_{ij}^1 = \mu_j (u_i) \quad (6)$$

Where:

μ denote membership functions;

O_{ij}^1 represent the value of j^{th} linguistic term of u_i .

Rule antecedent layer: In this layer, each processing element contains a conditional component of the fuzzy rule (If u_i is A) which reflects the strength of the rule in relation to the opponent's rule. It is defined as

$$O_j^2 = \mu_j(u_1), \mu_j(u_1) \dots \mu_j(u_{N_{inputs}}) = \prod_{i=1}^{N_{rules}} \mu_j(u_1) \quad (7)$$

Rule Consequent Layer:

In this layer, two key roles are carried out: the conditional elements of various fuzzy rules are combined, and the membership degrees are evaluated relative to opposing linguistic outputs. Moreover, the number of processing elements corresponds to the number of fuzzy rules utilized.

$$O_k^3 = \frac{O_{j,k}^2}{\sum N_{Rules} O_{j,k}^2}; k = 1, 2, \dots \dots N_{Rules} \quad (8)$$

Defuzzification layer: This layer applies the inferred logical rules, and the output is determined using the height method, which can be expressed as follows

$$O_{kn} = \frac{\sum N_{Rules} w_i \mu_i}{\sum N_{Rules} w_i} \quad (9)$$

2.5 Genetic algorithm

Genetic algorithm is a search heuristic and optimization technique inspired by the principles of natural selection and genetics (Pavan et al., 2024). GA is subset of evolutionary algorithm and used to find approximate solutions to optimization and search problems. The key components of a genetic algorithm (GA) include chromosome representation, selection, crossover, mutation, and fitness function evaluation. In the initial phase of GA, the first population P_0 is created by randomly generating N chromosomes. The initial population of chromosome is represented as below (Pavan et al., 2024)

$$P_0 = \{C_1, C_2, C_3, \dots, C_N\} \quad (10)$$

Where, N is chromosomes.

The fitness value of individual I is calculated as below

$$P_i = \frac{F_i}{\sum_{j=1}^N F_j} \quad (11)$$

Where:

F_i is the fitness of individual I ;

$\sum_{j=1}^N F_j$ is the sum of fitness values of all individual in the population;

N is the population size.

2.6 Development of hybrid CANFIS-MOGA

The operational flowchart of integrated CANFIS-MOGA is shown in Figure 4. The Coactive Neuro-Fuzzy Inference System (canfis) model was constructed with “anfis” function in Matlab 2021a. The training of the network was performed using combine backpropagation with least squares. For each variable, a Takagi-Sugeno-type fuzzy inference system was generated with two membership functions and other default parameters like optimal hybrid train FIS, laws (36) were employed. The epoch and error

goal was set as 100 and 0.01, respectively. The bell shaped membership function and grid partition was employed to generate FIS. In this study, 54 patterns of input and output obtained from laboratory experiment. Out of the total dataset, 70% (*i.e.*, 38 data points) were used to train the model and 30% (*i.e.*, 16 data points) were used to test the model. This splitting also observed in the other research studies (Tahmasebi and Hezarkhani, 2012). To speed up the training and prevent extreme values, dataset are normalized within the interval of $[0, 1]$.

$$x_{norm} = \frac{(x - x_{min})}{x_{max} - x_{min}} \quad (12)$$

Where, x_{norm} denotes the normalized value of x given the maximum (x_{max}) and minimum (x_{min}) value of x .

In this study, performance of the developed model was assessed by measuring the coefficient of determination (R^2). The R^2 value indicates the robustness of the predictive model and describes the proportion of total variance in the observed data that the model can explain.

$$R^2 = \frac{\sum_{i=1}^n [(x_a - \bar{x}_a)(x_p - \bar{x}_p)]}{\sqrt{\sum_{i=1}^n (x_a - \bar{x}_a)^2 \sum_{i=1}^n (x_p - \bar{x}_p)^2}} \quad (13)$$

Where:

x_a is the experimental values;

x_p is the CANFIS predicted value;

\bar{x}_a are average value of observed;

\bar{x}_p CANFIS predicted value.

Once the dataset was trained, predicted results were utilized to generate fitness equation for GA. Simultaneous optimization of M_i , M_{ui} and P_i falls within the realm of the multiobjective optimization. The objective function of this study is to minimize miss, multiple and precision index for selected independent parameters *i.e.*, forward speed, cell size and seed metering plate inclination which were denoted as x_1 , x_2 and x_3 , respectively. Thus objective function are given below:

$$f_1 = M_i; \quad f_2 = M_{ui}; \quad f_3 = P_i \quad (14)$$

The mathematical expression of this multiobjective optimization problem is expressed as equation.

$$\begin{aligned}
 & \text{Objectives} = \\
 & \left\{ \begin{array}{l} \text{Find : } x = [x_1, x_2, x_3]^T \\ \text{Min : } f(x) = [f_1(x), f_2(x), f_3(x)]^T \\ \text{subjected to} \\ \quad 2 \leq x_1 \leq 4.5 \\ \quad 10 \leq x_2 \leq 14 \\ \quad 40 \leq x_3 \leq 60 \end{array} \right. \quad (15)
 \end{aligned}$$

Where $f(x)$ represents the objective function vectors and x denotes the design variables in this multi-objective optimization problem.

The parameters for the MOGA include a population size of 200, a total of 1000 generations, a crossover rate of 90%, and a mutation rate of 10%. A population of 200 individuals is initialized in a three-dimensional solution space. Each individual represents a potential solution to the multi-objective problem. A larger population size (200 in this case) allows the algorithm to cover a more extensive portion of the

solution space and improve the exploration of trade-offs between multiple objectives. The algorithm runs for 1000 generations (iterations), during which the population evolves through selection, crossover, and mutation. Finally, individuals evolve to approach the Pareto front by balancing these three objectives. The Pareto front shows the trade-off between objectives. Subsequently, 20 non dominated Pareto optimal solutions were obtained. These results obtained from the hybrid CANFIS-GA were further validated by conducting experiments on optimized parameters. The three replications were taken and average values were compared with model simulated results and relative error (RE) was calculated using equation (Kumar et al., 2024).

$$RE = \frac{(x_{exp} - x_{pred})}{x_{exp}} \quad (16)$$

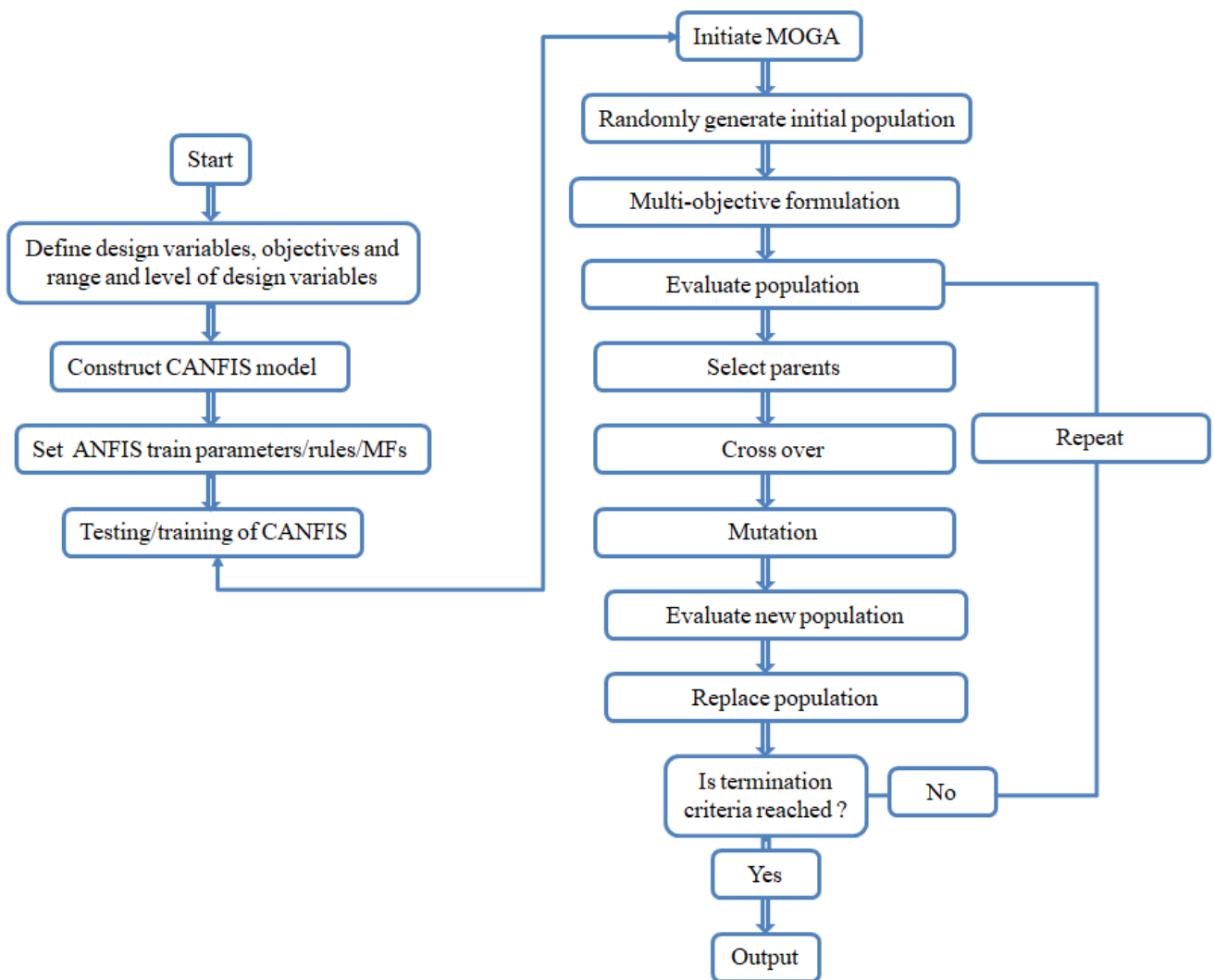


Figure4 Flowchart of integrated CANFIS-GA

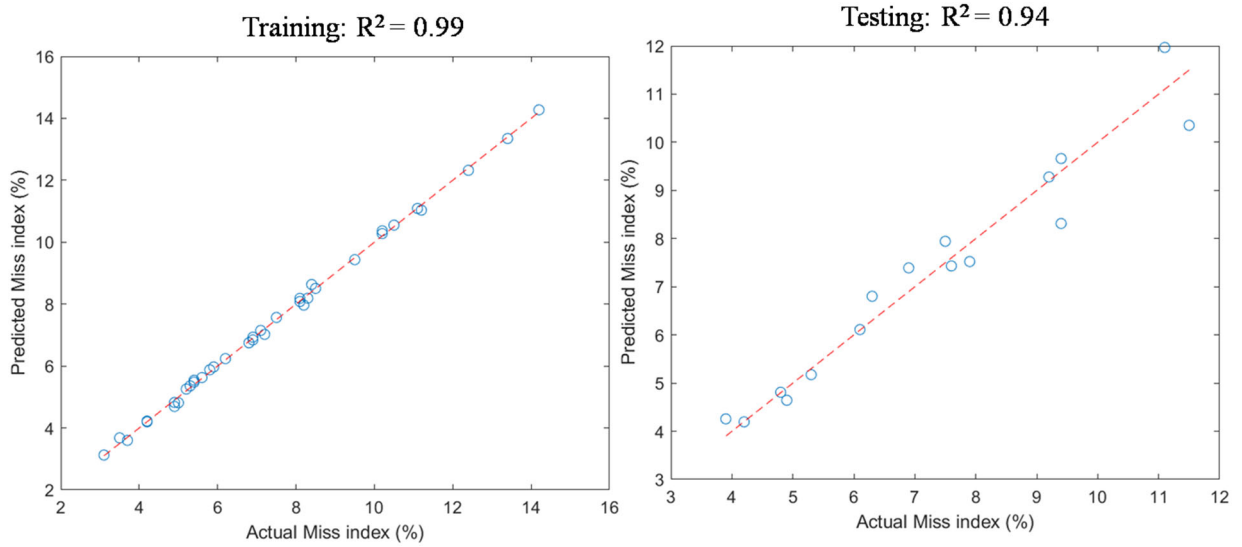


Figure 5 Scatter plot of actual and predicted M_i by CANFIS model for training and testing phase

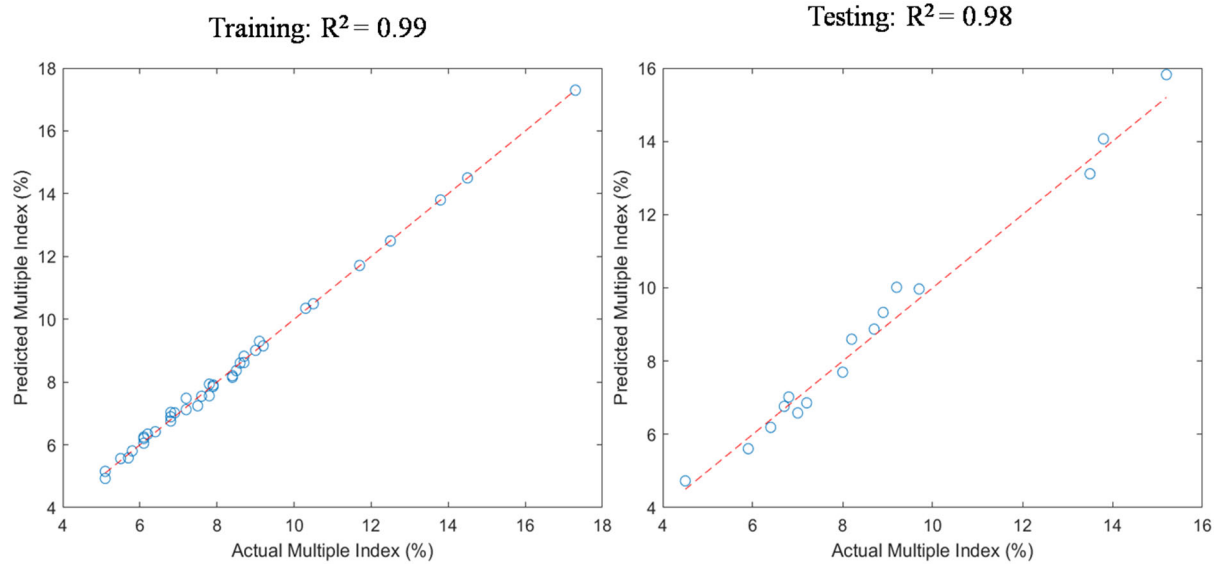


Figure 6 Scatter plot of actual and predicted M_{ui} by CANFIS model for training and testing phase

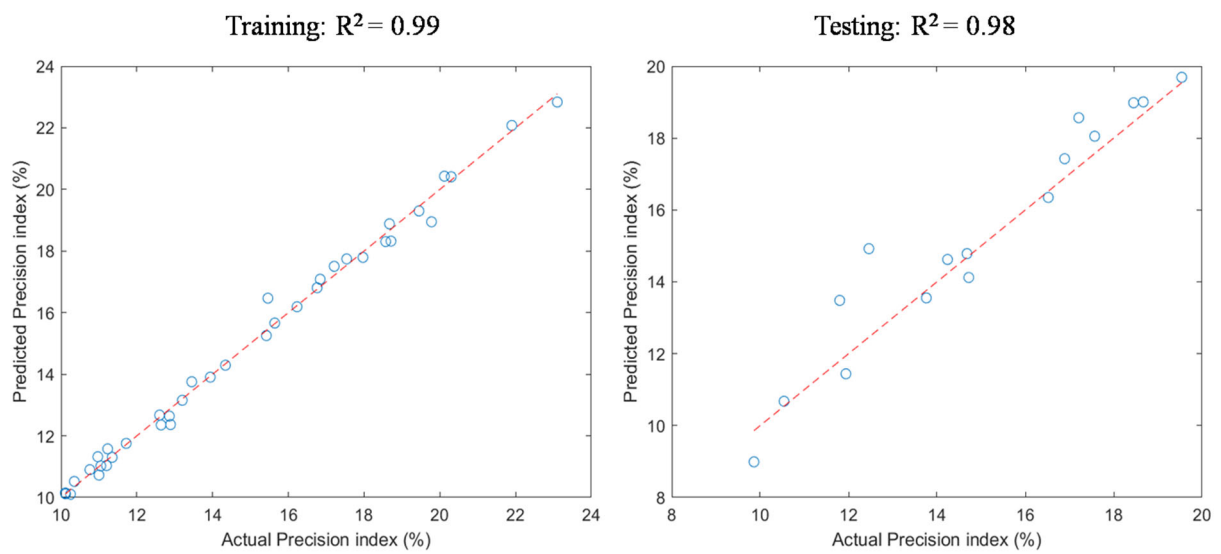


Figure 7 Scatter plot of actual and predicted P_i by CANFIS model for training and testing phase

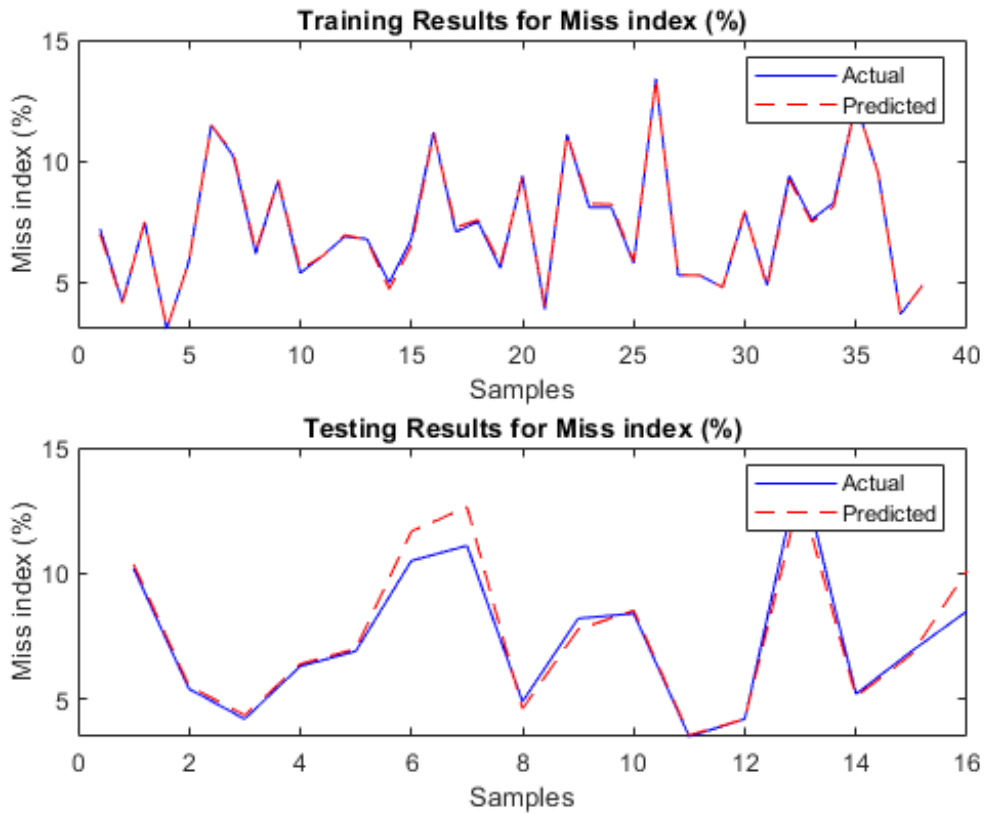


Figure8 Comparison of experimental and CANFIS predicted value of M_i

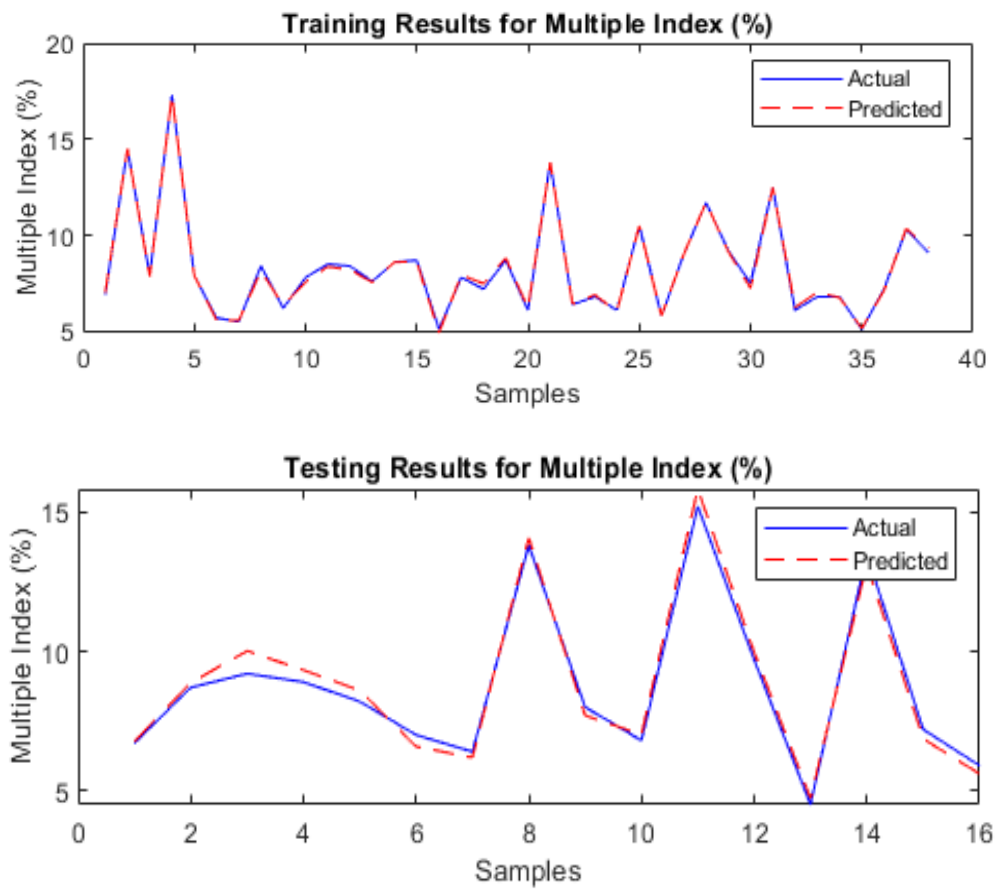


Figure 9 Comparison of experimental and CANFIS predicted value of M_{ui}

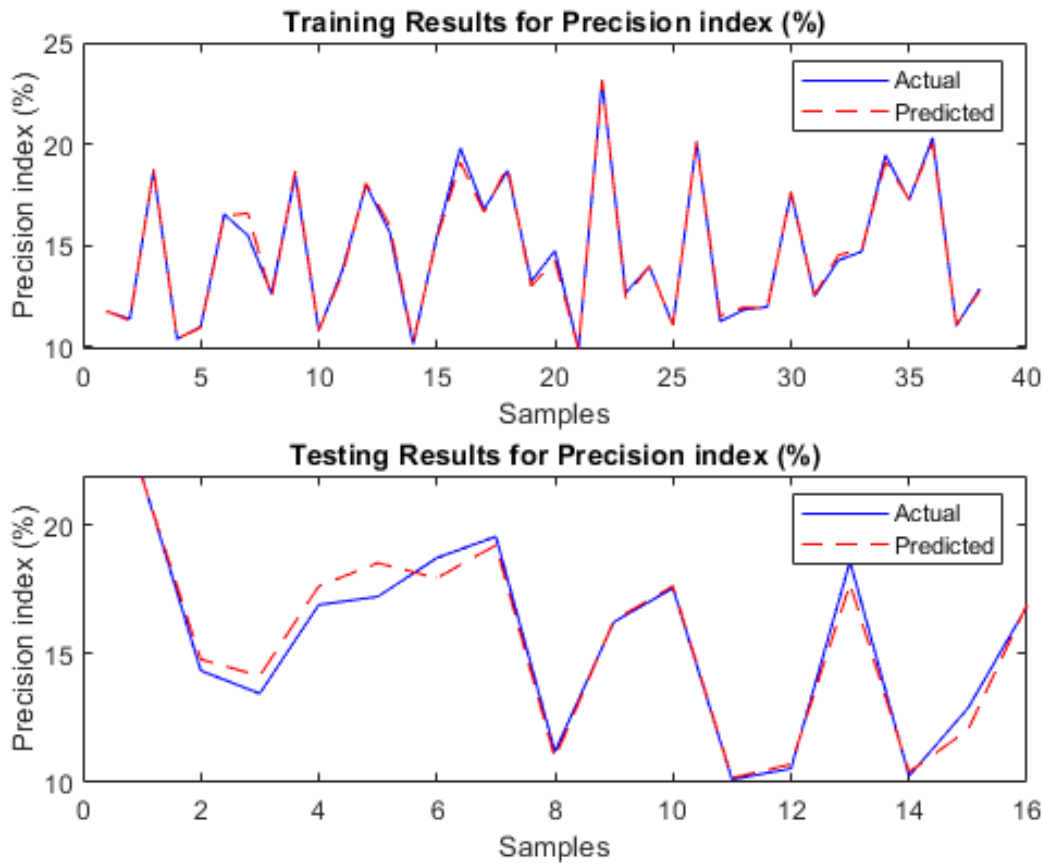


Figure10 Comparison of experimental and CANFIS predicted value of P_i

2.7 Sensitivity analysis

The sensitive analysis of the developed CANFIS model was carried out using input perturbation method (Rosa, 2016), where small perturbations were applied to each input parameter and the resulting change in sensitivity was measured. In this study, perturbation percentage was 0.01.

3 Results and discussion

The integrated CANFIS-MOGA was executed in the Matlab after setting parameters of CANFIS and GA. The developed CANFIS model comprises 34 nodes, 32 linear parameters, 18 nonlinear parameters, total of 50 parameters, 38 training data pairs, and 8 fuzzy rules. For three response variables, single ANFIS model was developed, trained and tested. The scatter plot with coefficient of determination for three response variables i.e., M_i , M_{ui} and P_i are generated. Additionally, comparison between the experimental results and CANFIS predicted results plot were also generated.

The scatter plot comparing actual and predicted value for M_i , M_{ui} and P_i for training and testing phase is shown in Figures 5-7. A high degree of regression (R^2 value of $M_i=0.99$, R^2 value of $M_{ui}=0.99$ and R^2 value of $P_i=0.99$) between actual and predicted values. This indicates that the developed CANFIS model can explain at least 99% of the variability in M_i and M_{ui} , and P_i in training phase. In testing the developed model, the R^2 values were 0.94, 0.98, and 0.98 for M_i , M_{ui} , and P_i , respectively. These values indicate that the model can explain at least 98% of the variability in M_{ui} and P_i , and 94% in M_i with unseen data sets.

Figures 8-10 shows the comparison of CANFIS predicted and experimental test results of M_i , M_{ui} , and P_i . The results predicted by the CANFIS model closely match the experimental test results, confirming the model's excellent approximation capability in training phase. The predicted values for the testing set exhibit a similar pattern to the actual values, although with slightly deviations, indicating the model's capacity to generalize to new, unseen data.

3.1 Effect of operational parameters on seeding performances indices

After the model was trained and tested, the predicted test results were used to generate 3D surface plots of performance indices of M_i , M_{ui} , and P_i with respect to different input variables.

As shown in Figure 11, the highest M_i (14.2%) was observed at a forward speed of 4.5 kmh^{-1} , with a cell size of 10 mm and a seed metering plate inclination of 60 degree, while the lowest M_i (3.1%) found at a slower speed of 2 kmh^{-1} , with a cell size of 14 mm and a plate inclination of 40 degree. At fixed cell size of 10 mm, the M_i increased with increase in forward speed. This is because of reduced exposure time for cells to pick seeds from the seed hopper and higher centrifugal

force throw the seed out of the cell too early (Badgujar et al., 2017). The M_i decreased with increase in the size of cell because, with smaller cell size, the chances of properly accommodating seeds are low, leading to a higher M_i . In contrast, higher cell size increases the chances of accommodating more than one seed, which results in a lower M_i . The M_i increased with the rise in the angle of inclination of the seed metering plate. This could be because, at higher angles, the exposure area for seeds is reduced, leading to fewer seeds being collected in the cells. Conversely, at lower angles, the exposure area is larger, allowing more seeds to accumulate in the cells. The similar results were reported by the previous studies (Rajaiah et al., 2016; Abhyankar et al., 2023; Badgujar et al., 2017).

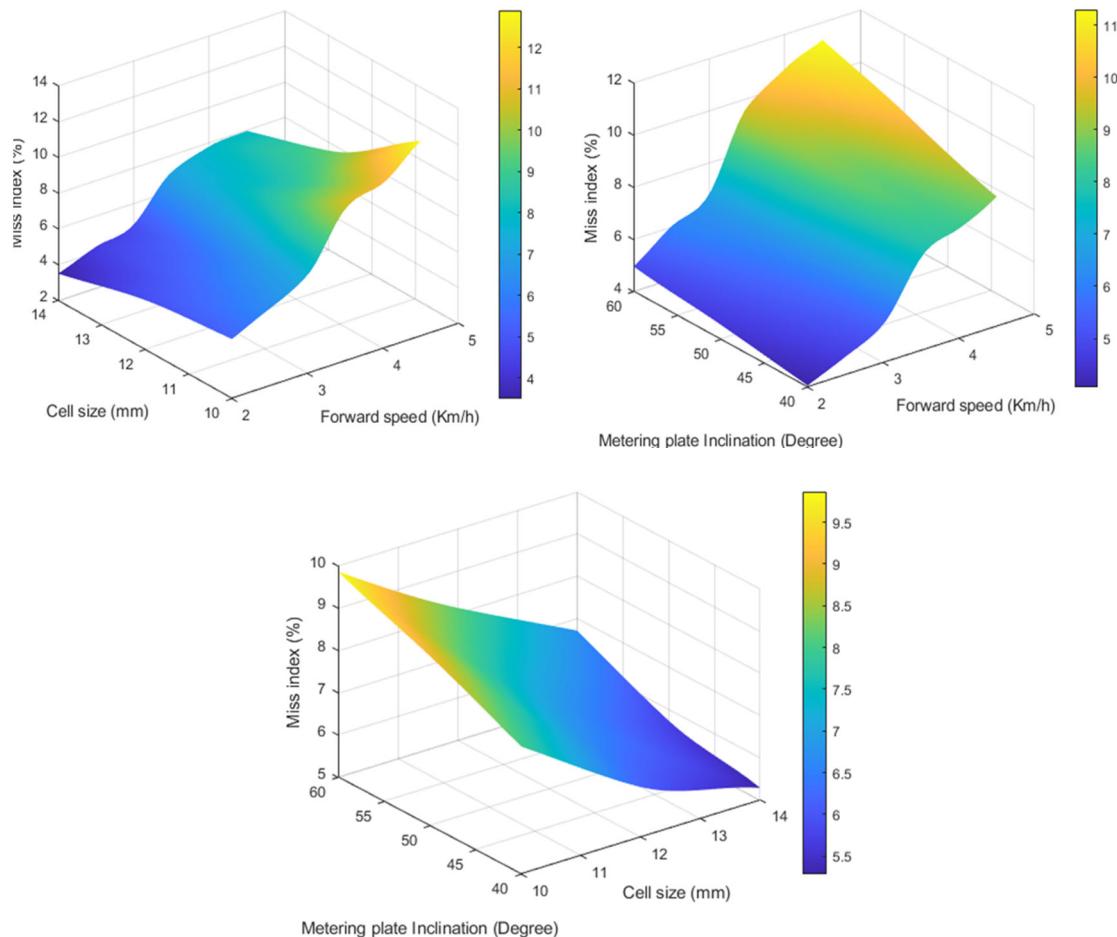


Figure 11 3D surface plots of CANFIS predicted M_i as function of different independent parameters

The variation of the M_{ui} with forward speed, cell size and seed metering plate inclination is shown in Figure 12. At fixed forward speed of 2 kmh^{-1} , the highest predicted M_{ui} (17.3%) was found for 14 mm size and 40 degree seed plate inclination and lowest

predicted M_{ui} (10.5%) was observed for 10 mm at 60 degree seed plate inclination. Increase of M_{ui} with change of cell size from 10 to 14 mm is because larger cell size more likely to accommodate more than one seed in the seed plate cells (Abhyankar et al., 2023).

The M_{ii} decreased as the angle of inclination of the seed metering plate increased. This may be because, at higher angles, the exposure area for seeds is reduced, leads to fewer seeds accumulating in the cells. In contrast, at lower angles of inclination, seed cells exposed to seed pool, allowing for more seeds to be collected in the cells. Additionally, the M_{ii} decreased with increasing forward speed from 2 to 4.5 kmh^{-1} due

to the higher rotational speed of the seed plate, which reduced the exposure time for the seeds. Consequently, this led to fewer chances for the cells to pick up seeds. At lower speeds, seeds had more exposure time to the cells, resulting in a higher accumulation of seeds and more multiple seed drops at once. Similar trends were reported by Gautam (2017) and Rajaiah et al., (2016).

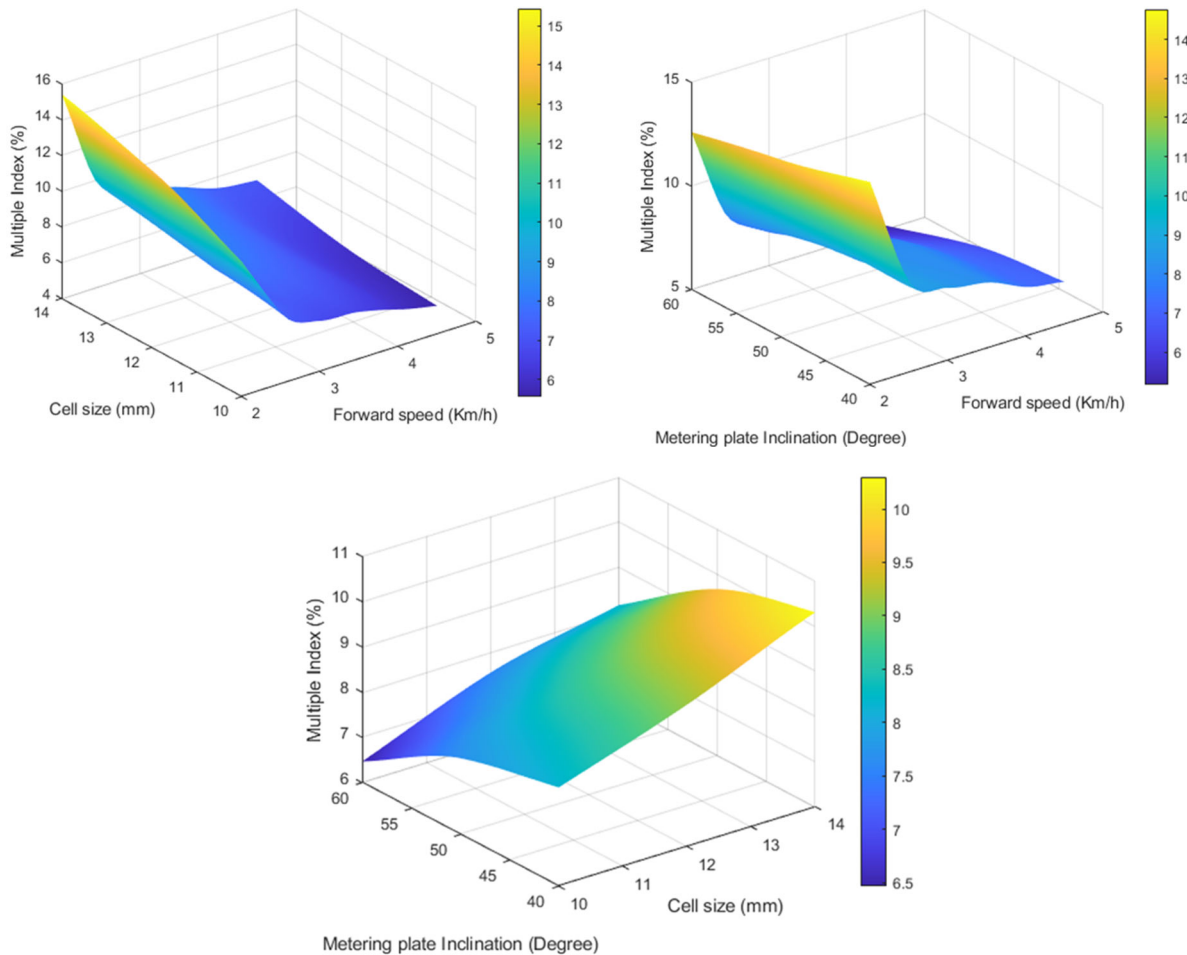


Figure12 3D surface plots of CANFIS predicted M_{ii} as function of different independent parameters

3D continuous response surface plots of model predicted P_i as function of various independent parameters shown in Figure 13. The highest P_i (23.1%) was obtained at 14 mm cell size, 40 degree seed metering plate inclination and forward speed of 4.5 km/h . while low P_i (9.86 %) was obtained at lower speed and low angle of inclination of seed metering plate with 14 mm cell size. The predicted P_i increased with increase in forward speed, indicating that decreased seeding uniformity. The P_i increased with increase in seed metering plate inclination which means that observed seed spacing is not closer to

theoretical spacing. Similar trend were reported by Cay et al.(2018), Dowlati and Namjoo (2016) and Anantacharet al. (2010).

3.2 Sensitivity analysis

Sensitivity analysis of each independent parameter by applying perturbation percentage of 0.01 was carried out and results are shown in Figure 14. It is evident from the figure that the forward speed is the most sensitive parameter among all the independent parameters, followed by cell size, which exhibits relatively high sensitivity, and seed metering plate inclination, which is the least sensitive parameter.

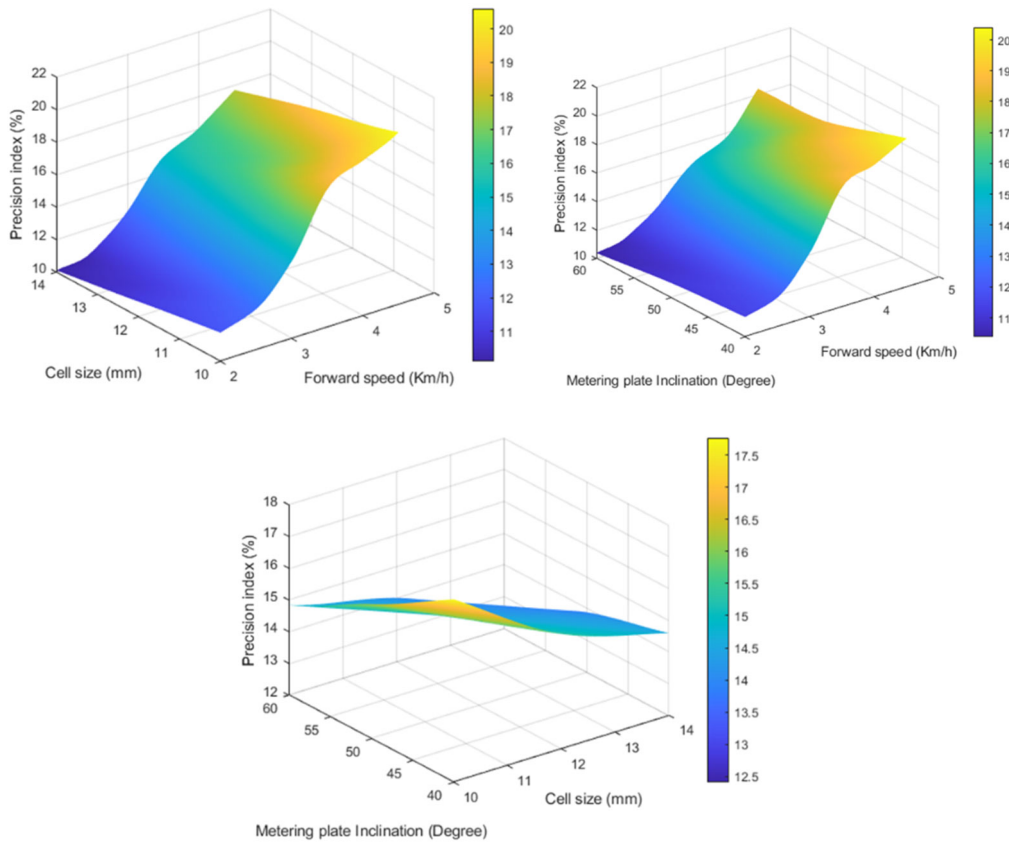


Figure13 3D surface plots of CANFIS predicted P_i as function of different independent parameters

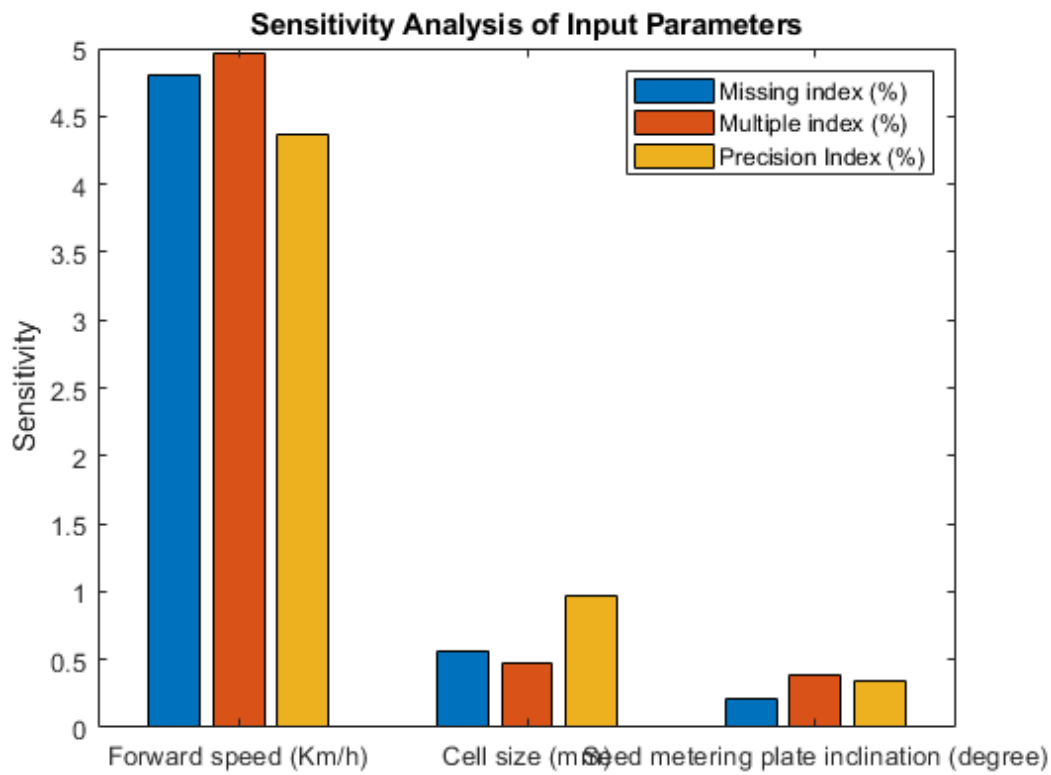


Figure14 Sensitivity analysis of input parameters on response variables

3.3 Optimization and validation of operational parameters by integrated CANFIS-MOGA

The three objective 3D Pareto-optimal fronts

indicate potential non dominated solutions are shown in Figure 15 (a). In this figure, x-axis shows the M_i , y-axis shows the M_{ii} and z-axis shows the P_i . It can be

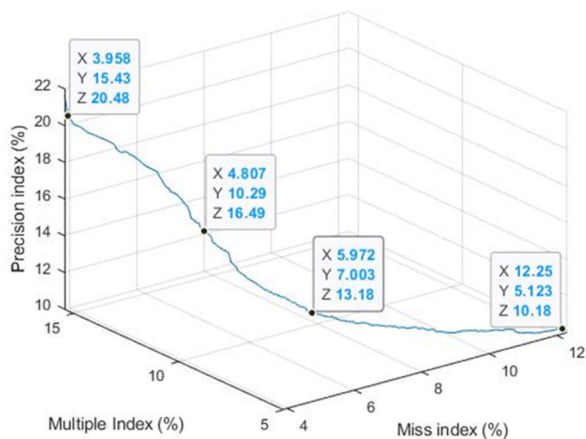
seen from the figure that M_i , M_{ui} , and P_i cannot reach to optimal solution without compromise. The Pareto front demonstrates the trade-off among three objectives. If one objective increases, there is a generally decrease in other objectives. From figure (Figure 15 (b), (c)), it can be inferred that as M_i increases, M_{ui} decreases and M_i increases, P_i decreases. Further, there is a trade-off between M_{ui} and P_i (Figure15 (d)). For selection of best non-dominated solution, first and second objective were preferred than precision index because non uniform of seeding results in variation in precision index. Hence, optimal solution i.e., M_i of 5.04%, M_{ui} of 6.60% and P_i of 11.06% as best solution for this study. The corresponding

optimum operational parameters are 3.24 kmh^{-1} forward speed, 14 mm cell size and 50 degree seed metering plate inclination.

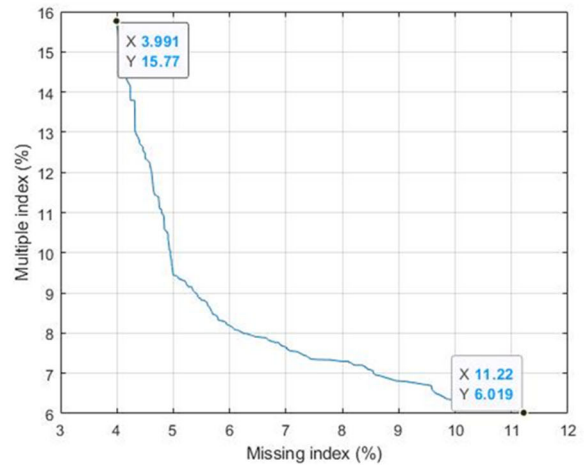
To verify the reliability of the simulated results of CANFIS-MOGA, the validation test was conducted and results are presented in Table 1. From this table, it is evident that proposed CANFIS-MOGA yielded the optimum values of M_i , M_{ui} and P_i with a relative error of 1.30%, -3.12% and 0.80%, respectively between predicted and actual values. These results clearly indicate the effectiveness of the integrated CANFIS-MOGA to retrieve optimum values of the operating parameters of the mechatronic seed metering unit of planter.

Table1 Optimized parameters of CANFIS-MOGA with validation results

Particulars	Independent parameters			Response variables		
	Forward speed (km/h)	Cell size (mm)	Seed metering plate inclination (Degree)	Miss index (%)	Multiple index (%)	Precision index (%)
Predicted	3.24	14	50	5.04	6.60	11.06
Actual	3.24	14	50	5.11	6.40	11.15



a)



b)

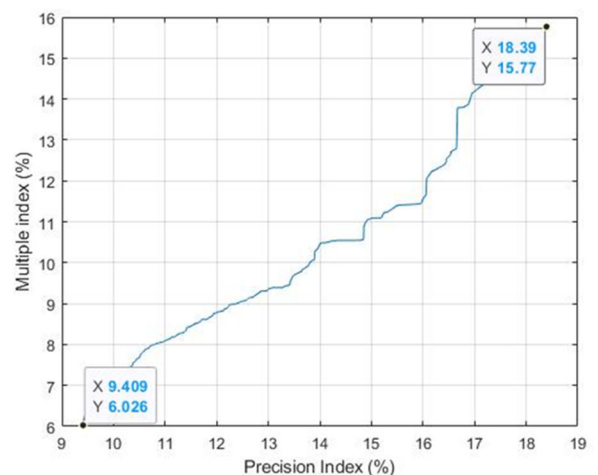
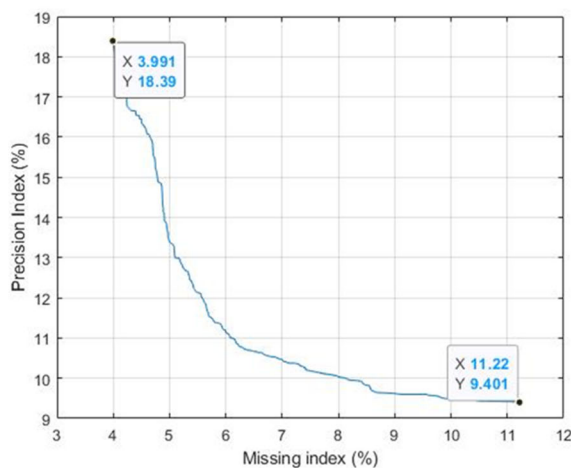


Figure15Triple objective 3D pareto front

4 Conclusion

In this study, hybrid multi-objective optimization methodology comprising Coactive Neuro-Fuzzy Inference System (CANFIS) and multi-objective genetic algorithm was developed to obtain the optimal operational parameters of a mechatronic seed metering device of planter. The laboratory experiment was conducted using the sticky belt test setup to study the effect of selected operational parameters on response variables. Initially, CANFIS was developed for predicting the response variables of miss, multiple and precision index by considering forward speed, cell size and inclination angle of seed metering plate as model input. Sensitive analysis of the independent parameters revealed that the forward speed is the most sensitive parameter, followed by cell size and seed metering plate inclination. CANFIS predicted results indicate that all the selected independent parameters had effect on response variables. The predicted results of the CANFIS were utilized as a fitness function in the genetic algorithm to obtain the optimal operational parameters of the mechatronic seed metering device corresponding to minimum miss, multiple and precision index. The optimum parameters of seed metering device were found to be 3.24 kmh⁻¹ forward speed, 14 mm cell size and 50 degree seed metering plate inclination with M_i of 5.04%, M_{ui} as 6.60% and P_i 11.06%. To verify the reliability of the simulated results of CANFIS-MOGA, the validation test was conducted and found relative error of 1.30, -3.12 and 0.80, respectively between predicted and actual values of M_i , M_{ui} , and P_i , respectively. The proposed hybrid CANFIS-MOGA demonstrated feasible and effective in determining Pareto-optimal parameters of a mechatronic seed metering unit. This approach could also be used in multi-objective optimization of other agricultural machineries.

In the present study, a multi-objective genetic algorithm was employed to optimize parameters. A primary constraint of the multi-objective Pareto front is that it generates a large number of solutions, making it difficult to analyze and select the most appropriate

one. Choosing the best solution often requires a compromise. Future research could focus on incorporating multi-criteria decision-making (MCDM) techniques into Hybrid CANFIS-MOGA (CANFIS-MOGA-MCDM), such as the Analytic Hierarchy Process (AHP) or TOPSIS, to identify a single optimal solution without comprising.

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