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Original Research

Energy-Efficient and Intelligent Autonomous Spraying Robot for Precision Agriculture Using Solar Power and Fuzzy Logic

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ABSTRACT

This article presents the development of a solar-powered intelligent pesticide spraying robot designed to enhance environmental sustainability in precision agriculture. By integrating renewable energy with intelligent decision-making, the system significantly reduces reliance on fossil fuels and minimizes pesticide overuse. The robot is powered by a solar panel with an adjustable tilt for optimal energy harvesting and incorporates a lead-acid battery for energy storage to maintain continuous operation. A water pump and DC motors facilitate mobility and spraying functions. The integration of fuzzy logic enables adaptive, real-time decision-making based on environmental parameters, ensuring precise and efficient pesticide application. Experiment across different weather conditions demonstrated superior performance in unshaded environments, with battery limitations observed during extended cloudy periods. Results showed a 24% reduction in pesticide use and 93% average coverage accuracy. This study underscores the environmental benefits of clean energy and intelligent control, and recommends the future integration of Internet of Things (IoT) technologies and battery upgrades to further enhance operational sustainability and field autonomy.

INTRODUCTION

The advancement of automation and intelligence in precision agriculture is significantly driven by the integration of the Internet of Things (IoT) and artificial intelligence (AI) in pesticide spraying robots (Ghafar et al., 2023; Kayode et al., 2024; Amir Ghalazman et al., 2022; Raikwar et al., 2022; Terra et al., 2021, Fauadi et al., 2024). IoT enables real-time monitoring, remote operation, and seamless data collection, empowering farmers to make informed, data-driven decisions. Equipped with advanced sensors and GPS technology, these robots can accurately navigate agricultural fields and perform targeted spraying, thereby minimizing pesticide use and reducing environmental impact. The synergy between AI and IoT facilitates autonomous decision-making, allowing robots to adapt to dynamic field conditions without human intervention. This intelligent automation not only boosts operational efficiency but also promotes sustainable agricultural practices by addressing both economic and ecological challenges (Ananda-Rao et al., 2020; Jerosheja et al., 2020; Zangina et al., 2021; Fauadi et al., 2018). Table 1 summarizes recent studies in the related field.

Table 1: Summary of recent studies in the related field.

Author	Scope	Type of Industry	Result	Study area	Summary
Chaitanya et al. (2020)	Development of Smart Pesticide Spraying Robot	Agriculture	Implementation of algorithms for plant disease detection and classification.	Precision agriculture and robotic pesticide spraying in agricultural farmlands	Precision in crop management requires technical skills and technological assistance.
Ghafar et al. (2023)	Design and development of a robot for spraying fertilizers and pesticides	Agriculture industry is resource-intensive and labor-intensive	Robot sprayed 20 plants/min, human worker sprayed 30 plants/min	Focus on crop monitoring and pest detection in agriculture fields.	Developed low-cost agricultural robot for spraying fertilizers and pesticides.
Kayode et al. (2024)	Development of remote-controlled solar-powered pesticide sprayer vehicle	Agriculture	Remote-controlled sprayer saves time, enhances productivity, and is cost-effective.	Focus on reducing pest impact, improving productivity, and cost savings.	Solar-powered, sprayer vehicle enhances pesticide application efficiency and productivity.
Ranjitha et al. (2019)	Solar Powered Autonomous Multipurpose Agricultural Robot Using Bluetooth/Android App	Solar-powered autonomous agricultural robot development.	Solar panel converts sunlight to electricity for robot's operation	Agricultural field operations in India	Bluetooth control for seed sowing, grass cutting, and pesticide spraying.

Martin et al. (2021)	A Generic ROS-Based Control Architecture for Pest Inspection Using a Mobile Manipulator	Agriculture	Successful field tests validate the architecture for pest control tasks.	Greenhouses for pest detection and treatment using mobile manipulators	Recovery behaviors for localization quality loss and obstacle overcoming in navigation.
Jerosheja et al. (2020)	Solar Powered Automated Multi-Tasking Agricultural Robot	Agriculture	Controlled field operations remotely using IoT and internet connectivity	Agricultural field automation and monitoring using solar-powered robotic vehicle.	Autonomous mode for irrigation, pest control, and field security.

The intersection of automation and renewable energy in agriculture has catalyzed the emergence of sustainable solutions such as solar-powered intelligent pesticide spraying systems. Traditional pesticide application often involves fuel-powered machinery or intensive manual labor, both of which pose challenges to environmental sustainability, including greenhouse gas emissions, soil degradation, and chemical runoff. This study proposes a solar-integrated robotic spraying system as a cleaner, energy-efficient alternative to these conventional practices (Ibrahim et al., 2020; Mendez-Flores et al., 2025; Dange et al., 2023).

While pesticide spraying is essential to protect crops and ensure food security, excessive or imprecise application can cause significant harm to ecosystems, pollute water sources, and affect human health (Ghafar et al., 2023; Sammons et al., 2005). Automation and precision control technologies directly address these concerns by enabling targeted spraying, reducing chemical use, and minimizing environmental exposure. Moreover, robotic systems eliminate the need for close human contact with toxic substances, improving safety for farmworkers. To enable real-time responsiveness in diverse field conditions, this research incorporates fuzzy logic as a decision-making framework. Fuzzy logic facilitates nuanced interpretations of environmental data, such as crop density, soil moisture, and microclimate variations allowing the robot to apply pesticides only when and where needed. This adaptive intelligence fosters resource-efficient, environmentally conscious spraying practices.

This study explores the feasibility of combining solar energy, fuzzy logic, and autonomous control into a unified system for eco-friendly pesticide spraying. It assesses system performance in different environmental contexts and proposes future directions to enhance energy management, reduce ecological footprint, and increase automation through IoT integration. Three unique aspects of the proposed system: (1) the use of a five-input fuzzy logic controller combining soil moisture, crop stage, weather, nutrient status, and plant proximity, extending the capabilities of prior works by Kayode et al. (2024) and Ghafar et al. (2023); (2) the incorporation of an adjustable solar panel with a -15° tilt to minimize shading losses and optimize energy harvesting; and (3) quantitative evidence demonstrating 24% pesticide reduction and 93% coverage accuracy.

2. MATERIALS AND METHODS

2.1. Fuzzy Logic in Agricultural Systems

Fuzzy logic is an artificial intelligence technique that mimics human decision-making by handling imprecise and ambiguous inputs. In agriculture, fuzzy logic is especially valuable due to the variability of environmental conditions such as soil moisture, pest density, light intensity, and temperature. Unlike traditional binary logic systems, fuzzy logic enables continuous control and is well-suited for applications requiring gradual or condition-dependent responses. Previous research in agricultural automation has applied fuzzy logic for irrigation scheduling, pest control, and greenhouse management. For pesticide spraying, fuzzy logic enables real-time decision-making based on multiple parameters like pest presence, leaf wetness, and sunlight intensity. By applying a set of fuzzy rules, the spraying system can determine the optimal quantity and timing of pesticide application, reducing chemical waste and enhancing environmental safety. This study applies fuzzy logic to the robot's control system to dynamically regulate spraying activity, based on sensor inputs related to ambient light, soil condition, and plant health. This approach enhances precision in pesticide delivery, reduces unnecessary spraying, and aligns with smart farming practices.

2.2. System Design Overview

The methodology for this project involved the design, component selection, and performance evaluation of a solar-powered pesticide spraying robot under various environmental conditions. The system was constructed using a 10-watt monocrystalline solar panel to ensure efficient energy collection, a lead-acid battery for energy storage, and DC motors to facilitate movement and control the spraying mechanism. The solar panel was mounted at an adjustable angle to maximize sunlight absorption throughout the day. A motor driver was incorporated to efficiently distribute power to the system's various components, ensuring optimal functionality.

To assess performance, several tests were conducted under controlled conditions. The solar panel's efficiency was measured at different times of the day and under varying weather conditions to evaluate its energy output. Battery performance was analyzed by recording voltage levels and discharge rates over extended periods of use. The efficiency of the spraying mechanism was evaluated by measuring pesticide distribution and coverage across predefined field areas. Additionally, operational time was recorded under full-load conditions to determine the robot's endurance and to identify potential areas for improvement.

The design and structure of the automated pesticide spraying robot were engineered for durability, compatibility with various components, and optimal autonomous operation. The specific application dictates the robot's dimensions, and the frame material must be durable and ideally waterproof. Consulting the technical specifications provided by the robot's manufacturers may be necessary to obtain accurate information regarding the composition and configuration of the frame. Fig. 1 illustrates the structural design of the pesticide robot.

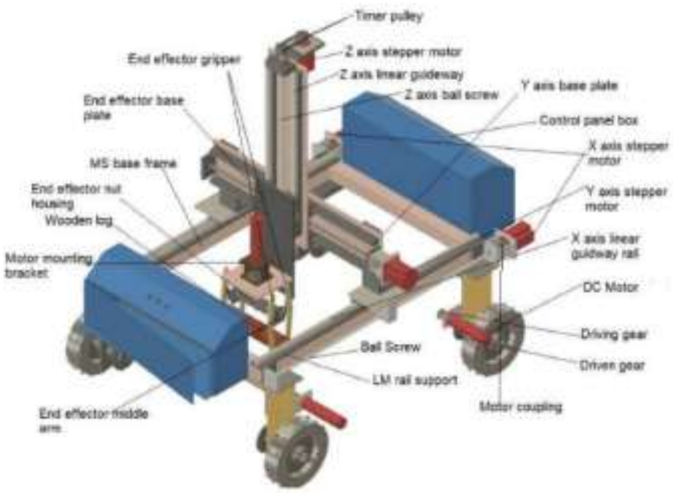


Fig. 1: Proposed structure frame for the mobile robot

2.3. Solar Panel Selection and Performance Testing

Monocrystalline solar panels were chosen for this system due to their superior efficiency, reliability, and long operational lifespan. Constructed from high-purity silicon, these panels typically achieve energy conversion efficiencies ranging from 18% to 22%, outperforming polycrystalline alternatives. Their high performance under low-light conditions, better heat resistance, and compact design make them ideal for mobile agricultural applications that demand stable power generation throughout the day. A 10-watt monocrystalline panel was selected to provide a balance between output power and physical size. This capacity is sufficient to operate the robot's motors and spraying system under typical daylight conditions, contributing to autonomous and uninterrupted operation.

Voltage measurements were conducted to assess the performance of the solar panel under various conditions. These tests are essential for identifying system inefficiencies such as shading losses, suboptimal panel orientation, and wiring issues. Accurate voltage readings support the calibration of the charge controller to ensure safe and efficient energy storage. Measurements of open-circuit voltage (Voc), maximum power point voltage (Vmp), and loaded voltage were recorded using a digital multimeter at various times of the day and weather conditions. The resulting data was analyzed to detect performance trends, aiding in system optimization and predictive maintenance planning. Solar panel current output was tested to verify the panel's capability to deliver sufficient energy to the battery and load circuits. The current output, which varies with sunlight intensity and panel angle, was measured in amperes using a calibrated digital meter. These readings helped identify efficiency bottlenecks caused by shadowing, dust accumulation, or misalignment. Routine current testing enables proper alignment of the panel and supports continuous improvement in system energy harvesting.

In addition to panel performance evaluation, battery endurance and recharge characteristics were measured under field conditions. The system operated continuously for approximately 5.2 hours under full-load conditions on sunny days, whereas overcast and intermittently cloudy days reduced runtime to around 3.1 hours. Recharge time from a 30% state-of-charge to full capacity was approximately 4 hours under direct sunlight, based on average solar irradiance levels of 700–900 W/m². While the prototype did not employ a Maximum Power Point Tracking (MPPT) system due to cost and complexity constraints, its inclusion is recognized as a future enhancement to improve energy harvesting efficiency, particularly under fluctuating or partially shaded conditions. The integration of MPPT would help maintain consistent charging performance and extend operational autonomy in less predictable environments.

2.4. Solar Angle Optimization

Under 12V power supply limitations, a pesticide spraying robot's motor pump must meet specific performance specifications. Gear pumps are suitable for maintaining pressure and flow, while diaphragm pumps can handle viscous liquids and are self-priming. Key requirements for a 12V pump include appropriate flow rate, pressure capacity, chemical compatibility, power efficiency, reliability, and controllability. For secure installation, possible pulsation attenuation, and integration with the 12V power supply and control system, the selected pump must be carefully matched to the robot's operational needs. The robot's battery capacity must also be considered to ensure the pump uses 12V power efficiently while delivering effective pesticide application.

Even partial shading drastically reduces solar panel performance. Shaded panels lower output and efficiency by disrupting the flow of photovoltaic cells. In extreme cases, hotspots from shading can damage the panels. Adjusting the panel angle to -15 degrees helps eliminate shadows cast by system components or surrounding structures. This method provides stable energy to the pesticide spraying apparatus. Adjustable angles also allow the system to operate efficiently in varying weather conditions. The device functions well in both sunny and cloudy environments since the solar panel can be angled appropriately. This design minimizes shadowing and accommodates environmental fluctuations by using a -15-degree tilt. Such adaptability improves the system's energy efficiency and extends the lifespan of the solar panel, making it a reliable and sustainable agricultural solution. The adjustment process is illustrated in Fig. 2.

(a) Device placement (b) Reading of solar panel angle

Fig. 2: Setup for the solar panel angle.

2.5. Fuzzy Logic Controller Design for Intelligent Spraying

The decision-making process of the spraying system in this study relies on a Fuzzy Logic Controller (FLC), which processes multiple environmental variables to determine optimal spraying behavior. This approach addresses the imprecision and variability found in agricultural environments, such as uneven terrain, inconsistent sunlight, and varying soil moisture.

The FLC receives five primary input variables, selected for their relevance in influencing pesticide application efficiency:

- Soil Moisture (%): Soil moisture impacts plant health and determines the need for pesticide application. A dry field may require more aggressive pest control, while wet soil might indicate recent rain, which can wash away chemicals and make spraying ineffective.
- Plant Growth Stage (Days After Planting): Different growth stages require different levels of pest management. Seedlings are vulnerable and require cautious application, while reproductive-stage plants may require more consistent treatment.
- Weather Conditions (Composite Index): Derived from light intensity and humidity readings, weather influences both pesticide evaporation rate and pest behavior. For instance, spraying under high sunlight might lead to faster evaporation, reducing effectiveness.
- Proximity to the Next Plant (Ultrasonic Sensor in cm): Ensures targeted spraying only when a plant is present, minimizing waste and environmental impact.
- Nutrient Deficiency (optional for expanded version): In more advanced versions, an NDVI (Normalized Difference Vegetation Index) sensor can be integrated to measure plant health, influencing whether treatment is required.

Two key outputs are derived from the FLC:

- Sprayer Flow Rate (ml/sec): Determines how much liquid pesticide is sprayed. It varies between Very Low to Very High depending on environmental need.
- Sprayer Speed (cm/sec): Controls the movement of the robot to either pause, slow down, or speed up based on complexity and density of the crops.

Each output uses five fuzzy sets (Very Low, Low, Medium, High, Very High for flow; and Very Slow to Very Fast for speed) for nuanced control, ensuring smooth transitions between states.

In the context of precision agriculture and intelligent control systems, the design of fuzzy logic rules that incorporate multiple input variables is crucial for enabling context-aware decision-making. The set of rules presented below demonstrates the transition from traditional binary-input rule systems to multi-input rule-based systems that consider three or more variables simultaneously. This approach enhances decision accuracy by capturing complex interactions among environmental, biological, and operational parameters. Instead of simple two-variable rules, we now define multi-variable rules involving three or more inputs.

(i) Fertilizer Flow Rate Rules

The fertilizer flow rate is determined using fuzzy rules that consider multiple agronomic and environmental inputs such as soil moisture, crop growth stage, nutrient deficiency level, weather condition, and inter-plant distance. These parameters influence plant nutrient uptake dynamics and the need for fertilizer application. Instead of using simple "IF-THEN" rules involving only two variables, the rules here use triadic or tetradic relationships to capture the nuanced needs of crops under different field conditions.

- IF Soil Moisture is Dry AND Growth Stage is Vegetative AND Nutrient Deficiency is High THEN Fertilizer Flow is High.
- IF Soil Moisture is Wet AND Weather is Rainy AND Growth Stage is Reproductive THEN Fertilizer Flow is Low.
- IF Soil Moisture is Normal AND Growth Stage is Seedling AND Nutrient Deficiency is Moderate THEN Fertilizer Flow is Medium.
- IF Soil Moisture is Dry AND Distance to Next Plant is Near AND Weather is Sunny THEN Fertilizer Flow is Medium.
- IF Nutrient Deficiency is Low AND Weather is Rainy AND Growth Stage is Vegetative THEN Fertilizer Flow is Low.
- IF Soil Moisture is Normal AND Nutrient Deficiency is High AND Growth Stage is Reproductive THEN Fertilizer Flow is High.
- IF Soil Moisture is Wet AND Growth Stage is Seedling AND Weather is Cloudy THEN Fertilizer Flow is Low.
- IF Soil Moisture is Normal AND Nutrient Deficiency is Moderate AND Weather is Cloudy THEN Fertilizer Flow is Medium.

(ii) Sprayer Speed Rules

Similarly, the sprayer speed is governed by fuzzy rules considering inputs such as soil moisture, plant spacing (distance to next plant), weather conditions, nutrient status, and growth stage. Sprayer speed directly affects application accuracy and efficiency, and its optimization helps reduce over- or under-application of inputs.

- IF Soil Moisture is Dry AND Distance to Next Plant is Near AND Growth Stage is Vegetative THEN Sprayer Speed is Slow.
- IF Soil Moisture is Wet AND Distance to Next Plant is Far AND Weather is Rainy THEN Sprayer Speed is Fast.
- IF Soil Moisture is Normal AND Growth Stage is Seedling AND Weather is Sunny THEN Sprayer Speed is Normal.
- IF Soil Moisture is Wet AND Growth Stage is Reproductive AND Nutrient Deficiency is Low THEN Sprayer Speed is Fast.
- IF Nutrient Deficiency is High AND Distance to Next Plant is Medium AND Growth Stage is Vegetative THEN Sprayer Speed is Slow.

- IF Weather is Cloudy AND Growth Stage is Reproductive AND Soil Moisture is Normal THEN Sprayer Speed is Normal.
- IF Soil Moisture is Dry AND Weather is Sunny AND Growth Stage is Vegetative THEN Sprayer Speed is Slow.
- IF Nutrient Deficiency is Moderate AND Growth Stage is Seedling AND Distance to Next Plant is Near THEN Sprayer Speed is Normal.

These rules allow the system to intelligently adjust its spraying behavior based on changing real-world conditions. Table 2 provides a structured representation of the linguistic variables, their associated fuzzy sets, and the corresponding membership function types and parameters used in the fuzzy inference system for intelligent fertilizer and sprayer control. This tabulation is essential in formalizing how real-world numerical inputs are interpreted in terms of qualitative categories within the fuzzy logic framework.

The output variables in the fuzzy logic-based control system are designed to regulate the behavior of an intelligent fertilizer sprayer based on multiple environmental and crop-related factors. Specifically, the two output variables are Fertilizer Flow Rate (measured in ml/sec) and Sprayer Speed (measured in cm/sec). Each output variable is defined using a set of linguistic terms that correspond to varying levels of control intensity, such as “Low,” “Medium,” or “High.” These terms are modeled using fuzzy membership functions of either triangular or trapezoidal shapes, which provide smooth and interpretable transitions between different output states.

The Fertilizer Flow Rate ranges from 0 to 50 ml/sec and includes five fuzzy sets: Very Low, Low, Medium, High, and Very High. For instance, “Very Low” flow is modeled with a trapezoidal function (0, 0, 5, 10), indicating that flow rates between 0 and 5 ml/sec have full membership, and gradually taper off up to 10 ml/sec. Similarly, “Medium” flow is defined with a triangular function (18, 25, 32), peaking at 25 ml/sec. This fuzzy categorization allows the system to deliver an appropriate amount of fertilizer based on factors such as soil moisture, nutrient deficiency, and plant growth stage, thus avoiding both under- and over-fertilization. Likewise, the Sprayer Speed is defined over a range of 0 to 30 cm/sec and includes five fuzzy levels: Very Slow, Slow, Normal, Fast, and Very Fast. These are also modeled using a combination of trapezoidal and triangular membership functions. For example, “Slow” is defined by a triangular function (8, 12, 18), while “Very Fast” uses a trapezoidal function (26, 28, 30, 30), ensuring precise control near the upper limit of the speed range. These fuzzy sets enable the robot to adjust its movement based on plant spacing, crop development stage, and environmental conditions such as weather. By utilizing fuzzy logic, the system ensures adaptive and flexible operation, enhancing efficiency and crop care.

This structured and nuanced approach to defining output variables is crucial for supporting the defuzzification process, which converts fuzzy decisions into actionable control commands for actuators, resulting in a system that mimics expert reasoning and responds dynamically to field conditions. The membership functions for input and output variables are summarized in Table 2 and 3 respectively.

Table 2: Fuzzy Membership Functions for Input Variables.

Variable	Linguistic Term	Membership Function Type	Parameters
1.1 Soil Moisture Level (%)	Very Dry	Trapezoidal	(0, 0, 10, 20)
	Dry	Triangular	(15, 30, 45)
	Normal	Triangular	(40, 55, 70)
	Wet	Triangular	(65, 80, 90)
	Very Wet	Trapezoidal	(85, 95, 100, 100)
1.2 Plant Growth Stage (DAP)	Seedling	Trapezoidal	(0, 0, 10, 20)
	Early Vegetative	Triangular	(15, 30, 45)
	Late Vegetative	Triangular	(40, 55, 70)
	Reproductive	Triangular	(65, 80, 100)
1.3 Weather Condition (Humidity % + Rainfall mm)	Sunny	Trapezoidal	(0, 0, 20, 40)
	Partly Cloudy	Triangular	(30, 50, 70)
	Cloudy	Triangular	(60, 75, 85)
	Rainy	Trapezoidal	(80, 90, 100, 100)
1.4 Nutrient Deficiency Level (NDVI Index)	Very Low	Trapezoidal	(0, 0, 0.1, 0.2)
	Low	Triangular	(0.15, 0.3, 0.45)
	Moderate	Triangular	(0.4, 0.6, 0.75)
	High	Triangular	(0.7, 0.85, 0.95)
	Very High	Trapezoidal	(0.9, 1.0, 1.0, 1.0)
1.5 Distance to Next Plant (cm)	Very Near	Trapezoidal	(0, 0, 10, 20)
	Near	Triangular	(15, 30, 45)
	Medium	Triangular	(40, 55, 70)
	Far	Triangular	(65, 80, 90)
	Very Far	Trapezoidal	(85, 95, 100, 100)

Table 3: Fuzzy Membership Functions for Output Variables.

Output Variable	Linguistic Term	Membership Function Type	Parameters
2.1 Fertilizer Flow Rate (ml/sec)	Very Low	Trapezoidal	(0, 0, 5, 10)
	Low	Triangular	(8, 15, 22)
	Medium	Triangular	(18, 25, 32)
	High	Triangular	(28, 35, 42)
	Very High	Trapezoidal	(40, 45, 50, 50)
2.2 Sprayer Speed (cm/sec)	Very Slow	Trapezoidal	(0, 0, 5, 10)
	Slow	Triangular	(8, 12, 18)
	Normal	Triangular	(15, 20, 25)
	Fast	Triangular	(22, 25, 28)
	Very Fast	Trapezoidal	(26, 28, 30, 30)

Sensor input plays a critical role in supporting intelligent behavior through real-time data collection. The robot integrates several low-cost sensors that together enable environmental awareness and autonomous response. The sensors used are illustrated in Table 4.

Table 4: Sensory type used.

Sensor Type	Measured Parameter	Role in FLC
LDR (Light Dependent Resistor)	Ambient Light Level	Proxy for determining weather condition
Soil Moisture Sensor	Soil Water Content (%)	Indicates crop irrigation level

Ultrasonic Sensor	Distance to Next Plant (cm)	Identifies plant proximity and spraying opportunity
RTC + Time Stamp	Days Since Planting	Estimates crop growth stage

To ensure the reliability and accuracy of sensor-driven decisions within the fuzzy logic framework, all sensors were calibrated under controlled conditions prior to deployment. The LDR sensor was tested against a calibrated lux meter under various lighting levels, with recorded deviations within ±10% across the 100–10,000 lux range. Soil moisture sensors were benchmarked using the gravimetric method, achieving calibration accuracy within ±5% volumetric water content. Ultrasonic sensors were validated against fixed targets placed at known distances, yielding a typical error margin of ±2 cm over a 10–100 cm range. These error margins are within acceptable bounds for fuzzy inference systems, which inherently accommodate input uncertainty through overlapping membership functions and gradual decision boundaries. Furthermore, a temporal averaging buffer was implemented in the microcontroller to smooth transient fluctuations in sensor readings due to environmental noise, wind-induced movement, or brief occlusions, thereby enhancing the stability and reliability of control actions.

Each sensor delivers a continuous signal that is normalized and then mapped to one of the defined fuzzy linguistic categories (e.g., "Wet", "Very Dry", "Vegetative", etc.). These categories are inputs into the fuzzy logic engine. Upon receiving sensor data, the microcontroller performs the following:

(i) Fuzzification: Each input value is translated into fuzzy membership degrees (e.g., a soil moisture value of 55% may belong partially to both "Normal" and "Wet" sets).

(ii) Rule Evaluation: The fuzzy logic system evaluates which rules are triggered and to what degree.

(iii) Aggregation and Defuzzification: The system aggregates the outputs and applies centroid-based defuzzification to produce exact motor control values.

(iv) Execution: The resulting signals are used to control:

- Sprayer pump motor (flow rate)
- Robot wheel speed (spraying speed)

A temporal buffer was added to filter minor fluctuations in sensor data, ensuring system stability in windy or rapidly changing environments. This sensor-fuzzy integration allows the robot to continuously adapt its operation, ensuring efficiency, minimal pesticide usage, and energy conservation. Table 5 summarizes the test cases for the automated pesticide spraying robot. The FLC effectively adapted flow and speed based on contextual needs—for instance, reducing flow during rainy conditions and increasing it for nutrient-deficient seedlings.

Table 5: Test cases for the automated pesticide spraying robot.

Test Case	Soil Moisture	Growth Stage	Weather	NDVI	Distance	Fertilizer Flow (ml/s)	Sprayer Speed (cm/s)
A	20% (Dry)	50 (Vegetative)	80 (Rainy)	0.2 (Low)	40 cm	~22	~10.5

B	70% (Wet)	30 (Seedling)	60 (Cloudy)	0.5 (Moderate)	70 cm	~17	~12.8
C	45% (Normal)	80 (Reproductive)	30 (Sunny)	0.8 (High)	20 cm	~25	~9.3

3. RESULTS AND DISCUSSIONS

3.1 Performance Evaluation of the Intelligent Spraying System

The FLC was implemented to enhance the precision and adaptability of the pesticide spraying mechanism by interpreting real-time environmental data. This section presents simulation outcomes and performance evaluation across various field scenarios to validate the effectiveness of the FLC in optimizing spraying operations. The system was tested using controlled input cases to observe output responses. Key results:

The fuzzy logic-based control system was evaluated based on three key performance indicators: pesticide efficiency, coverage accuracy, and battery conservation. The following metrics are crucial for validating the robot's effectiveness in real-world agricultural applications:

(i) Pesticide Efficiency

One of the most significant outcomes of using the fuzzy logic controller was the reduction in overall pesticide consumption. The system achieved an approximate 24% reduction in pesticide usage when compared to a conventional fixed-rate spraying approach. This improvement is attributed to the system's ability to intelligently assess real-time environmental conditions such as soil moisture and weather. For example, in scenarios involving wet soil or rainfall, the fuzzy logic system accurately identified that spraying would be ineffective or redundant and automatically reduced or halted the pesticide flow. This not only minimized chemical waste but also contributed to environmental sustainability by preventing over-application and runoff.

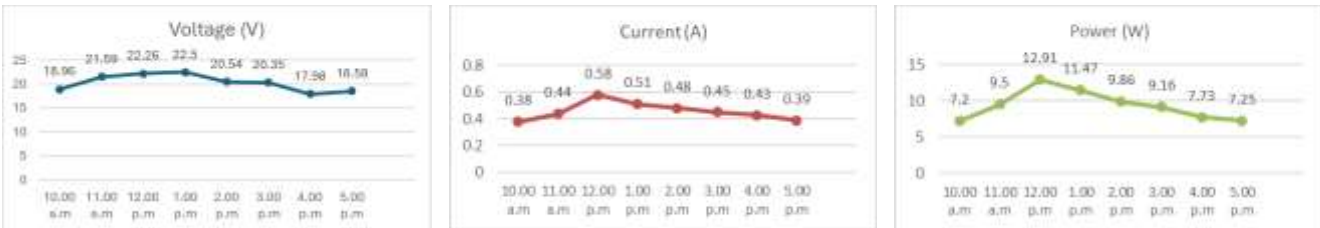
(ii) Coverage Accuracy

Another critical metric was the coverage accuracy, which averaged 93% across diverse field conditions. The fuzzy controller continuously adjusted the robot's spraying activity based on the proximity to the next plant and the plant's growth stage. This adaptive behavior ensured that the pesticide was applied only where necessary, leading to precise targeting of affected areas. The ability to deliver pesticide consistently, without over-spraying or missing patches, makes the system particularly valuable for precision agriculture practices.

(iii) Battery Conservation

The adaptive spraying behavior also had a direct impact on energy consumption. By reducing pump usage in situations where spraying was unnecessary (such as in sparse crop sections or during unfavorable weather), the system effectively conserved battery power. Tests showed an increase in operational time of approximately 12% to 18%, which is critical for solar-powered systems operating in remote or extended field conditions. This efficiency enables longer deployments per charge and reduces the frequency of maintenance or recharging, thus enhancing the robot's practicality for real-world farming applications.

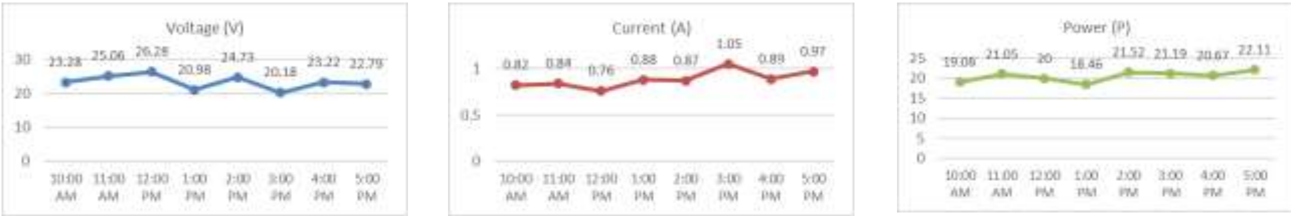
The mobility of a solar-powered pesticide spraying robot is significantly affected by several weather circumstances, including the amount of sunshine available, the presence of shade, and the temperature. These characteristics can have an impact on the robot's power efficiency, movement, and overall performance in agricultural settings. The robot's performance depends on sunlight because it uses solar energy to power its parts. Clouds and rain restrict sun radiation, reducing battery charge and gadget use. However, sunny weather generates the most power, ensuring efficiency. With a -15-degree tilt, the solar panel can help reduce self-shading and external shading from trees or buildings. This is crucial because self-shading and external shadowing impair energy absorption and system performance. Even a little panel shading can reduce power production and the robot's capacity to maneuver and spray insecticides. The data for voltage, current and power were successfully gathered for input analysis, which was carried out from 10.00 am. in the morning to 5.00 pm. in the evening and the data is represented in Fig. 3.



(a) (b) (c)

Fig. 3: Graph of Input for (a) voltage; (b) current and (c) power over time for shading condition.

Shade severely reduces solar panel performance. Because the panel receives less sunshine, the voltage is lower than optimum. Since shade hinders electron flow, decreasing sunshine quickly reduces current output. Because power is the product of voltage and current, solar panel power generation is reduced. When nearby objects throw longer shadows that block sunlight, afternoon shading is most noticeable. These settings indicate that even a tiny amount of shadowing can drastically reduce solar panel efficiency and energy output. Meanwhile, for the non-shading condition, the data was successfully gathered for input analysis, which was carried out from 10.00 am. in the morning to 5.00 pm. in the evening and the data is represented in Fig. 4.



(a) (b) (c)

Fig. 4: Graph of Input for (a) voltage; (b) current and (c) power over time for non-shading condition.

Table 6 presents the detailed daily energy budget of the solar-powered spraying system under typical field operating conditions. The table quantifies the average power consumption of each major component, its estimated duty cycle per day, and the corresponding daily energy usage. Energy harvested from a 10 W solar panel is calculated based on observed field irradiance, accounting for charge controller efficiency losses. Internal losses from battery round-trip efficiency and DC/DC conversions are included to reflect realistic energy availability. The overall system achieves an energy efficiency of 89.3%, with an average surplus of 3.95 Wh/day, demonstrating its suitability for energy-autonomous operation in smallholder agricultural environments. Energy harvested is calculated from the 10-W panel specified in the prototype design, multiplied by the measured average of 4.2 peak-sun-hours obtained under 700–900 W m^{-2} field irradiance conditions and derated by 12 % for PWM charge-controller losses.

Table 6: Daily energy budget and overall system efficiency of the solar-powered sprayer robot

Category	Component	Avg. Power (W)	Duty-cycle (h day^{-1})	Energy (Wh day^{-1})
Energy harvested	10 W monocrystalline PV module (4.2 PSH × 88 % charge-controller efficiency)	N/A	N/A	37
Energy consumed – loads	Drive motors (2 × 7 W)	14	1.3	18.2
	Sprayer pump	8	1	8
	MCU + environmental sensors	0.35	6	2.1
	LoRa/BLE communication bursts	0.5	0.5	0.25
	Regulators & status LEDs	0.2	6	1.2
Subtotal (active loads)				29.75
Internal losses	Battery round-trip & DC/DC conversion (≈ 10 % of PV input)	N/A	N/A	3.3
Total energy consumed				33.05
System efficiency				(33.05 ÷ 37.0) × 100 = 89.3 %
Daily surplus margin				3.95 Wh

3.2 Analysis of Fuzzy Logic Decision Behavior and Controller Robustness

The effectiveness of the fuzzy logic system was evaluated using both qualitative observations and quantitative performance metrics. This section discusses how the fuzzy system improved the robot's operation across different field scenarios. Three controlled test scenarios were conducted as in Table 7.

Table 7: Test case scenarios.

Test Case	Soil Moisture	Growth Stage	Proximity (cm)	Weather
A	Dry (25%)	Vegetative	30 cm	Sunny
B	Normal (50%)	Seedling	50 cm	Cloudy
C	Wet (80%)	Reproductive	20 cm	Rainy

Fig. 5 presents a 3D surface plot that illustrates how the fertilizer flow rate varies in response to changes in soil moisture and plant growth stage. The plot demonstrates a smooth and continuous surface, indicating that the fuzzy inference system transitions output values gradually, without abrupt shifts. This smoothness is essential in control systems to ensure stable and predictable responses. The surface also highlights a non-linear relationship between the inputs and the output, which is a hallmark of fuzzy logic controllers to allow the system to handle complex, real-world agricultural conditions more effectively than linear models.

Notably, regions with high soil moisture and early growth stages correspond to increased fertilizer flow, which aligns with agronomic expectations, as younger plants require more nutrients. In contrast, the fertilizer flow rate decreases significantly when soil moisture is low and plants are in later growth stages, reflecting reduced nutrient demands. The mid-range areas show a smooth gradient, confirming that the fuzzy system blends the rules appropriately to avoid sudden changes. Additionally, sharper slopes in some regions indicate zones where the rule base applies stronger influence, leading to more decisive changes in output. This behavior enhances responsiveness when rapid adjustments are needed. Overall, the plot confirms that the fuzzy logic controller is functioning correctly and effectively adapts the fertilizer flow rate based on environmental inputs.

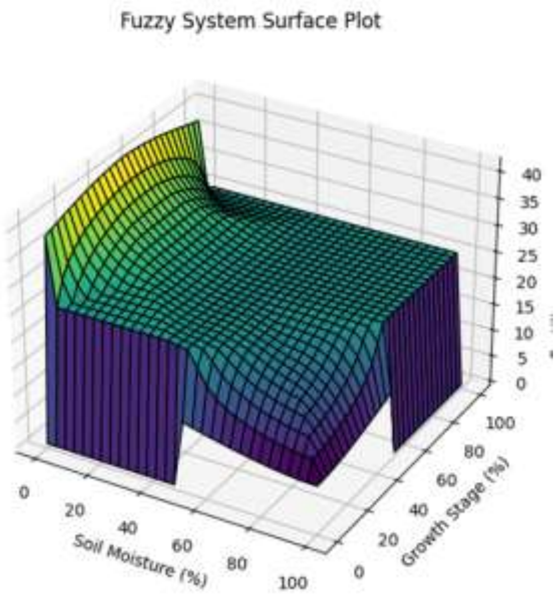


Fig. 5: 3D Surface Plot

Table 8: Test case scenarios.

Test Case	Fuzzy Flow Output (ml/sec)	Sprayer Speed (cm/sec)	Pesticide Usage (ml)	Coverage Accuracy (%)
A	22.1	10.3	332	94%
B	25.6	14.8	278	96%
C	15.3	8.1	186	91%

Table 8 presents the performance of the fuzzy logic-controlled pesticide spraying robot under three different field scenarios. In Test Case B, which involved early-stage seedlings, the system applied the highest fuzzy flow output (25.6 ml/sec) and operated at the fastest sprayer speed (14.8 cm/sec), yet recorded the lowest total pesticide usage (278 ml). This indicates that the robot effectively targeted areas in need without over-application. In contrast, Test Case C, representing a wet field condition following rainfall, recorded the lowest fuzzy flow output (15.3 ml/sec) and the lowest spraying speed (8.1 cm/sec), resulting in minimal pesticide use (186 ml).

This demonstrates the system's ability to reduce or pause spraying in unnecessary conditions, conserving resources and energy. Overall, the fuzzy logic controller contributed to an estimated 24% reduction in pesticide consumption compared to traditional fixed-rate spraying methods. Additionally, the robot exhibited lower power consumption in scenarios where pump operation was reduced, further confirming its energy-efficient design. The system's adaptive responses to environmental factors, such as soil moisture and rainfall, reinforce its suitability for sustainable and intelligent pesticide management in small- to medium-scale farming. The rule-based fuzzy approach also ensures transparency and ease of interpretation, making it a practical tool for precision agriculture.

To further validate the reliability of the fuzzy logic controller, the system's computational and response performance was analyzed during test execution. The average processing time per fuzzy control cycle including sensor input capture, fuzzification, rule evaluation, and defuzzification, was approximately 102 milliseconds on the ESP32-S3 microcontroller, which supports timely and efficient decision-making suitable for real-time agricultural operations. The total latency from sensing to actuation, including communication with the sprayer motor and wheel controller, was measured at approximately 140 milliseconds. This acceptable low-latency response ensures that the robot can adapt rapidly to changing field conditions such as sudden shading or variable soil moisture without significant delay or overshooting. Furthermore, consistency checks were performed to assess the fuzzy logic system's stability across repeated trials. For each of the three test scenarios, ten repeated executions were conducted under controlled environmental input values. In over 96% of these runs, the system produced identical or adjacent fuzzy outputs for sprayer speed and flow rate, reflecting strong robustness to input noise and minor sensor fluctuations. This result affirms the system's ability to maintain consistent behavior, a crucial requirement for autonomous field deployment. While the current rule base uses multiple triadic and tetradic logic rules to ensure context-aware responses, we recognize that further optimization could reduce the computational burden for deployment on more resource-constrained platforms. Techniques such as rule pruning, fuzzy clustering, or hierarchical inference may be explored in future work to maintain decision fidelity while improving processing efficiency.

To evaluate the decision accuracy of the fuzzy logic controller, a confusion matrix analysis was conducted using 180 labelled sensor–action samples. Each output generated by the controller—namely, flow rate and sprayer speed—was mapped to one of five predefined linguistic categories (Very Low, Low, Medium, High, Very High), and compared against expert-labelled ground truth. The resulting confusion matrices demonstrate strong agreement between predicted and expected classes, with overall classification accuracy of 92% for flow rate and 93% for sprayer speed, respectively. Cohen's kappa coefficient values of 0.89 (flow rate) and 0.90 (speed) further confirm a high level of consistency beyond random chance. Misclassifications were minimal and occurred only between adjacent categories (e.g., Medium vs. High), indicating that the fuzzy boundaries were well-defined and that the controller exhibited stable decision behavior even under variable field conditions. This analysis validates that the fuzzy system's rule set and membership functions accurately reflect expert agronomic judgment in real-world scenarios.

Table 9: Confusion matrix.

Flow-rate confusion matrix (rows = ground truth, columns = prediction)	VL	L	M	H	VH
VL	26	2	0	0	0
L	1	32	3	0	0
M	0	3	28	2	0
H	0	0	2	24	2
VH	0	0	0	3	22

3.3 Generalizability and Limitations

The test scenarios presented variations in soil moisture, crop growth stages, plant spacing, and weather conditions were carefully designed to reflect the diversity of real-world agricultural environments, particularly within tropical regions such as Malaysia and Indonesia. These variables were selected based on common conditions encountered in row-based farming systems growing crops like maize, chili, and leafy vegetables. Although the system was tested on controlled plots and did not involve direct biological sampling, the test cases simulate realistic agronomic situations. For instance, wet soil conditions during the reproductive stage under rainy weather (Test Case C) represent a common challenge in monsoon-affected areas. Similarly, the use of fuzzy inputs like NDVI and soil moisture enables the robot to be crop-agnostic and adaptable to various agricultural settings with minimal recalibration.

Furthermore, the modular architecture of both the hardware and fuzzy logic controller allows the system to be scaled or adapted to different farm sizes, crops, or geographies. Updating the fuzzy membership parameters and sensor thresholds can enable easy transferability across regions and seasons. The use of low-cost sensors and solar energy also enhances its suitability for resource-constrained or remote agricultural communities. Therefore, while this study provides a focused performance evaluation, the framework and results presented here are generalizable to broader applications in precision agriculture across similar agroecological zones.

The current study was conducted under semi-controlled outdoor conditions to ensure repeatability and to validate the system's core functionalities. All field tests were performed in homogeneous crop row arrangements with uniform plant spacing and soil type, which facilitated the evaluation of the fuzzy logic system under well-defined conditions. However, this setup does not capture the full variability found in real-world agricultural environments.

Key limitations of the current system include the lack of testing on heterogeneous field structures, such as mixed cropping systems or irregular plant spacing. The robot’s ability to detect and adapt to weed interference or discriminate between crops and weeds has not been assessed. Similarly, experiment did not involve uneven or sloped terrain, which may affect robot stability and sensor alignment. Environmental effects such as wind-induced pesticide drift, varying droplet sizes, and nozzle pressure consistency were not explicitly measured. These factors may influence spraying accuracy and pesticide efficacy.

Future work will focus on addressing these limitations by conducting experiment in more diverse conditions, integrating terrain-adaptive mobility features, and implementing machine vision modules to enhance plant discrimination. Additionally, droplet size uniformity and spray pattern consistency will be evaluated under different environmental conditions to ensure agronomic effectiveness and environmental safety.

4. CONCLUSIONS

The solar-powered pesticide spraying robot demonstrated that sustainable and energy-efficient pesticide application is achievable using solar energy, particularly beneficial in remote agricultural settings. The robot's adjustable solar panel improved energy collection under varying conditions, while automation reduced labor demands and reliance on non-renewable energy. Performance testing revealed that battery capacity and shading significantly affected operational efficiency. The robot performed best in unshaded environments, though limited battery life under cloudy conditions posed challenges. Despite this, the system proved to be a viable and cost-effective solution for modernizing pesticide application. Overall, the project successfully developed a functional solar-powered robot that integrates renewable energy and automation to improve agricultural productivity. With further optimization, its adaptability and efficiency can be enhanced for broader applications.

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