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IoT-Enabled Robotic Herbicide Spraying for Grass Control: A Cross-Disciplinary Engineering Solution

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ABSTRACT

This study presented the design, implementation, and evaluation of an IoT-enabled robotic system for automated herbicide spraying in grass control applications. The platform integrated a four-wheel mobile robotic base, Raspberry Pi 4 embedded control unit, ultrasonic and GPS sensors, a flow-regulated solenoid spraying mechanism, and Wi-Fi/MQTT communication for real-time monitoring and data logging. The system was evaluated through controlled experimental testing in an approximately 100 m² grass area and through stakeholder-based effectiveness assessment involving IT experts, hardware engineers, administrators, and end users. Results showed that the IoT robotic sprayer improved spraying accuracy from 75% to 92%, reduced herbicide consumption from 1.0 L to 0.75 L per 100 m², and shortened operation time from 60 minutes to 35 minutes per 100 m² compared with conventional manual spraying. Survey ratings further indicated favorable perceptions of system effectiveness, with mean scores of 3.46 from IT experts, 3.71 from hardware experts, 4.00 from administrators, and 3.66 from end users. The findings confirm the feasibility of integrating robotics, embedded systems, sensor feedback, and IoT connectivity as a cross-disciplinary engineering solution for precise, efficient, and sustainable grass management. The study concludes that IoT-enabled robotic spraying can reduce labor requirements and chemical use while improving application uniformity, although future work should address uneven-terrain performance and connectivity limitations.

Keywords: *IoT, automated spraying, grass management, precision agriculture, robotic sprayer, smart systems*

INTRODUCTION

Effective grass and weed management is essential in agricultural, urban, institutional, and recreational spaces because uncontrolled vegetation can affect productivity, safety, aesthetics, and maintenance efficiency. Conventional manual herbicide spraying remains common, yet it is labor-intensive, inconsistent in coverage, and prone to excessive chemical application. These limitations can increase operational cost and environmental risk, especially when herbicides are applied without precise targeting or controlled flow regulation (Babu et al., 2023; El-Fotouh, 2024).

Precision agriculture and smart systems offer alternative approaches to field and grounds maintenance by integrating sensing, actuation, wireless communication, and automated decision-making. IoT-based agriculture allows field devices to collect and transmit operational data, while robotic platforms can reduce repetitive labor and improve the consistency of application tasks (Ayaz et al., 2019; Wolfert et al., 2017). In spraying systems, the integration of navigation sensors, automated valves, and data communication can help reduce chemical consumption and improve operational monitoring (Baltazar et al., 2021).

Robotic weed and herbicide management has developed through guidance, target detection, precision actuation, and mapping technologies. Earlier reviews emphasized that autonomous weed-control systems require reliable mobility, detection, and treatment mechanisms to function effectively in real-world environments (Slaughter et al., 2008). Recent developments also show that robotic and computer-vision-based spraying tools can reduce herbicide use through selective and targeted application (Azghadi et al., 2024; Kamilaris & Prenafeta-Boldu, 2018).

Despite these advances, the practical integration of robotic mobility, embedded control, targeted spraying, and IoT-enabled monitoring remains a relevant engineering challenge, particularly for localized grass-control applications. This study therefore developed and evaluated an IoT-enabled robotic herbicide spraying system designed to improve spraying precision, reduce herbicide consumption, shorten operation time, and provide a remotely monitorable platform for sustainable grass management.

Literature Review

IoT and Smart Agriculture

Smart agriculture relies on connected sensing and data-driven control to improve the accuracy and timeliness of farm or field operations. Ayaz et al. (2019) explained that IoT-based smart agriculture supports wireless monitoring, automation, and real-time decision support, while Wolfert et al. (2017) emphasized that smart-farming data systems can influence both field-level operations and broader resource-management decisions. These principles are relevant to herbicide spraying because spray activity, flow rate, machine condition, and operational location can be monitored continuously through connected devices.

In the context of agricultural automation, FAO (2022) described automation as the use of machinery, equipment, and digital tools to improve diagnosis, decision-making, and field operations while reducing drudgery and increasing precision. For herbicide application, this means that automation can move the task from manual blanket spraying toward controlled, repeatable, and monitored application. IoT connectivity strengthens this automation by allowing operators to supervise system status remotely and maintain operational records for evaluation and improvement.

Robotic Spraying and Precision Weed Management

Robotic weed and grass management systems typically combine mobility, perception, actuation, and control. Slaughter et al. (2008) identified guidance, weed detection, precision treatment, and mapping as core technologies in robotic weed control. In more recent systems, intelligent sprayers use sensor feedback, computer vision, and actuation control to target plants more accurately and reduce unnecessary chemical dispersion (Azghadi et al., 2024; Baltazar et al., 2021).

Prior studies on robotic sprayers show that precision application can reduce pesticide or herbicide use while improving coverage. Babu et al. (2023) presented an IoT-based pesticide spraying robot for smart farming, while El-Fotouh (2024) discussed IoT-enabled fertilizer and spraying agricultural robots. Similarly, P.B. et al. (2021) proposed an autonomous herbicide spraying system using AI and IoT, reinforcing the feasibility of combining automation and connected systems in spraying applications. The present study extends this line of work by focusing on grass-control operations using a mobile IoT-enabled robotic prototype.

Cross-Disciplinary Engineering Integration

The system examined in this study is cross-disciplinary because it combines mechanical design, electronics, embedded systems, communication protocols, and agricultural or grounds-maintenance application. Agricultural robotics research increasingly recognizes that field robots must integrate navigation, sensing, actuation, human supervision, and robust operation under variable environmental conditions (Duckett et al., 2018; Fountas et al., 2020).

The development of a spraying robot also requires attention to usability and implementation feasibility. Even when a system shows technical gains in accuracy or efficiency, users must perceive it as functional, manageable, and applicable. For this reason, the present study combined controlled performance testing with stakeholder evaluation, allowing both technical performance and perceived usability to inform the overall assessment of the IoT-enabled robotic spraying platform.

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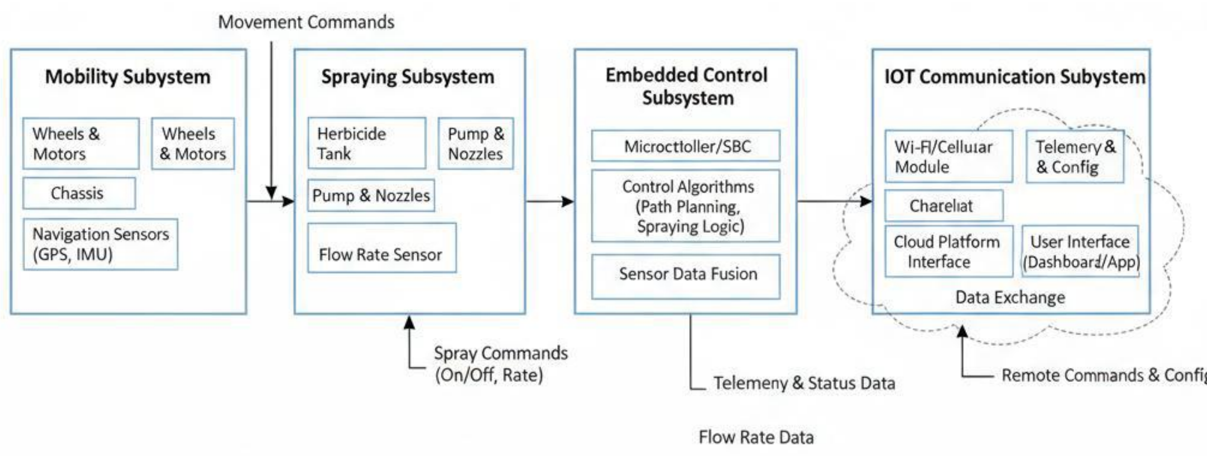

Figure 1. *System design architecture of the IoT-enabled robotic herbicide spraying platform.*

METHODS

Research Design

The study employed an applied engineering research design with experimental performance evaluation and survey-based usability assessment. The system was designed, implemented as a functional prototype, and evaluated against conventional manual spraying using spraying accuracy, herbicide consumption, and operation time as performance indicators. A stakeholder survey was also used to assess perceived system effectiveness and applicability.

System Architecture and Prototype Development

The system consisted of four primary subsystems: robotic mobility, spraying mechanism, embedded control, and IoT communication. The robotic mobility subsystem used a four-wheel differential-drive platform with DC motors and motor drivers. The spraying subsystem used an electronically controlled herbicide tank, pump, nozzles, flow sensor, and solenoid-controlled nozzle. The embedded control subsystem coordinated sensor input, navigation, path planning, and spray actuation through a Raspberry Pi 4. The IoT communication subsystem used Wi-Fi and MQTT to transmit telemetry, spray activity, and sensor readings to a centralized monitoring interface.

Table 1. Summary of Key Hardware Components

Component	Specification	Function
Mobile robot base	4-wheel differential drive	Supports movement across terrain
Microcontroller	Raspberry Pi 4	Coordinates sensors, motors, and spraying mechanism
Sensors	Ultrasonic, GPS, flow sensor	Obstacle detection, position tracking, and spray control
Spraying unit	Solenoid-controlled nozzle	Electronic regulation of herbicide flow
Communication	Wi-Fi/MQTT	Data transmission and remote monitoring/control

Software and Control Flow

The embedded algorithm executed the main operational sequence: system initialization and calibration, autonomous path navigation, obstacle detection, trajectory correction, spray activation, IoT data transmission, and logging. GPS and sensor data supported navigation, while ultrasonic sensors enabled obstacle detection. The solenoid valve activated spraying based on programmed coordinates and flow-rate requirements. The cloud or dashboard interface received data for remote supervision.

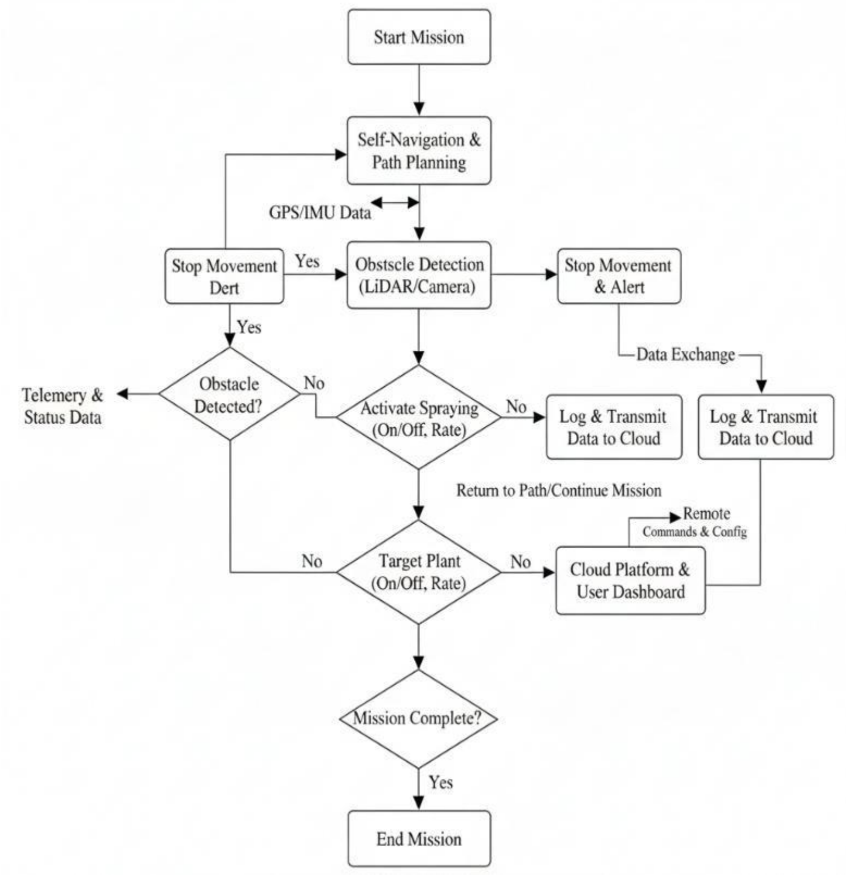

Figure 2. *System workflow from mission start to navigation, obstacle detection, spraying activation, data transmission, and mission completion.*

Research Site and Experimental Environment

The functional prototype was tested in a designated grass area measuring approximately 100 m². The experimental environment simulated typical urban park conditions with minor obstacles and uneven terrain. Manual spraying operations were conducted under comparable conditions to provide a baseline for performance comparison.

Respondents and Sampling Technique

A purposive sampling technique was used to select respondents with relevant expertise or experience in system development, hardware evaluation, administration, and grass-maintenance operations. The survey included 3 IT experts, 3 hardware engineers, 3 administrators, and 5 end users. These groups were selected to provide technical and user-oriented evaluations of the system.

Data Gathering Procedure

Experimental testing compared manual spraying and robotic spraying using identical 100 m² field conditions. The system was initialized, calibrated, and operated across the designated area. Performance data were recorded for spraying accuracy, herbicide consumption, and operation time. After prototype demonstration and/or evaluation, respondents assessed the system using a 5-point Likert scale measuring functionality, usability, and applicability.

Data Analysis

Experimental results were analyzed using descriptive comparison of manual and robotic spraying values. Spraying accuracy was expressed as percentage coverage; herbicide consumption was expressed in liters per 100 m²; and operation time was expressed in minutes per 100 m². Percentage improvement or reduction was computed to show the performance difference between the two methods. Survey results were summarized using mean ratings by respondent group.

Ethical Consideration

The evaluation involved technical and operational respondents who assessed the system for research purposes. Participation in the survey evaluation was voluntary, and responses were reported in aggregate form. The experimental testing was conducted in a controlled area to minimize risk, and herbicide spraying procedures were framed within responsible and regulated application practices.

RESULTS AND DISCUSSION

Experimental Performance of Manual and IoT Robotic Spraying

The comparative results showed measurable improvement in the IoT-enabled robotic spraying system over manual spraying. The robotic system achieved 92% spraying accuracy compared with 75% for manual spraying, indicating a 17-percentage-point gain in target coverage. Herbicide consumption decreased from 1.0 L to 0.75 L per 100 m², equivalent to a 25% reduction. Operation time also decreased from 60 minutes to 35 minutes per 100 m², equivalent to a 41.7% reduction. These improvements indicate that sensor-guided navigation, controlled nozzle actuation, and structured movement can improve uniformity and efficiency.

Table 2. *Experimental Results Comparing Manual and IoT Robotic Spraying*

Metric	Manual Spraying	IoT Robotic Sprayer	Improvement
Spraying accuracy	75%	92%	+17 percentage points
Herbicide consumption	1.0 L/100 m²	0.75 L/100 m²	25% reduction
Operation time	60 min/100 m²	35 min/100 m²	41.7% reduction

Spraying Accuracy and Coverage Uniformity

The improved spraying accuracy may be attributed to the system's programmed path planning and flow-regulated spraying mechanism. Manual spraying depended on operator consistency, which could lead to uneven coverage and missed areas. In contrast, the robotic sprayer followed a repeatable route and applied herbicide through electronic control. This finding is consistent with prior precision spraying research showing that robotic and sensor-based spraying can improve target coverage and reduce uncontrolled chemical dispersion (Baltazar et al., 2021; Azghadi et al., 2024).

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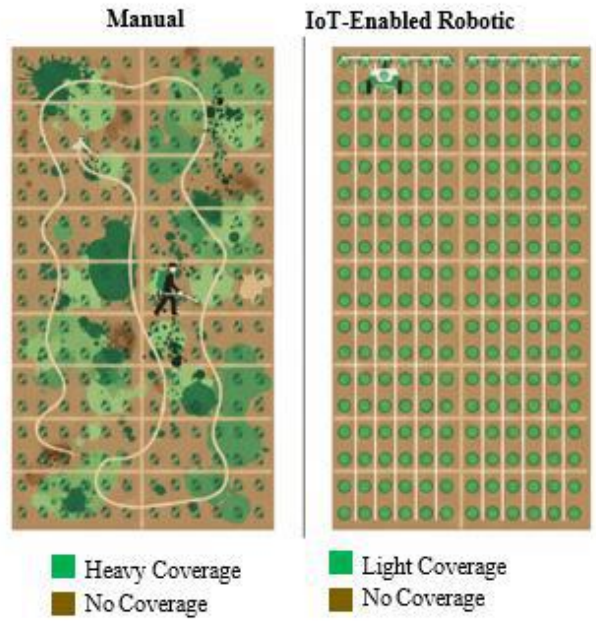

Figure 3. *Comparison of manual and IoT-enabled robotic spraying coverage showing improved uniformity and precision with robotic implementation.*

Herbicide Consumption and Operation Time

The 25% reduction in herbicide consumption suggests that targeted activation and flow regulation can reduce chemical use. This is important for both cost and environmental considerations, since herbicide overuse can contribute to waste and unnecessary exposure. The 41.7% decrease in operation time further indicates potential labor savings. These results support the practical value of robotics and IoT integration in field-maintenance operations, particularly for repetitive tasks that require consistency and monitoring.

Stakeholder Evaluation of System Effectiveness

Survey-based evaluation showed generally favorable ratings across respondent groups. Administrators gave the highest mean rating of 4.00, followed by hardware experts at 3.71, end users at 3.66, and IT experts at 3.46. These ratings indicate agreement that the system is functional and applicable, although the lower technical rating from IT experts suggests that communication reliability, software robustness, or interface features may still be improved.

Table 3. *Mean Effectiveness Ratings by Respondent Group*

Respondent Group	Number of Respondents	Mean Rating	Interpretation
IT experts	3	3.46	High agreement
Hardware engineers	3	3.71	High agreement
Administrators	3	4.00	High agreement
End users	5	3.66	High agreement

Summary of Technical Gains and Implementation Concerns

The results confirm that the prototype improved accuracy, reduced chemical use, and shortened operation time compared with manual spraying. However, the source evaluation also identified practical limitations, particularly minor challenges on uneven terrain and reliance on Wi-Fi connectivity. These limitations are common in mobile robotic systems and indicate that future versions should improve localization, terrain adaptability, battery endurance, communications redundancy, and system safety features before large-scale field deployment.

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Table 4. *Proposed Enhancement Plan for Future Prototype Refinement*

Area of Concern	Recommended Enhancement	Expected Improvement
Uneven-terrain mobility	Improve wheel traction, chassis stability, and suspension design	More stable navigation on irregular surfaces
Connectivity dependence	Add alternative protocols such as cellular, LoRa, or offline logging	More reliable operation in weak Wi-Fi areas
Localization accuracy	Enhance GPS or integrate additional positioning sensors	More precise route execution and spray activation
Spray safety and calibration	Strengthen calibration, flow validation, and emergency stop functions	Safer and more consistent herbicide application
User interface	Improve dashboard clarity, alerts, and operation logs	Better user monitoring and maintenance decisions

CONCLUSION

The study demonstrated that an IoT-enabled robotic herbicide spraying system can improve grass-control operations through more accurate, efficient, and resource-conscious spraying. Compared with manual spraying, the robotic system achieved higher spraying accuracy, lower herbicide consumption, and faster operation. These findings show that sensor-based navigation, embedded control, flow-regulated spraying, and IoT monitoring can work together to support sustainable grounds management.

Stakeholder evaluations also confirmed the practical value of the system, with high mean ratings from IT experts, hardware engineers, administrators, and end users. Although challenges remain in uneven-terrain operation and Wi-Fi dependence, the prototype provides evidence that cross-disciplinary engineering solutions can reduce labor requirements and chemical waste while improving the consistency of herbicide application.

Recommendation

Future development should improve the system's terrain adaptability by strengthening the chassis, traction, and navigation control for uneven and outdoor environments. The prototype should also be tested in larger and more diverse field conditions to determine its performance under different grass densities, slopes, obstacles, and weather-related conditions.

The communication subsystem should be enhanced by integrating alternative connectivity options such as cellular, LoRa, or offline data buffering to reduce dependence on Wi-Fi coverage. The dashboard may also be improved with clearer telemetry display, alerts, route maps, and maintenance logs.

For implementation, administrators and maintenance personnel should be trained on calibration, safe herbicide handling, system operation, troubleshooting, and emergency shutdown procedures. Future researchers may conduct long-term cost-benefit analysis, environmental impact assessment, and comparative testing against other automated spraying technologies.

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