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A computer vision-based weed control system for low-land rice precision farming

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Article Info

ABSTRACT

Agricultural sector is one of the economic pillars of developing nations, because it provides means of boosting gross domestic profit. However, weeds pose a threat to food crop by competing with it for nutrients and undermining the profit to be made from it. The treatment of these weeds is necessary, but at minimal impact on the actual food crop. Herbicide usage is one major means of weed control, owning to the expensive and labour-intensive nature of hand weeding. Recently, the need for site specific spraying has been on the rise because of health concerns which have been raised on the effect of herbicides on food crops and the effect on the environment. Most research on the field focuses on accurately identifying the weeds whilst neglecting the weed control. In this research, we apply fuzzy logic-based expert system to control how herbicide is sprayed on low-land rice in order to reduce excessive herbicide usage. The system supplies the control with weed density (Box size) and confidence level. The values of both are then passed to the fuzzy logic control for spray decision. The Sugeno as well as Mamdani models were tested using generated values for detected weed box size and confidence levels of the computer vision. The mean absolute error obtained was 0.9 for both, and 0.3 and 0.2 respectively, for the mean square error. The error shows how accurate the system can be and with low error value, it shows that the system implementation is capable of providing control for spraying of herbicides which in turn will yield more returns for low-land rice farmers.

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1. INTRODUCTION

Precision farming is a cohesive production and information-based farming system with a goal to promote efficiency, boost production and lucrativeness of the farm production activities while avoiding the adverse effects of excessive chemical usage on the environment or inadequate application of input [1, 2]. Precision farming has been affirmed as the solution to sustainable agriculture with focus on production boost [3]. Agricultural sector is an important sector of any economy as a mean of providing food supplies to meet the populace demand.

Rice (*Oryza sativa*), a plant species, is a seed of grass species grown as an annual plant, which is fast becoming a main food crop because of high patronage by a lot of people. It is consumed by more than half of world's population and provides twenty percent of the calories consumed worldwide by humans. It also a major staple food of most elite homes in Nigeria [4]. Rice production goes through three stages, which are the vegetative phase, reproductive phase and the maturity phase. The difference in rice varieties of the world is the vegetative phase. Rice is farmed in about 1.7 million hectares of the estimated 4.6 million to 4.9 million hectares' potential land for its production. The production environment for rice in Nigeria are the rain-fed lowland, rain-fed upland, irrigated lowland, deep water/floating and mangrove swamp [5]. Weeds are some of the major problems facing rice production in Africa [6]. Weed control mechanism be applied within 40 to 50 days of planting, else the control might prove difficult [7]. Likewise, author in [8] stated that weed control has high chances of improving production. Weeds cause increase in production cost, reduction in profit and contamination of food crops [9, 10] Other constraints on rice production are labour shortages, illiteracy, ignorance, poor milling system, pest infestation, poor drainage, inputs and credits [5, 11].

Due to increase in civility and knowledge of weed, means of weed control have been sought after by researchers to remove the notorious pest at minimal damage to the plant. Cultural methods, chemical methods and automated methods are the major means of weed control. The cultural method of weed control consists of maintaining clean reaper, mulching, fire clearance, early flooding, bush fallowing, hand weeding and shifting cultivation [12-16]. This method suffers from high cost and huge labour intensiveness. Herbicide application is seen as an important substitute to hand weeding. But over application of herbicides can lead to losses at harvest, environmental damage, high cost of production and building of resistance to the herbicide [7, 8, 17]. Some of these herbicides even end up on food crop and the soil without reaching the weeds [18] The spraying on food crop is seen as threat to safety of food consumed, this therefore breeds a need for comprehensive control system for management of weed. However, author in [19] proposed an image processing method based on complex pre-processing steps to accurately identify weeds in farm lands but provide no removal techniques for the weeds identified. In the same vein, [20] proposed a robotic system that classifies weeds based on visual texture. The system uses knives for removing the weeds and this might cause damage to the plant. The designed system also consumes a lot of power.

Consequently, Pulido et al., in [21] developed a system that uses patterns from texture to identify weeds from vegetables using Support Vector Machine (SVM) classifier. Features space was calculated from grey level co-occurrence matrix (GLCM). The system obtained 90% for sensitivity, specificity and precision but provides no removal techniques for the weeds. In addition, author in [7] designed a weed detection system for rice in order to avoid uniform spraying of rice farm, the system used SVM for the classification of the weed and uses blur detector for weed detection. The system had an accuracy of 68.95% with blur and an accuracy of 76.16% when the blur was removed. However, no means of weed control was proposed or implemented. There are other existing methods that detect weeds in wheat, soya beans and maize with less accuracy in real life field application in literature.

From the reviewed literatures, it is evident that implementation of weed control systems to solve the problem of excessive herbicide spraying has not gained much attention in recent times. Hence, this paper proposes a fuzzy logic-based expert control system for herbicide spraying control to help address the problem of uniform spraying and excessive herbicide usage. The remaining part of this paper is organised as follows: section 2 presents the fuzzy logic control system, section 3 presents the system design, section four presents the results obtained and section 5 presents the conclusion and recommendation for future works.

2. FUZZY LOGIC CONTROL SYSTEM
2.1. Fuzzy inference system

Explaining The fuzzy logic is based on the work of Jan Lukasiewicz (1878-1956) and the term was coined out and developed by Dr. Lotfi Zadeh in 1965 [22]. Fuzzy logic is a pattern of reasoning which sets out to mimic the reasoning abilities of humans. It involves the use of continuous values from 0 to 1. These values can also be taken as true and false so that decisions can be made even with incomplete or uncertain data. It works on the levels of different possibilities in order to achieve an output. Fuzzy logic helps to give a reasonable solution to uncertain engineering problems. There are basically two models of fuzzy inference system which are the Mamdani model created by Mamdani and Assilian in 1975 and Takagi Sugeno Kang model created in 1985 [23].

Sari *et al.* described the four parts of the fuzzy logic inference system as: Fuzzification module which is the part first part that transforms the input of the system into (crisp) fuzzy set [24]. The knowledge

base forms the second, it holds the if -then rules provided. The inference engine which is the third simulates human decisions by taking decisions based on the knowledge based created. The fourth is the defuzzification module that transforms the fuzzy set into crisp value in the Mamdani FIS. In the Sugeno FIS, weighted average or weighted sum is used for obtaining crisp value for the output. Figure 1 shows the block diagram that shows the four basic parts of fuzzy inference system.
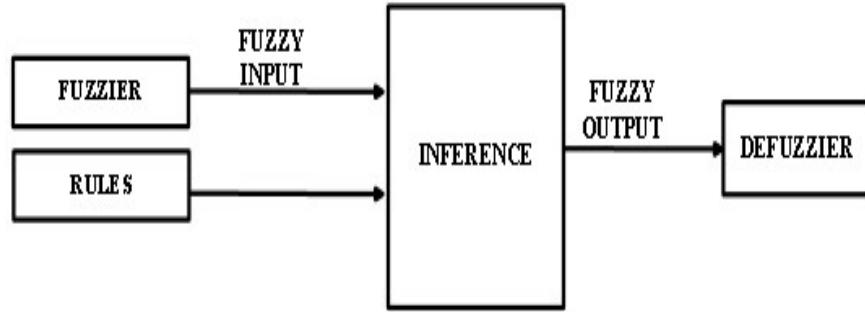

Figure 1. Block diagram showing the different parts of FIS

There are five defuzzification methods for Mamdani which are, smallest of maximum, centroid of area, largest of maximum, bisector of area and mean of maximum. Table 1 shows the defuzzification methods used in Mamdani and Sugeno, together with their mathematical formulas. Finally, the membership function shows graphically the relationship between the elements. The membership function works on fuzzy sets of the variable. There are different types of membership functions which are used in fuzzy inference systems and examples are singleton, Gaussian, triangular and trapezoidal. For this research both the Sugeno FIS and the Mamdani FIS were simulated for the control system, but the Sugeno was selected for implementation because of the flexibility, adaptive nature and its computational efficiency.

Table 1. Methods of obtaining crisp output for Mamdani and Sugeno [23-25]

Serial number	FIS model	Defuzzification method	Meaning	Formula
1	Mamdani	Smallest of maximum	It uses the smallest value which gives the maximum membership degree of the fuzzy set to generate the crisp output	$y_{SOM} = \min\{y / \mu_B(y) = \max (\mu_B(y))\}$
2	Mamdani	Centroid of area	It generates the centroid of the area formed by the fuzzy set. It uses the value to calculate crisp output	$\int_v \frac{y \cdot \mu_B(y)dy}{\mu_B(y)dy}$
3	Mamdani	Largest of maximum	Just like SOM but it uses the largest value which gives the maximum membership degree to yield the final crisp output	$y_{LOM} = \max\{y / \mu_B(y) = \max (\mu_B(y))\}$
4	Mamdani	Bisector of area	Bisector of area generates a vertical line which splits the fuzzy set into two equal areas. The vertical line corresponds to the output generated.	$\int_\alpha^{BOA} \mu_B(y)dy = \int_{BOA}^\beta \mu_B(y)dy$ $\alpha = \min\{v/v \in V\}$ $\beta = \max\{v/v \in V\}$
5	Mamdani	Mean of maximum	This takes the mean of the maximum as the crisp output	$y_{MOM} = \frac{y_{SOM} + y_{LOM}}{2}$
6	Sugeno	Weighted average	It uses the weighted output of the rule to generate the final output	$y_{WA} = \frac{\sum_{i=1}^m Wi\, yi}{\sum_{i=1}^m Wi}$
7	Sugeno	Weighted sum	It reduces the computation by using the sum of the weighted output of the rule.	$y_{WS} = \sum_{i=1}^m Wi\, yi$

3. MATERIALS AND METHODS

This section describes the materials and procedures used in the design and development of the computer vision-based weed control system for low- land rice precision farming. The method is explained from the prism of system overview, fuzzy logic control, hardware design considerations, software design considerations, and performance evaluation.

3.1. System fuzzy logic control design

The fuzzy logic-based weed control system was simulated using Sugeno and Mamdani fuzzy logic models, and was designed using the fuzzy logic designer toolbox of MATLAB. It comprises of two inputs, the weed bounding box size (boxSize) and the confidence level of the recognition model to drive an output which is the spray rate (volume of herbicides sprayed per time). The box size is taken from 0 to 10 and confidence level from 0 to 100. Each of the input has its triangular membership function as shown in Figure 2 and Figure 3 for Sugeno, and Figure 4 and Figure 5 for Mamdani FIS.
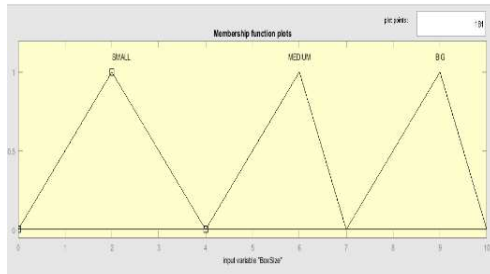
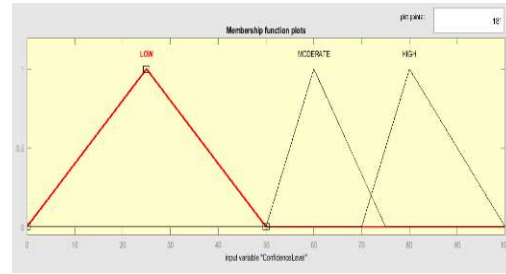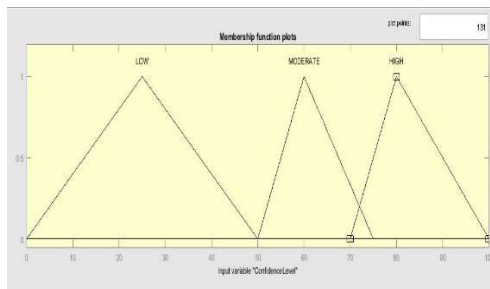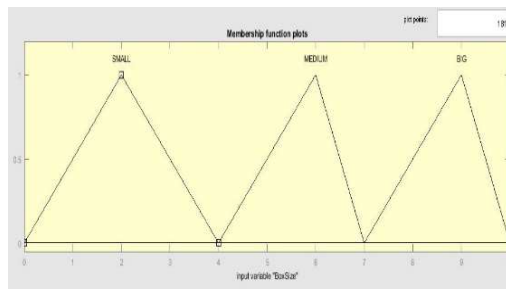|	
Figure 2. Sugeno triangular membership function for box size	Figure 3. Sugeno triangular membership function for confidence level
Figure 4. Mamdani membership function for box size	Figure 5. Mamdani membership function for confidence level

Weighted average was used for obtaining crisp output of Sugeno FIS and centroid method of defuzzification was used for getting out crisp output of Mamdani. The Mamdani FIS has output membership function while the Sugeno does not have, rather it has a table of constant for flexibility. Table 2 and Figure 6 show the output for Sugeno and Mamdani FIS respectively. For this research Sugeno is adopted because it is less time consuming in terms of defuzzification by using weighted average instead of defuzzification as used by Mamdani model. It is more efficient, works well with optimization and has adaptative ability [26]. Table 3 and Table 4 show that both Sugeno and Mamdani uses the same rule set. The rules which set the control are shown in both tables.

Table 2. Sugeno output table

Spray rate	Constant value
Off	0
Low	0.3333
Medium	0.6667
High	1

Table 3. System fuzzy control rules for Sugeno

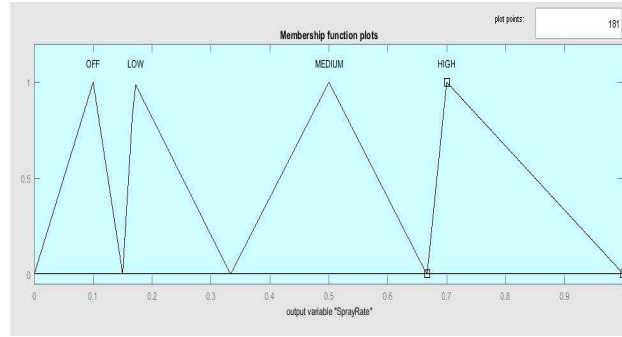| Rules	Box size	Confidence level	Spray rate
1	SMALL	LOW	OFF
2	SMALL	MODERATE	LOW
3	SMALL	HIGH	MEDIUM
4	MEDIUM	LOW	LOW
5	MEDIUM	MODERATE	MEDIUM
6	MEDIUM	HIGH	HIGH
7	BIG	LOW	LOW
8	BIG	MODERATE	MEDIUM
9	BIG	HIGH	HIGH

Figure 6. Mamdani triangular membership function for spray rate

Table 4. System fuzzy control rules for Mamdani

Rules	Box size	Confidence level	Spray rate
1	SMALL	LOW	OFF
2	SMALL	MODERATE	LOW
3	SMALL	HIGH	MEDIUM
4	MEDIUM	LOW	LOW
5	MEDIUM	MODERATE	MEDIUM
6	MEDIUM	HIGH	HIGH
7	BIG	LOW	LOW
8	BIG	MODERATE	MEDIUM
9	BIG	HIGH	HIGH

3.2. System hardware design consideration

Raspberry pi 3B was used as the microcontroller of the computer vision system. The raspberry Pi 3B is a third-generation single board computer that has processing speed of 1.2GHz enabling it to process the image at fast speed and send the weed image size and confidence level of image recognition to the fuzzy inference system for control. The mechanical unit consists of the five-litre tank, hose and nozzle which are connected to make the spraying tank. Other components used are the DC pump, Raspberry pi 8Mp camera, LEDs and L293N motor driver which are all connected to the raspberry pi for control. The DC pump is powered by 12V DC while the raspberry pi is powered by 5v DC battery.

3.2.1. System mathematical modelling

The system model consists of the controller connected in series with the pump. The block diagram of the model system is in Figure 7, while Figure 9 shows the simulink modelling of the system in MATLAB. G(s) represents the pump and in modelled in terms of a DC motor. The input to the model is electrical voltage which in turns gives an output of angular velocity to drive the motor [27]. The angular velocity of the shaft drive determines the rate at which the herbicide comes out of the pump. The model of the DC motor is shown in Figure 8. Table 5 presents the parameter and value.
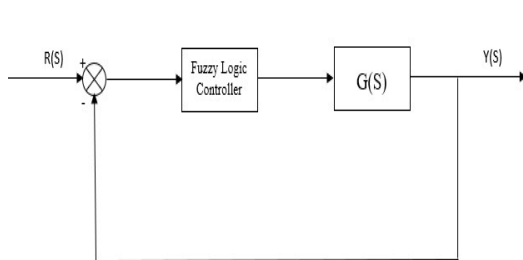

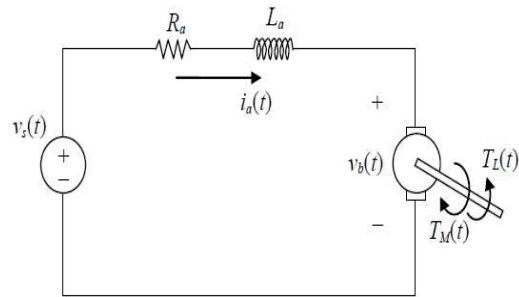Figure 7. Block diagram of the system model   Figure 8. Model diagram of the pump (Chen, 2015)

Where:

$i_a(t)$ = Armature current
R_a = Armature resistance
L_a = Armature inductance
$V_s(t)$ = Applied voltage
$V_b(t)$ = Back EMF
$T_M(t)$ = Motor torque
J_M = Rotor moment of inertia
B_M = Frictional coefficient

From Kirchhoff's voltage law the equation for the DC motor is

$$V_s(t) = R_a i_a(t) + L_a \frac{di_a(t)}{dt} + V_b(t) \tag{1}$$

The back EMF, $V_b(t)$ is proportional to angular velocity. It is given as

$$V_b(t) = k_b \omega(t) \tag{2}$$

k_b is the constant of the back EMF. The torque of the motor is proportional to armature current, it is given as

$$T_M(t) = k_t \, ia(t) \tag{3}$$

Where k_t is the constant of the motor torque.
The equation of the dc motor can now be written as

$$V_s(t) = R_a \, i_a(t) + L_a \frac{di_a(t)}{dt} + k_b \omega(t) \tag{4}$$

Using (3),

$$ia(t) = \frac{T_M(t)}{k_t} \tag{5}$$

Substituting (3) into (4), we obtain

$$V_s(t) = R_a \frac{T_M(t)}{k_t} + L_a \frac{d}{dt}\left(\frac{T_M(t)}{k_t}\right) + k_b \omega(t) \tag{6}$$

$$k_t V_s(t) = R_a T_M(t) + L_a \frac{d}{dt}\big(T_M(t)\big) + k_t k_b \omega(t) \tag{7}$$

The mechanical behaviour of the motor can be described as

$$T_M(t) = J_M \frac{d\omega(t)}{dt}(t) + B_M \omega(t) \tag{8}$$

Taking the Laplace transform of (7) and (8)

$$k_t V_s(s) = R_a T_M(s) + S L_a T_M(s) + k_t k_b \Omega(s) \tag{9}$$

$$T_M(s) = S J_M \, \Omega(s) + B_M \Omega(s) \tag{10}$$

Putting (10) into (9), we obtain

$$k_t V_s(s) = (R_a + S L_a)\big(S J_M \, \Omega(s) + B_M \Omega(s)\big) + k_t k_b \Omega(s) \tag{11}$$

$$G_2(s) = \frac{output}{input}$$
$$\frac{\Omega(s)}{V_s(s)} = \frac{k_t}{S^2 L_a J_M + S(R_a J_M + L_a B_M) + (k_t k_b + R_a B_M)} \tag{12}$$

The values from the standard motor equation (Chen, 2015), are shown in Table 7.

Table 5. Parameter table

Parameter	Value
R_a	0.5Ω
L_a	0.0015 H
J_M	0.00025 N-m/ (rad/s^2)
K_T	0.05 N-m/A
K_b	0.05V/rad/s
B_m	0.0001 N-m/ rad/s

Substituting each value into (12), we finally obtain

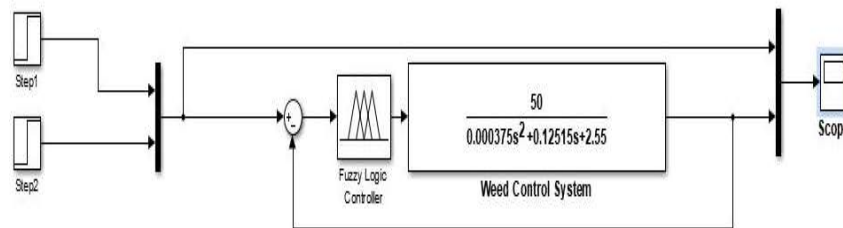$$G_2(s) = \frac{50}{S^2 0.000375 + S0.12515 \quad .55} \tag{13}$$

Figure 9. System model simulation in simulink

3.3. System software design consideration

The software used in the computer vision system was chosen using criteria such as ease of implementation, how it supports the components selected and how it reacts to flaws in the systems. Python (version 3.6) programming language was used in the design and development of the system because it was the official programming language of Raspberry Pi; highly efficient and fault tolerant in nature. Proteus software (ISIS 8) was used to design the circuit diagram and MATLAB (R2017A) was used for system modelling, simulation and fuzzy logic control because of its modelling and simulation capability and ease of interfacing with other programming languages.

3.4. System performance evaluation

Performance evaluation is carried out to know the effectiveness and efficiency of the methods which were adopted in the development of this project. The fuzzy logic model was evaluated using the Mean Absolute Error (MAE) and Mean Square Error (MSE) of the Sugeno model which were the methods as adopted by [28-31]. Database of 50 different samples of box size and confidence level was generated randomly to test the spray rate of the Sugeno and mamdani model using the 'evalfis' command in MATLAB. The MAE and MSE were calculated for each deviation of the model. The metrics can be represented mathematically as:

$$\text{MAE} = \frac{\sum |Actual - Predicted|}{Total\ number\ of\ samples} \tag{14}$$

$$\text{MSE} = \frac{\sum (Actual - Predict\quad)^2}{Total\ number\ of\ samples} \tag{15}$$

4. RESULTS AND DISCUSSION

This section presents the result obtained from the simulation of both the Sugeno and Mamdani on MATLAB R2017A. Figure 10 shows the surface view for the Sugeno model. Figure 11 shows how the spray rate is affected by the confidence level. The model shows the relationship between the box size of the recognised weed and the confidence level obtained and how they both affect the spray rate of the pump. Figure 14 shows the step response of the designed control system.

Figure 12 and Figure 13 show the surface view for the Mamdani FIS and how the confidence level affects the Spray Rate. It shows how the box size of the recognized weed and the confidence level of the recognition system affects the spray rate of the sprayer. The result obtained for Sugeno model and Mamdani shows that the Sugeno model helps to get the maximum use of the sprayer while the Mamdani shows expressiveness in terms of the output membership function. Figure 15 shows the developed the computer vision system after programming and integrating materials selected in section 3.2.
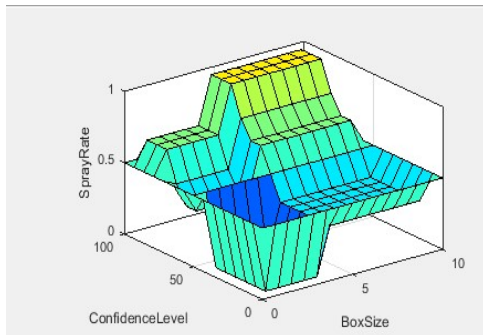
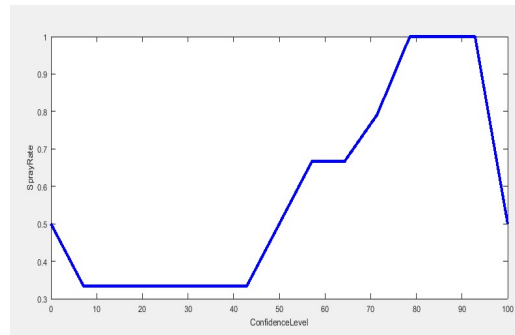Figure 10. Surface view for the Sugeno
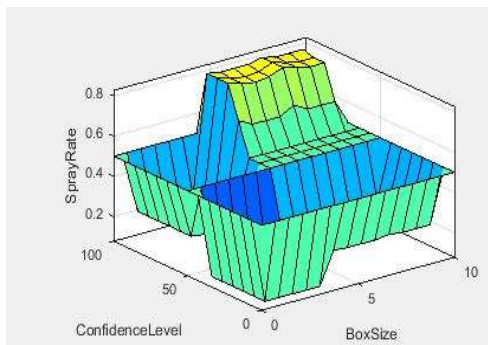
Figure 11. Spray rate versus confidence level
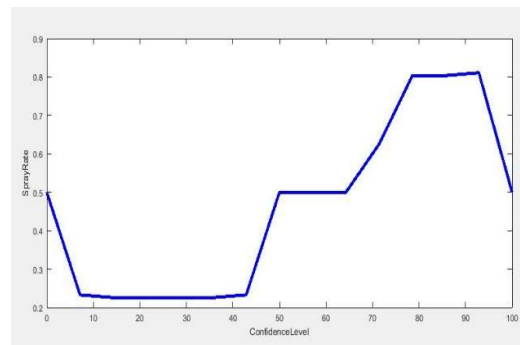
Figure 12. Surface view for Mamdani

Figure 13. Spray rate vs confidence level
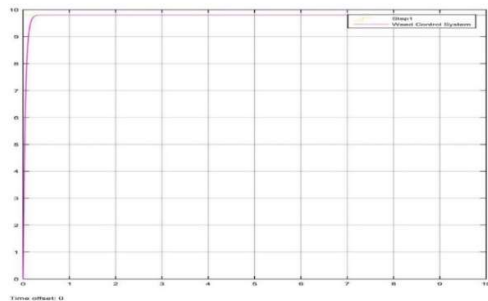
Figure 14. Step response of weed control system

Figure 15. Designed control system

4.1. Performance evaluation for the fuzzy logic model

50 random data were generated to evaluate the Sugeno model and the Mamdani model. The deviation of the model was calculated and recorded. MAE and MSE were the metrics used to evaluate the model. Table 6 and Table 7 show the summary of the results obtained for performance evaluation measurement for 50 generated samples for both Sugeno and Mamdani fuzzy logic system. The equation is adopted from Section 3.4.

$$MAE = \frac{\sum |Actual - Predic \quad |}{Total\ number\ of\ samples}$$

$$MSE = \frac{\sum (Actual - Predic \quad)^2}{Total\ number\ of\ samples}$$

For Sugeno

$$MAE = \frac{4.5675}{50} = 0.09135$$

$$MSE = \frac{1.739311}{50} = 0.034786$$

For Mamdani

$$MAE = \frac{4.5282}{50} = 0.09054$$

$$MSE = \frac{1.2149134}{50} = 0.02429$$

Table 6. Summary of performance measurement for the 50 test samples for Sugeno

Performance measure	50 Test samples
MAE	0.09
MSE	0.03

Table 7. Summary of performance measurement for the 50 test samples for Mamdani

Performance measure	50 Test samples
MAE	0.09
MSE	0.02

5.   CONCLUSION

The result obtained from the simulation shows 0.09 for mean absolute error and 0.03 for mean square error of Sugeno, similar value was obtained for the evaluation of Mamdani fuzzy inference system. This result shows that fuzzy logic can be applied to monitor the spraying action of a tank which in turn will lead to reduction in herbicide usage and reduce environmental damage associated with uniform spraying. The system modelling on Simulink shows a rise time of 0.1012, settling time of 0.1829, overshoot of 0.0045 and peak time of 2.3734. Since the system error is negligible, it shows that the system can be applied on a real rice farm to control herbicide usage, thus boosting rice production at reduced production cost. This will therefore yield more returns for the farmers. However, in this research, the actual amount of herbicide to kill the weeds was not calculated. Therefore, future research should endeavour to carry out quantitative amount of herbicides capable of killing the recognized weeds. Furthermore, the sprayer arm for the system was static, so future work can work a robotic hand for the sprayer to enable it turn and spray in respect to viewed areas.

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