Journal of Applied Research and Technology

www.jart.icat.unam.mx

*Journal of Applied Research and Technology* 22 (2024) 759-767

Original

# Mobile crawler robot for seed sowing and route planning through neuro-diffuse control

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Received 01 22 2024; accepted 06 26 2024
Available 10 31 2024

**Abstract:** The main objective of this project is to build a mobile terrestrial robot that allows the sowing of seeds of several types of plants that are cultivated in an artisanal way. A structure based on tracked locomotion has been designed that involves the use of several sensors, DC motors, and control systems based on two Arduino boards, which together allow the mobile robot to interact with the irregular environment through which it moves. The locomotion process carried out by the seeding robot is configured through an HMI interface implemented on a touch screen, where the user chooses the type and quantity of seeds to be sown so that the robot then follows an autonomous rectilinear trajectory which is supervised and corrected utilizing a neuro-diffuse control such as ANFIS. In addition, the mobile robot has a battery feeding and charging system through solar panels, which gives it complete autonomy to conduct the work entrusted to it.

*Keywords:* mobile robot, seeds, neuro-diffuse, ANFIS, autonomy

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Peer Review under the responsibility of Universidad Nacional Autónoma de México.

## 1. Introduction

Sowing seeds is an activity related to agriculture, which consists of placing, burying, and/or scattering seeds in a field prepared for that purpose. Farmers in general have empirical knowledge of such planting and the process of sowing the land is carried out following an irregular pattern, therefore, the final production of the crop is not as efficient compared to that of cultivated land with technical specifications where the distance between the plants, the depth of the hole, etc. number of seeds, among other factors. Sowing in a large plantation is a repetitive process that produces long-term tiredness and fatigue to the farmer and under this perspective, the development of a mobile terrestrial robot with an automatic control system that helps and facilitates the sowing activity has been considered.

There are several robots available on the market and research has been conducted on many more, which perform the functions indicated above, and of which some were taken as a reference to develop the final design of the proposed prototype. In the work developed by Agetano et al. (2018), the researchers built an automated seed-sowing robot with an android mobile application using a rechargeable battery to energize the different electromechanical components of the robot. The app allows you to connect with the robot via Bluetooth connection, display the battery level and the number of seeds, set the length and width of the hole, as well as control the start, stop and maneuvers that the robot must execute. In Javidan's research (Javidan & Mohamadzamani, 2018), to solve the process of automatic sowing of legumes in the field, a solar-powered seed sowing robot was designed and built with row detection technology and can automatically perform circular operations at the end of each crop row.

In the article published by Dutta et al. (2019), an autonomous seed-sowing robot is designed, which divides the field into a grid with intersection points and where the depth of the hole, as well as the distance between the sowing points, are calculated according to the data configured to the robot; The robot also uses sensors to detect obstacles and possible trajectorial changes. Very similarly, Godse's project (Godse et al., 2021) was designed for a 4x4 robot that does the work of sowing seeds on plowed agricultural land, tracing the path, and sowing seeds. This robot consists of an Arduino Uno board that performs the controller actions and an ultrasonic sensor on the front that allows it to detect and evade obstacles.

Taking this background as a reference, this project seeks to implement an autonomous terrestrial mobile robot that meets the hardware and software requirements that allow the seed deposition process to be conducted under standardized standards and timesaving, to reduce the physical effort of farmers and subsequently obtain quality crops that improve production. An intelligent neuro-fuzzy control known as adaptive networks based on fuzzy inference systems (ANFIS) has been developed to regulate and correct the trajectory that the mobile robot must follow in the seeding process.

This project, unlike the bibliography consulted, incorporates an ANFIS-type intelligent controller to correct the deviation of the robot's orientation angle, which highlights the applicability and advantages of deep learning through adaptive neural networks with fuzzy inference in planting activities in the agricultural sector.

## 2. Materials and methods

### *2.1. Adaptive networks based on fuzzy inference systems: ANFIS*

The adaptive network-based fuzzy inference system (ANFIS) or systematically equivalent adaptive neuro-fuzzy inference system, are systems based on adaptive neural networks with fuzzy inference. In these systems, the principle is the use of different methods for the adjustment of the parameters, among them is the method of backpropagation of the error employing the descending gradient and the Recursive Least Squares (Jang & Sun, 1995). The working principle of this type of topology was proposed by Jang in his thesis work "ANFIS: Adaptive network-based fuzzy inference system" (Jang et al., 1997).

The architecture of the ANFIS network that is presented in the development of this work is a type of adaptive network, which is functionally equivalent to a fuzzy inference system. This architecture can represent both fuzzy models such as first-order Sugeno and zero-order Sugeno (Du & Swamy, 2006). Due to the faster training and the better characteristics of first-order systems over zero-order systems, these are the ones that are developed in the present work.

The neuro-fuzzy ANFIS model consists of five layers as shown in Figure 1, which is a graphical representation of the TSK model (or Sugeno model) and where each layer has some elements distributed in (*nK, M, M, M*, 1) respectively.

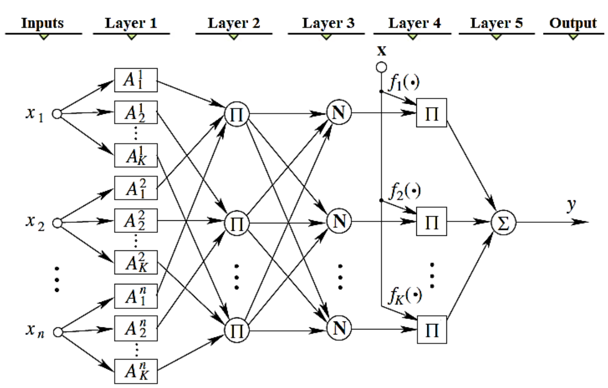



Figure 1. The architecture of the ANFIS model (Siddique & Adeli, 2013).

To explain how the architecture shown in Figure 1 works, the fuzzy inference system is considered to consist of $n$ inputs $\boldsymbol{x} = [x_1, x_2, \dots, x_n]^T$ and an output $y$. For the fuzzy model of the Takagi and Sugeno type, we have a set of fuzzy rules *if-then,* where the $j$-$th$ rule for the ANFIS model can be defined as:

$$\textbf{\textit{if}}\ \ x_1\ es\ A_j^1\ \ y\ \ x_2\ es\ A_j^2\ \ y\ \dots\ x_n\ es\ A_j^n\ \ \textbf{\textit{then}}\ \ y = f_j(x_1, x_2, \dots, x_n) = \sum_{i=1}^{n} a_{ji} x_i + a_{j0} \tag{1}$$

Or expressed in matrix form:

$$Ruler\ j\text{-}th\text{: } \textbf{\textit{if}}\ \ \boldsymbol{x}\ es\ \boldsymbol{A}_j\ \ \textbf{\textit{then}}\ \ y = f_j(\boldsymbol{x}) = \sum_{i=1}^{n} a_{ji} x_i + a_{j0} \tag{2}$$

For $j = 1, 2, \dots, K$ and where $\boldsymbol{A}_j = \{A_j^1,\ A_j^2, \dots, A_j^n\}$ is the fuzzy set or set of linguistic tags (long, short, etc.) associated with the node function and $a_{ji}$ with $i = 1, 2, \dots, n$ are the parameters of the consequent. The following lines describe the operation and formulas associated with each layer.

*Layer 1 (fuzzification layer):* In this layer, fuzzification takes place. This means that each non-fuzzy input is assigned a membership value for each fuzzy subset comprising the discourse universe of this input. This layer consists of $nK$ nodes, and each node in this layer is an adaptive node whose output is defined by the following function:

$$O_{ij}^{(1)} = \mu_{A_j^i}(x_i) \tag{3}$$

Which corresponds to $j$- $th$ linguistic term of the $i$- $th$ input variable $x_i$, para $i = 1, 2, \dots, n$ and $j = 1, 2, \dots, K$. In this context, $A_j^i$ defines a partition of an input space $x_i$ by a linguistic label (such as "small" or "tall") associated with node $i, j$ (Fuller, 2000). In other words, $O_{ij}^{(1)}$ is the degree of belonging of a fuzzy set $A_j^i$ and specifies the degree to which the input $x_i$ satisfies the quantifier $A_j^i$. The membership function MF used for $A_j^i$, expressed as $\mu_{A_j^i}(x_i)$, is the generalized bell function whose mathematical expression is given by:

$$\mu_{A_j^i}(x_i) = \mu(x_i;\ a_j^i,\ b_j^i, c_j^i) = \frac{1}{1 + \left[\left(\frac{x_i - c_j^i}{a_j^i}\right)^2\right]^{b_j^i}} \tag{4}$$

Where $\{a_j^i,\ b_j^i, c_j^i\}$ is the set of parameters that define the position and shape of the bell: $a_j^i$ specifies half the width of the bell, $b_j^i$ (along with $a_j^i$) control the slopes at the crossing points (where the MF value is 0.5), and $c_j^i$ represents the center of the FM.

The parameters $\{a_j^i,\ b_j^i, c_j^i\}$ in this layer are referred to as *premise parameters* or *nonlinear parameters* and are adjusted during the training process by the *error backpropagation* algorithm (Zeghlache et al., 2014). When the values of these parameters change, the shape of the bell will therefore vary, as will the diversity of forms that the membership functions can present in the linguistic tags $A_j^i$. If the bell function is taken as a function of membership, then the total number of nonlinear parameters in this layer is given by the following expression:

$$\#total\ nonlinear\ parameters = 3 * \#input\ variables * \#fuzzy\ subsets$$
$$\#total\ nonlinear\ parameters = 3 * n * K \tag{5}$$

*Layer 2 (rule antecedent layer):* This layer has $M$ fuzzy nodes, where the value $M$ depends on the type of partition of the input space, for example for a grid partition you would have to:

$$M = \#rules = \#fuzzy\ subsets^{\#input\ variables} = K^n \tag{6}$$

and each node performs an AND fuzzy operation, so a node in this layer represents the antecedent part of a rule. The nodes in this layer are fixed nodes and are labeled with the symbol $\Pi$; the output of each node is the T-standard operation of all the signals entering it, this results in the output of the node being the product of all its inputs:

$$O_m^{(2)} = w_m = \prod_{i=1}^{n} O_{ij}^{(1)} = \prod_{i=1}^{n} \mu_{A_j^i}(x_i) \tag{7}$$

For $m = 1, 2, \dots, M$ and $j = 1, 2, \dots, K$. The output of each node in this layer represents the trigger intensity (or trigger value) of the corresponding fuzzy rule. In general, any T-standard operator (which performs the AND fuzzy operation) can be used as a node function in this layer (Bravo Narváez & García Vélez, 2002).

*Layer 3 (ruler normalization layer):* This layer consists only of fixed nodes labeled with the symbol N. The $m$-$th$ node calculates the ratio of the $m$-$th$ ruler with respect to the sum of the trip intensities of all fuzzy rulers. This results in the normalization of the trigger value for each fuzzy rule. This operation can be written as:

$$O_m^{(3)} = \overline{w_m} = \frac{O_m^{(2)}}{\sum_{k=1}^{M} O_k^{(2)}} \tag{8}$$

For $m = 1, 2, \dots, M$. Each output in this layer is called *normalized trigger intensity*.

*Layer 4 (rule consequent layer):* Each node in this layer is an adaptive node with a function defined by Abraham (2005):

$$O_m^{(4)} = O_m^{(3)} . f_m(\boldsymbol{x}) = \overline{w_m} . f_m(\boldsymbol{x}) = \overline{w_m} . f_m(x_1, x_2, \dots, x_n) = \overline{w_m} . \left[\sum_{i=1}^{n} (a_{mi} x_i) + a_{m0}\right]$$

For $m = 1, 2, \dots, M$ and $i = 1, 2, \dots, n$; where $f_m(\cdot)$ is given for the $m$- $th$ node in layer 4. Expanding the sum term, the output of the node $m$ can also be expressed as the following linear function:

$$O_m^{(4)} = \overline{w_m} \cdot (a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n + a_{m0}) \quad (9)$$

Where $\overline{w_m}$ is the normalized activation value of the $m$- $th$ rule, calculated with the help of Equation 8, and $\{a_{m1}, a_{m2}, \dots, a_{mn}, a_{m0}\}$ is the set of adjustable parameters at this node. The parameters in this layer are referred to as *parameters of the consequent* or *linear parameters* of the ANFIS system and are adjusted by the *Recursive Least Squares (RLS)* algorithm explained in Jang and Sun (1995), Neuro-fuzzy modeling and control. The total number of linear parameters in this layer is given by the following expression:

$$\#total\ linear\ parameters = (\#input\ variables + 1) * \#rules$$
$$\#total\ linear\ parameters = (n + 1) * \#rules$$

If a grid-like input space partition is taken into consideration, then $\#rules = \#fuzzy\ subsets^{\#input\ variables} = K^n$ and the above equation would look like:

$$\#total\ linear\ parameters = (n + 1) * K^n \quad (10)$$

*Layer 5 (rule inference layer):* The only node present in this layer is a fixed node denoted by the symbol **Σ**, which calculates the overall output as the sum of all the signals entering it (Caicedo Bravo & López Sotelo, 2009):

$$O^{(5)} = global\ output = y = \sum_{m=1}^{M} O_m^{(4)} = \sum_{m=1}^{M} \overline{w_m} \cdot f_m(\boldsymbol{x}) = \frac{\sum_{m=1}^{M} w_m \cdot f_m(\boldsymbol{x})}{\sum_{m=1}^{M} w_m}$$

$$y = \frac{\sum_{m=1}^{M} \left[ \left( \prod_{i=1}^{n} \mu_{A_j^i}(x_i) \right) \left( \sum_{i=1}^{n} (a_{mi}x_i) + a_{m0} \right) \right]}{\sum_{m=1}^{M} \left( \prod_{i=1}^{n} \mu_{A_j^i}(x_i) \right)} \quad (11)$$

In this way, what is obtained is an adaptive network that is functionally equivalent to a Sugeno-type fuzzy inference system. This is the control method that will be programmed onto the mobile crawler robot so that it can follow the rectilinear trajectories configured in the seed-sowing process.

## 2.2. Description of the mobile crawler robot

The mechanical system of the mobile robot is characterized by solid elements or parts, to make movements in various parts of the mobile robot by the action or effect of a force. These elements are associated with the electromechanical system to move from various DC motors and servo motors driven by electrical energy. The mechanical system can be divided into three subsystems 1) the locomotion system of the track-based robot structure, 2) the drilling system to generate the hole where the seeds will be deposited, and 3) distribution and selection system of the type of seeds.

The electronic design of the mobile robot involves two fundamental aspects: The hardware that refers to everything that has to do with the connections of the controller boards, printed circuits, electronic components, and accessories; and the software that is related to the programs developed on the computer and that are later loaded into the memories of the Arduino cards.

The mobile robot has been designed and programmed to execute straight trajectories on not very sloping terrain, considering that the seeds of the selected plants are grown in rows within the plantation. From this reference, a gyroscopic sensor was incorporated into the robot that, together with the ANFIS neuro-diffuse controller, allows it to correct any deviation that could be generated by the conditions of the terrain. This device can measure the acceleration of gravity concerning each axis (from this principle the angle of rotation is obtained) and the angular velocity; in this case, it will be used purely as a gyroscope to calculate the rotation change. When starting the program, the rotation angle of the gyro sensor should be reset to 0 degrees, and then the number of degrees that the robot has rotated is added or subtracted so that the ANFIS controller can subsequently make the respective correction and maintain the established straight trajectory. In addition, to control the distance between holes that the robot must travel, two incremental optical encoders have been incorporated that work in conjunction with the control algorithm.

From the electromechanical elements explored so far, a pre-designed rectangular box, the base structure, and the mechanical subsystems, all the components of the seed sower robot were assembled, obtaining as a result the terrestrial mobile robot shown in Figure 2.

Figure 2. Final exterior view of the mobile crawler robot for seed sowing.

The HMI interface was designed in such a way that the operator can manually control all the DC motors and servo motors that make up the mobile robot to verify its correct operation before starting the work. In addition, this HMI interface allows you to configure the type of seeds to be sown, and the number of holes to be drilled per row and allows you to manually empty and store in a tank those seeds that were left over from a previous sowing process. Figure 3 shows some of the configuration windows implemented in the HMI interface.


Figure 3. Screens that make up the HMI interface are implemented on the Nextion touchscreen.

## 2.3. Implementation of the control algorithm

Once the farmers were consulted and in other technical documents about the quantity, depth, and distance at which each type of seed should be placed (Cherfas, 2009; Sari, 2001; Landis, 2000; Baskin & Baskin, 2014), it was possible to standardize each parameter by programming the mobile robot with the values shown in Table 1.

Table 1. Optimal values for the seed sowing process.

| Tipo de semilla | Distancia (cm) | Profundidad (cm) | Cantidad semillas |
|---|---|---|---|
| Maíz | 20-25 | 5 | 2 |
| Frejol | 20-25 | 4 | 2-3 |
| Arveja | 10-20 | 5-7 | 1-2 |
| Soya | 15-20 | 2-4 | 3-4 |

To comply with the different actions that the mobile robot must perform in the seed-sowing process depending on the operating specifications entered through the HMI interface of the touch screen, the programming codes were implemented on the two Arduino cards.

As already mentioned, the control of the robot's rectilinear trajectory is conducted through the implementation of an ANFIS neuro-fuzzy controller by the theoretical basis discussed in Section 2.1. The ANFIS hybrid network uses five consecutive layers and takes advantage of 2 training algorithms: error backpropagation and RLS. All the experience gained during the training is stored in 2 families of parameters, these are the parameters of Layer 1 (non-linear or premise parameters) and the parameters of Layer 4 (linear or consequential parameters). The premise parameters are tuned through the standard error backpropagation algorithm, while the parameters of the consequent through the classical RLS algorithm.

A grid ANFIS algorithm has been implemented for trajectory control, initially using MATLAB and Simulink tools to verify through simulation the correct configuration of the parameters of the ANFIS network and later the programming code developed in this environment was programmed on the controller board. The programming logic of the algorithm has been developed using MATLAB code syntax, while the verification phase of its operation has been implemented in the Simulink graphical environment; both environments communicate with each other using a special block known as an S-function.

## 2.4. Results and discussion

To corroborate the performance of the mobile robot in the process of sowing seeds in a previously tilled field, several tests were conducted considering the diverse types of seeds, as shown in Figure 4. In this verification process, the same number of holes was considered for all seed types, which in this case was set to 10. Then, for each type of seed, the distance between the holes, the depth of the hole, and the number of seeds deposited were verified.

Figure 4. Tests were conducted with the mobile robot on tilled ground.

Based on Table 1 and to conduct functional tests in the sowing process, the following parameters were established programmatically for the types of seeds shown in Table 2.

Table 2. Fixed values of seeding parameters for functional tests.

| Tipo de semilla | Distancia (cm) | Profundidad (cm) | Cantidad semillas |
|---|---|---|---|
| Maíz | 22 | 5 | 2 |
| Frejol | 23 | 4 | 2 |
| Arveja | 15 | 6 | 2 |
| Soya | 18 | 3 | 3 |

The mobile robot planted all the seeds indicated in Table 2 in separate rows, but in the same field to ensure comparable conditions. The data on distance, depth and seed quantity were recorded manually. Once the sowing process of all the seeds in the previously tilled rows was completed and 10 holes (identified as M1 to M10) were constructed on each of them (which were configured through the HMI interface), the values shown in the following tables were obtained. The units of distance and depth are given in centimeters.

The results obtained in Table 3 to Table 6 show that the mobile robot is satisfactorily performing the seed sowing activity in the tilled field. The data collected was analyzed by comparing the recorded values with the programmed values to evaluate the robot's accuracy. The average efficiencies were calculated for the parameters of distance between holes, hole depth and quantity of seeds deposited. The results are presented graphically (Figures 5 to Figure 8) to facilitate the visual and numerical comparison of the data obtained.

Table 3. Determination of sowing parameters for maize seeds.

| Parámetro | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | Prom | Eficienc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distancia | 22 | 23 | 23 | 21 | 22 | 22 | 23 | 21 | 20 | 22 | 21.90 | 99.55% |
| Profundidad | 5 | 5 | 5 | 5 | 4 | 5 | 4 | 5 | 4 | 5 | 4.70 | 94.00% |
| Cantidad | 2 | 3 | 2 | 2 | 3 | 2 | 3 | 2 | 2 | 3 | 2.40 | 80.00% |

Table 4. Determination of sowing parameters for bean seeds.

| Parámetro | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | Prom | Eficienc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distancia | 23 | 23 | 23 | 23 | 21 | 23 | 22 | 22 | 23 | 21 | 22.40 | 97.39% |
| Profundidad | 3 | 4 | 4 | 4 | 3 | 3 | 4 | 3 | 4 | 4 | 3.60 | 90.00% |
| Cantidad | 3 | 3 | 2 | 2 | 2 | 3 | 3 | 3 | 2 | 2 | 2.50 | 75.00% |

Table 5. Determination of sowing parameters for pea seeds.

| Parámetro | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | Prom | Eficienc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distancia | 14 | 15 | 15 | 15 | 16 | 15 | 15 | 16 | 16 | 15 | 15.20 | 98.67% |
| Profundidad | 6 | 6 | 6 | 5 | 5 | 6 | 5 | 6 | 6 | 6 | 5.70 | 95.00% |
| Cantidad | 3 | 3 | 2 | 2 | 2 | 2 | 2 | 2 | 3 | 2 | 2.30 | 85.00% |

Table 6. Determination of sowing parameters for soybean seeds.

| Parámetro | M1 | M2 | M3 | M4 | M5 | M6 | M7 | M8 | M9 | M10 | Prom | Eficienc. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Distancia | 17 | 18 | 19 | 18 | 16 | 17 | 18 | 18 | 18 | 17 | 17.6 | 97.78% |
| Profundidad | 3 | 3 | 3 | 3 | 3 | 3 | 4 | 2 | 2 | 3 | 2.9 | 96.67% |
| Cantidad | 2 | 3 | 3 | 3 | 2 | 2 | 2 | 2 | 3 | 3 | 2.5 | 83.33% |

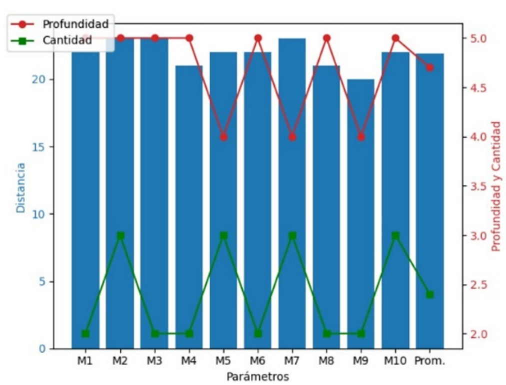



Figure 5. Determination of sowing parameters for maize seeds, according to Table 3.

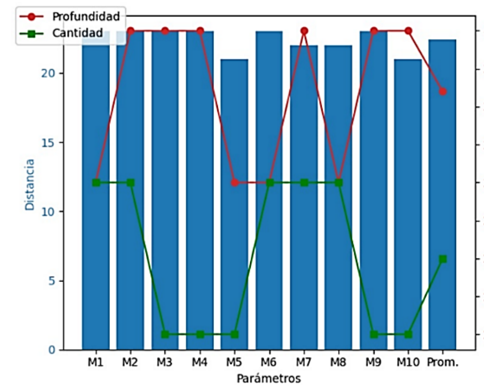



Figure 6. Determination of sowing parameters for bean seeds, according to Table 4.

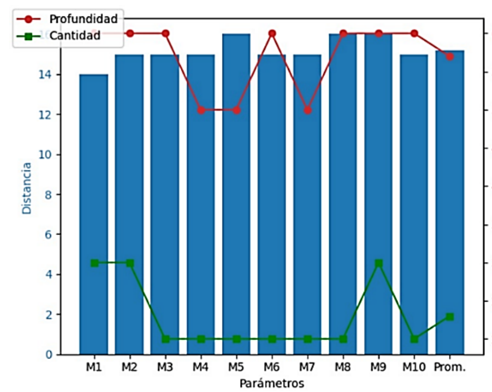



Figure 7. Determination of sowing parameters for pea seeds, according to Table 5.

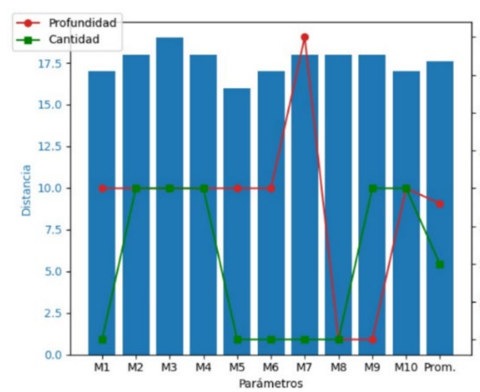



Figure 8. Determination of planting parameters for soybeans, according to Table 6.

For the control of the rectilinear trajectory in the seeding process of the different rows, simulated tests were conducted in the MATLAB and Simulink environment, to determine the appropriate values of the parameters of the ANFIS network and that were later used in the programming of the controller boards. Based on a generic mathematical model given in the Simulink environment, the ANFIS network was used to learn and replicate the behavior of the mobile robot when it moves executing different trajectories, taking as inputs random values of the supply voltages of the two DC motors, and as output the angle of rotation measured by a gyroscope. For this identification process, direct reverse identification was used, which is often used in the identification processes of systems based on neural networks.

The model obtained in the identification process through the ANFIS network was later used to implement an inverse forward controller, in this case, that same model goes from being an ANFIS identifier to becoming an ANFIS controller. Figure 9 shows the configuration and elements necessary for the previously trained ANFIS network to be part of the control system for the generation of rectilinear trajectories in the seeding process.

Keep in mind that now the step signal that enters the LE input of the ANFIS controller must always be 0 since the ANFIS network is no longer being trained, but the linear parameters (Layer 1) and the nonlinear parameters (Layer 4) obtained in the direct reverse identification process are being used. Once all the configurations were made and the simulation process was completed, the signals shown in Figure 10.a were obtained, where the error obtained between the reference signal and the output signal (rotation angle) was $-2.674x10^{-6}$.

To verify that the training process carried out with random input signals is valid for any type of reference input, another sinusoidal type of signal formed by different frequencies was entered and the results shown in Figure 10.b were obtained, where the error obtained between the reference signal and the output signal (rotation angle) was $7.33x10^{-4}$.

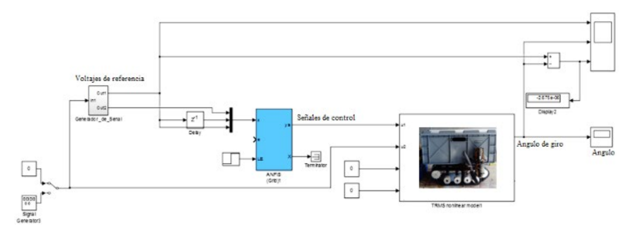
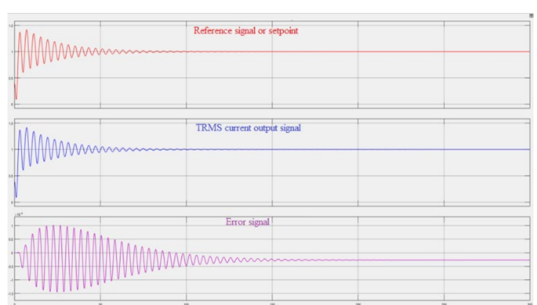
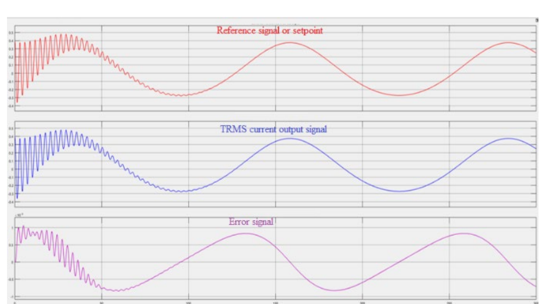



Figure 9. Reverse direct control system of the mobile robot using an ANFIS network.




(a)




(b)

Figure 10. Signals obtained in the reverse direct control process with a) damped sinusoidal signal, and b) undamped sinusoidal signal.

## 3. Conclusions

It was possible to develop a mobile robot with tracks that can be used in the sowing of diverse types of seeds such as corn, beans, peas, and soybeans in previously tilled land, obtaining satisfactory results according to the tests conducted. As for the distance that the robot must travel to deposit the seeds between each hole, an average efficiency of 98.35% was obtained, which reveals that the use of encoders coupled to DC motors in the tracks and the gyroscope is fulfilling their purpose. As for the depth parameter of the hole, good results were also obtained, having an average efficiency of 93.92% which will help the good growth of the plants, this is because the depth of the hole was pre-established through a timing process in the programming of each type of seed, which resulted in an easy and efficient option to implement. The parameter of the number of seeds deposited in a hole turned out to have an average efficiency of 80.83%, this is because the seed distribution and dispersal system does not have sensors to be able to count them, but rather it was possible to standardize through the mechanical system and programming codes to be able to deposit between 2 and 3 seeds in a hole; although the value of this parameter is not low, it can be improved by making modifications to the seed distribution system.

The mechanical structure of the mobile seed sower robot complies with all the technical specifications to be able to move in diverse types of terrain using the tracked locomotion system, which for this case was the most convenient. It was possible to reduce the weight of the structure by using a pre-designed rectangular plastic box as the body of the robot so that the DC motors coupled to the locomotion system had enough power to be able to move the entire weight of the chassis and the electronic and electromechanical components. It should be emphasized that the mobile robot was not designed to move on terrain with very steep slopes and according to the tests conducted, the angle of inclination should not exceed 30 degrees.

The electronic system of the mobile robot is designed in such a way that it is robust and with all the measures of electrical protection against stresses that merit greater energy consumption, thus guaranteeing the constant operation of the robot. Thanks to the battery power and recharging system through the solar panel, it was possible to provide autonomy to the mobile robot, if there was sufficient solar radiation in the sowing fields.

The performance of the ANFIS neuro-diffuse controller was simulated by applying it to the rectilinear trajectory control of the mobile robot, under different operating conditions corresponding to the variation of the reference signals of the control system. It was found that the error between the desired input signal (reference tilt angle) and the actual output signal (tilt angle given by the gyroscopic sensor) oscillated with small variations within the range of $3.18x10^{-4}$ to $3.65x10^{-4}$, which in terms of control engineering can be considered as a negligible error and therefore it can be assumed that the output signal is a faithful copy of the input signal the system has stabilized.

Although in the physical testing process, there was no external instrument to verify the validity of the generation of rectilinear trajectories, it was possible to visually corroborate that, in the event of a change in the orientation of the chassis, particularly due to the uneven terrain and the track system, the electromechanical system together with the programming of the ANFIS neuro-diffuse controller corrected this deviation. The findings of this study represent a significant advancement in precision agriculture and agricultural automation. By demonstrating the effectiveness of a mobile seeding robot using advanced control and simulation technologies, this research not only contributes to the optimization of current agricultural practices, but also lays the foundation for future innovations and developments in the field. The implementation of such technologies can transform agricultural practices, making them more efficient, sustainable, and adaptable to the changing needs of the global agricultural sector.

## Conflict of interest

The author(s) have no conflict of interest to declare.

## Acknowledgements

The study presented in this article is part of the unfunded research project titled “Evaluation of Heuristic Algorithms in Decision Making under Uncertainty” (code INCYT-PNF-2019-S73-120), led by the research group TECED (Technology, Science, and Education) of the Faculty of Systems and Telecommunications at the Universidad Estatal Península de Santa Elena. Consequently, the authors express their gratitude to the TECED project collaborators, whose objectives have served as the cornerstone for this article on route planning of a mobile robot in the seed sowing process using neuro-fuzzy control. The commitment and vision of this project in addressing problems in uncertain environments have been essential in guiding our work.

## Funding

The authors did not receive specific funding for this work.

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