

## Performance Analysis Of An Iot-Based 3-Dof Robotic Arm: A Case Study On Latency And Payload Variations

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### ABSTRACT

Digital transformation in the manufacturing sector demands the integration of efficient and responsive robotic systems. This study aims to analyze the performance of an Internet of Things (IoT)-based 3-Degree of Freedom (DOF) robotic arm, focusing on latency testing and payload variations. Conducted at the UMSU Mechanical Engineering Laboratory, the research utilizes an ESP32 microcontroller as the central processing unit and the Blynk platform as the wireless control interface. The robot's physical structure was fabricated using 3D printing technology, while joint actuation is powered by MG996R servo motors with an 11 kg/cm torque capacity. Electrical parameters were measured using a Fluke 17B+ digital multimeter to precisely monitor current consumption. Performance evaluation encompasses a multi-parameter analysis integrating information technology aspects, such as IoT network latency, with mechanical aspects including payload variations (15g, 35g, and 50g) and pick-and-place operational success. The IoT-based 3-DOF robotic arm control system was successfully implemented. The robot responded to commands within 0.5–0.9 seconds on a stable network. Performance is highly dependent on Wi-Fi signal quality, with latency increasing to >1 second at extended distances or when obstructed.

**Keywords:** 3-DOF, IoT, ESP32, Latency, Payload.

### INTRODUCTION

Contemporary manufacturing sectors increasingly rely on digital technology integration to optimize operational automation. Bechinie et al. (2024) assert that high levels of automation represent a tangible manifestation of continuous technological innovation [1]. This phenomenon has catalyzed significant breakthroughs, including the strategic implementation of robotic arms that contribute to enhanced product quality, accelerated manufacturing cycles, and strengthened overall organizational productivity [2]. This paradigm shift extends beyond general manufacturing into the food sector through specialized robotic end-effector mechanisms designed for food handling based on specific classifications and design parameters to ensure efficiency [3]. A robotic manipulator comprises a series of rigid links integrated via kinematic joints, serving as primary mechanical components that enable structured movement within the kinematic chain [2]. Two-degree-of-freedom systems provide end-effector flexibility, allowing independent movement across two distinct coordinate axes without mutual interference [3]. Furthermore, linear manipulators represent high-accuracy, flexible robotic systems that can be rapidly reprogrammed to efficiently handle repetitive tasks within dynamic industrial automation environments [4]. However, the heavy reliance on industrial robots presents critical maintenance challenges, particularly regarding servo motors susceptible to bearing failures. Torque from the base motor is transmitted to the arm joints through a flexible cable-conduit system that drives capstans on each link—a mechanism precisely engineered to be compactly foldable within CubeSat spatial constraints [5]. Addressing these constraints, Kumar

et al. (2024) proposed an innovative fault detection method by transforming current signals into scalogram images based on transfer learning [6]. This method has been proven to significantly accelerate the model training process, achieving detection accuracy exceeding 99% in identifying component failures. Beyond mechanical aspects, other technical challenges include residual vibrations that compromise robotic positioning accuracy. If not mitigated, this phenomenon adversely affects product quality through dimensional and geometric errors during the manufacturing process [7]. System optimization efforts also continue to evolve through the integration of bio-inspired (neuromorphic) pulse-based control with fractional-order control, known as Fractional Neuromorphic Control (FNC), which aims to synthesize the advantages of both methodologies [8].

Commensurate with massive technology adoption, Internet of Things (IoT) networks [9]—particularly Industrial IoT (IIoT)—have become primary targets for cyberattacks due to the expanding attack surface [10]. Data can be monitored via computer using Microsoft Excel integrated with PLX-DAQ software, where data is transmitted in real-time to Excel spreadsheets, enabling automated data acquisition, visualization, and analysis within a systematic single interface [11]. Although artificial intelligence-based models demonstrate high accuracy in threat detection, their practical implementation in corporate environments remains constrained [12]. Consequently, quantization techniques are proposed to optimize resource utilization without compromising detection accuracy. Within operational contexts, the integration of collaborative robots remains a central focus for enhancing efficiency and occupational safety [13], with contemporary models claimed to be more effective in detecting botnet attacks compared to other state-of-the-art anomaly systems [14].

Although prior studies [1], [15] have explored large-scale digital integration, a significant research gap persists regarding the empirical analysis of real-time latency. In-depth investigations into data communication performance between cloud platforms, such as Blynk, and the ESP32 microcontroller within physical manufacturing scenarios remain remarkably scarce. Furthermore, there is a lack of studies mapping the operational failure thresholds of low-cost robotic arms. The simultaneous correlation between payload weight, lift height, and power consumption in prototype robots for small-scale industries has not been comprehensively documented. These gaps raise critical questions concerning how internet network stability and distance influence the response latency of servo motors.

This research aims to address these voids by evaluating the reliability of an ESP32 and IoT-based 3-Degree of Freedom (DOF) robotic arm control system. The objective is to analyze performance through the Blynk platform. A comprehensive evaluation is conducted to measure the impact of workload variations and height on movement accuracy, current consumption, and pick-and-place operational success. The novelty of this study lies in its multi-parameter evaluation, which simultaneously integrates information technology aspects (IoT network latency) with physical-mechanical aspects (payload, torque, and power). By identifying technical constraints related to latency and torque, this study is expected to provide a strategic contribution to optimizing the efficiency and reliability of automation technology for light manufacturing applications, enabling small-scale industries to maintain competitiveness amidst the accelerating digital transformation.

## METHODE

The design and manufacturing process of the Internet of Things (IoT)-based 3-Degrees of Freedom (3-DOF) robotic arm was conducted at the Mechanical Engineering Laboratory, Faculty of Engineering, Universitas Muhammadiyah Sumatera Utara. This facility supported all functional stages, encompassing mechanical design, three-dimensional (3D) printing Fig (2a), and wireless control system performance testing. Instruments and Hardware To realize the robotic arm prototype, several primary hardware components with the following technical specifications were utilized:

ESP32 Microcontroller Fig 1(a): Serving as the open-source central processing unit (CPU). This module features integrated Wi-Fi and Bluetooth capabilities, which are essential for facilitating data communication within the IoT ecosystem. Expansion Shield Fig 1(b): An expansion board interfaced with the ESP32 to extend connectivity points for sensors and actuators, as well as to convert binary instructions into control signals stored in memory. MG996R Servo Motors Fig 1(c): Employed as joint actuators for precise position control. These metal-gear motors deliver a stall torque of up to 11 kg/cm at 6.0V. They feature an operational speed of 0.15 s/60° and a dead-band width of 1 μs. 3D Printer and Filament: Manufacturing equipment, as illustrated in Figure 2a, was used to fabricate the robot's physical structure based on Computer-Aided Design (CAD) models. Thermoplastic filament was used as the base material to create lightweight yet rigid components. Digital Multimeter: A Fluke 17B+ Fig (2b) digital multimeter was used to monitor operational current (I) and power (P) with high precision. This instrument supports DC voltage measurements up to 400.0 mV (1.0%+10 accuracy) and direct current up to 400.0 mA (1.5%+3 accuracy). Blynk Platform: A cloud-based graphical user interface (GUI) serving as the wireless control medium, allowing users to send instructions to the microcontroller via a mobile application Fig (2c).



Fig 1. (a) ESP32, (b) ESP32 Expansion Board, (c) Servo motor.



Fig. 2. (a) 3D Printer, (b) Digital Multimeter, (c) Blynk Platform

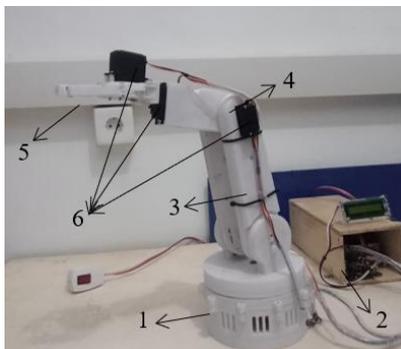
### Procedures and Experimental Design.

This study employed a laboratory experimental approach. The research procedure was systematically structured to develop, integrate, and test the reliability of an IoT-based 3-DOF robotic arm Fig 3. The stages encompassed hardware design, firmware development, and data validation. In the hardware design phase, the ESP32 microcontroller was connected to the servo motors via a structured wiring schematic. The software aspect was developed using the Arduino Integrated

Development Environment (IDE) with the C++ programming language. The program logic was designed to enable the ESP32 to handle wireless communication protocols through a mobile hotspot by configuring the SSID and password in the source code. This configuration allowed the Blynk platform to transmit command data packets that were subsequently executed by the actuators. To assess system effectiveness, a series of quantitative tests were conducted: Basic Function Test: Initial validation was performed to ensure that simple instructions from the Blynk interface were accurately translated into angular movements by the servo motors. Latency Analysis: Latency was measured to quantify the responsiveness of the remot control system.

Latency ( $\Delta t$ ) is defined as the time interval between sending a command from the application ( $t_1$ ) and the onset of the first mechanical response from the robot ( $t_2$ ). Measurements utilized a digital stopwatch and multiple repetitions were performed to ensure data accuracy. Communication Reliability Test: This evaluation assessed data connection stability under various scenarios, including variations in signal range distance and the presence of physical obstructions. Execution success was calculated using a success rate parameter (%).

This study emphasized performance evaluation through the mapping of the following variables: Independent Variables: Included variations in operational payload (light load: 15 grams, medium: 35 grams, and heavy: 50 grams), and the stability conditions of the Wi-Fi network. Dependent Variables: Comprised response time (latency), percentage of movement success, and electrical current consumption by the actuators. Control Variables: Parameters maintained constant included power supply voltage, servo motor type, ESP32 specifications, Blynk platform, and ambient testing environment conditions.



No	Caption	No	Caption
1	Base	4	joint
2	Power supply and ESP32	5	Gripper
3	Link	6	Servo

Fig.3. 3-DOF Robotic Arm

## RESULT AND DISCUSSION

This section presents the testing results of the Internet of Things (IoT)-based robotic arm control system utilizing the Blynk platform. The evaluation encompasses several parameters, including movement accuracy and Blynk latency under various network conditions, conducted through multiple scenarios for data validation. The control system program for the 3-Degree of Freedom (DOF) robotic arm was developed using C++ within the Arduino IDE. The `Arm_Robot_ESP32.ino` firmware implements the `WiFi.h` and `BlynkSimpleEsp32.h` libraries to facilitate internet connectivity and command reception from the Blynk platform. Additionally, the `Servo.h` library is utilized to control the three servo motors. The program structure includes servo pin initialization, network configuration (SSID and password), and Blynk authentication. The ESP32 processes commands from the platform into Pulse Width Modulation (PWM) signals to regulate the servo movement angles ( $0^{\circ}$ – $180^{\circ}$ ). The `Blynk.run()` function ensures real-time communication. The testing phase includes lifting maneuvers ( $90^{\circ}$ ) and pick-and-place operations.

### Robotic Arm Latency Testing

Robotic Arm Latency Testing Based on the conducted experiments, the robotic arm control system via the Blynk platform demonstrates rapid response times under stable network conditions. The response interval from command transmission to the onset of servo actuation is relatively brief, indicating efficient communication between Blynk and the ESP32. However, under suboptimal network conditions—such as weak signal strength or physical obstructions—certain commands experienced delays or failed to transmit. This indicates that system performance is heavily contingent upon the quality and stability of the Wi-Fi network. In this study, the ESP32 interfaced with the Blynk platform via a smartphone hotspot configured according to the SSID and password in the source code. Consequently, every command from the application is processed through the hotspot network before being executed by the ESP32; thus, the latency results also reflect the inherent limitations of the hotspot connection utilized. Tables 1 through 4 present the latency test results for the four servo motor units across distances of 1, 3, and 5 meters. The data reveal that Servo 1 and Servo 2 exhibit the most efficient performance, with the lowest average latency ( $\Delta t$ ) of 0.60 s and 0.59 s at a 1-meter distance, respectively. Conversely, Servo 4 demonstrates the highest latency, reaching an average of 1.13 s at 5 meters. Overall, a consistent positive correlation is observed between distance (s) and response time ( $\Delta t$ ) across all units, maintaining a 100% success rate throughout all experimental trials.

Table 1. Latency test results for Servo 1

No	$t_1$ (s)	$t_2$ (s)	s (m)	$\Delta t$ (s)	Successful
1	1.06	1.72	1	0.66	Yes
2	0.98	1.55	1	0.58	Yes
3	1.03	1.58	1	0.55	Yes
<b>Average</b>				<b>0.60</b>	
1	1.02	1.64	3	0.62	Yes
2	1.14	1.87	3	0.73	Yes
3	1.03	1.73	3	0.79	Yes
<b>Average</b>				<b>0.71</b>	
1	1.05	1.79	5	0.74	Yes
2	1.17	1.95	5	0.78	Yes
3	1.07	1.98	5	0.91	Yes
<b>Average</b>				<b>0.81</b>	

Table 2. Latency test results for Servo 2

No	$t_1$ (s)	$t_2$ (s)	s (m)	$\Delta t$ (s)	Successful
1	1.05	1.72	1	0.67	Yes
2	1.02	1.68	1	0.66	Yes
3	1.08	1.53	1	0.45	Yes
<b>Average</b>				<b>0.59</b>	
1	1.05	1.73	3	0.68	Yes
2	1.06	1.90	3	0.84	Yes

3	1.10	1.82	3	0.72	Yes
<b>Average</b>				<b>0.75</b>	
1	1.09	1.88	5	0.79	Yes
2	1.15	1.89	5	0.74	Yes
3	1.07	1.95	5	0.88	Yes
<b>Average</b>				<b>0.80</b>	

Table 3. Latency test results for Servo 3

No	t <sub>1</sub> (s)	t <sub>2</sub> (s)	s (m)	Δt (s)	Successful
1	1.02	1.91	1	0.89	Yes
2	1.07	1.80	1	0.73	Yes
3	1.05	1.75	1	0.70	Yes
<b>Average</b>				<b>0.77</b>	
1	1.03	1.89	3	0.86	Yes
2	1.08	1.98	3	0.90	Yes
3	1.01	1.84	3	0.83	Yes
<b>Average</b>				<b>0.86</b>	
1	1.04	1.86	5	0.82	Yes
2	1.08	1.86	5	0.78	Yes
3	1.06	1.99	5	0.93	Yes
<b>Average</b>				<b>0.84</b>	

Table 4. Latency test results for Servo 4

No	t <sub>1</sub> (s)	t <sub>2</sub> (s)	s (m)	Δt (s)	Successful
1	1.09	2.02	1	0.93	Yes
2	1.06	2.16	1	1.10	Yes
3	1.10	1.90	1	0.80	Yes
<b>Average</b>				<b>0.94</b>	
4	1.02	1.93	3	0.91	Yes
5	1.05	2.09	3	1.04	Yes
6	1.08	1.96	3	0.92	Yes
<b>Average</b>				<b>0.96</b>	
7	1.06	2.28	5	1.22	Yes
8	1.05	2.21	5	1.16	Yes
9	1.06	2.06	5	1.0	Yes
<b>Average</b>				<b>1.13</b>	

### Performance Evaluation of the Robotic Arm under Various Motion Conditions

Table 5 and Table 6 illustrate the testing results, demonstrating that increased payload directly impacts the robotic arm's performance. This effect was observed in both motion types: the 90° lift and the pick-and-place (A → B) sequences. Tests conducted at varying heights aimed to identify discrepancies in current consumption and overall robotic performance. These findings confirm that system performance is influenced by a combination of payload factors, servo torque constraints, and motion complexity. During the 50-gram payload test, the robotic arm successfully executed the lifting motion at the base position (0 cm) but failed when tested at heights of 10 cm and 20 cm. This

indicates the torque limitations of the servo motor[7] in counteracting gravitational forces under vertical conditions with heavy loads. Conversely, Table 6 shows that with a 50-gram payload, the pick-and-place scenario (horizontal movement) was successfully completed across all heights. This reinforces the conclusion that horizontal motion is more stable than vertical motion, as it is not entirely dominated by gravitational effects. The experimental results indicate that several factors influence the performance of the IoT-based robotic arm control system, particularly concerning latency, movement accuracy, and reliability across diverse network conditions.

The Influence of Blynk Latency on System Performance Assessing system latency is a crucial aspect of evaluating remote control efficiency via the Blynk platform. The primary metric employed is the system delay, denoted as ( $\Delta t$ ), which is precisely defined as the difference between ( $t_1$ ), the timestamp when the command is transmitted from the Blynk interface, and ( $t_2$ ), the initiation time of the robotic arm's movement. It is important to note that ( $\Delta t$ ) represents the initial delay—the duration from command transmission to the observed onset of motion—rather than the total time required to complete the full movement sequence. Experiments were conducted across several distance scenarios. Initial testing at a 1-meter range, as illustrated in Figure 4, revealed significant performance variations. Servo 1 recorded a response time of 0.577 s, and Servo 2 was slightly slower at 0.593 s; both exhibited superior performance compared to Servo 3 (0.773 s) and Servo 4 (0.943 s). This variability is inherently influenced by internal actuator factors, including control mechanisms, mechanical design, and internal component quality. Furthermore, comparative data from the 3-meter distance test (Figure 5) reinforced these findings. A clear causal relationship was observed, where the internal characteristics of the servo (independent variable) directly influenced the time required to reach the target position (dependent variable, in seconds). Servo 1 (0.713 s) and Servo 2 (0.747 s) maintained significantly faster performance than Servo 3 (0.863 s) and Servo 4 (0.957 s). Quantitatively lower response times directly indicate superior actuation performance. Additional testing (Figure 6) showed that average response times remained highly variable across units. Servo 2 (0.803 s) and Servo 1 (0.810 s) were consistently the fastest, while Servo 4 remained the slowest (1.127 s). This persistent discrepancy indicates a strong correlation between the specific characteristics of each servo unit and their actuation capabilities. Potential causes include differences in motor types (e.g., analog versus digital), feedback mechanism quality (potentiometer), or torque ratings. Experimental results demonstrate that latency is heavily influenced by Wi-Fi network quality [12]. The system responds rapidly under stable, short-to-medium range network conditions, yet performance degrades at extended distances or when signal obstructions are present. Key findings include:

- The average response time ranges from 0.5 to 0.9 seconds under stable network conditions and close proximity between the controller and the robot.
- At a distance of approximately 5 meters or when the signal is obstructed, the response time increases to over 1 second, with some commands failing to execute.
- Increased distance and signal obstructions exhibit a direct correlation with higher latency values.

Based on these results, it can be concluded that system performance is highly contingent upon Wi-Fi network stability. Low latency is only achievable under strong and stable signal conditions, whereas weak networks lead to delays or execution failures. The finding that specific units (Servo 2 and Servo 1) outperform others (Servo 3 and Servo 4) is consistent with prior research that identifies response time as a critical performance metric. Rapid responsiveness is paramount in applications such as industrial robotics or medical equipment, which demand immediate command execution and high precision[12].

Table 5. Results of the 90° lifting motion test with payload variations

No	W (gr)	h (cm)	T <sub>t</sub> (s)	P (kWh)	I (A)	Successful
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1	15	0	2.40	0.046	0.046	Yes
2	15	10	2.89	0.046	0.084	Yes
3	15	20	3.40	0.046	0.094	Yes
6	35	0	3.28	0.047	0.094	Yes
7	35	10	3.79	0.047	0.105	Yes
8	35	20	6.32	0.046	0.116	Yes
11	50	0	6.54	0.047	0.105	Yes
12	50	10	9.97	0.047	0.137	Not
13	50	20	2.20	0.047	0.147	Not

Table 6. Performance test results of the robotic arm for the pick-and-place scenario (A → B)

No	W (gr)	h (cm)	T <sub>t</sub> (s)	P (kWh)	I (A)	Successful I
1	15	0	9.64	0.045	0.105	Yes
2	15	10	11.37	0.044	0.105	Yes
3	15	20	10.28	0.044	0.116	Yes
4	35	0	10.45	0.042	0.116	Yes
5	35	10	12.21	0.042	0.105	Yes
6	35	20	13.99	0.041	0.126	Yes
7	50	0	6.27	0.048	0.116	Yes
8	50	10	6.59	0.048	0.116	Yes
9	50	20	6.46	0.047	0.116	Yes

### Performance Evaluation of the Robotic Arm under Diverse Motion Conditions

Experimental results demonstrate that the robotic arm's performance varies significantly across different motion types. Influencing factors include the applied payload and the trajectory distance on a 60 cm wide testbed. The following graphs illustrate the results for the pick-and-place sequences and the 90° lifting maneuvers.

Fig. 4–6 illustrate that servo response time variability stems from internal control mechanisms (digital versus analog), component quality (potentiometer, gear transmission), dynamic torque capability, and dead-band design. These factors indicate a strong causal relationship between the specific characteristics of each servo unit (independent variable) and the time required to achieve the target position (dependent variable).

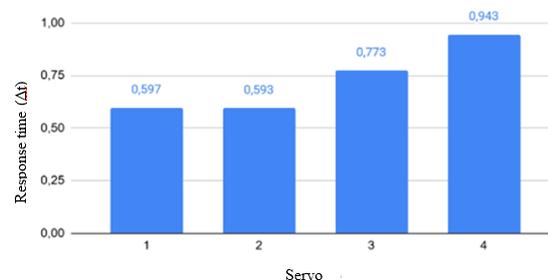


Fig. 4. Average latency test results for servos at a distance of 1 meter.

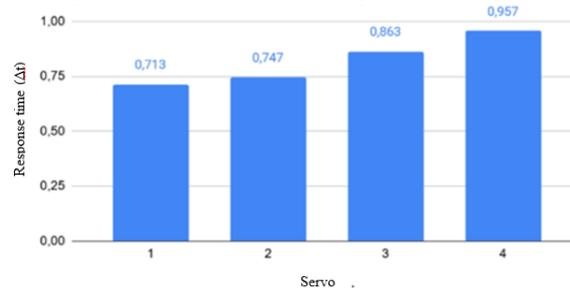


Fig. 5. Average latency test results at a distance of 3 meters.

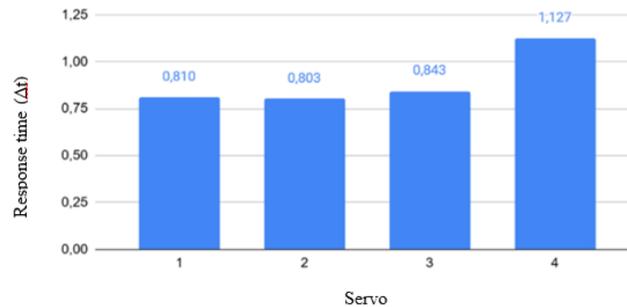


Fig. 6. Average latency test results at a distance of 5 meters.

Several key findings are summarized as follows:

- Horizontal movements exhibit shorter response times due to lower force requirements.
- Vertical movements adversely affect response times, which tend to increase significantly, particularly as the payload approaches the servo's maximum capacity.
- Current consumption increases proportionally with the payload, especially during vertical actuation. Measurements were conducted using a digital multimeter
- Operational success is defined as the payload reaching the target destination, whereas failure occurs if the arm stalls at a specific position and is unable to proceed with the lift.

Generally, the robotic arm performs adequately under light to medium payloads, particularly during horizontal maneuvers. However, under heavier payloads and vertical movements, performance begins to decline in terms of speed, power consumption, and success rate. The experimental results in Fig. 9 indicate that with light to medium payload variations, the robotic arm completes commands with a success rate approaching 100%. In the horizontal position, the success rate remains relatively stable at approximately 100% for payloads between 15g and 35g, before slightly decreasing to 90% at 50g. Meanwhile, a more significant decline is observed in the vertical position, dropping from 97% under light payloads to only 70% at 50g. This degradation occurs due to the torque limitations of the servo motors in executing vertical lifts, where gravitational influence is more pronounced compared to horizontal motion. Beyond mechanical factors, Wi-Fi network stability also influences the results, as weak network conditions can lead to failed command execution. Consequently, it can be concluded that the robotic arm operates optimally with payloads below 35g, especially for vertical lifting tasks.

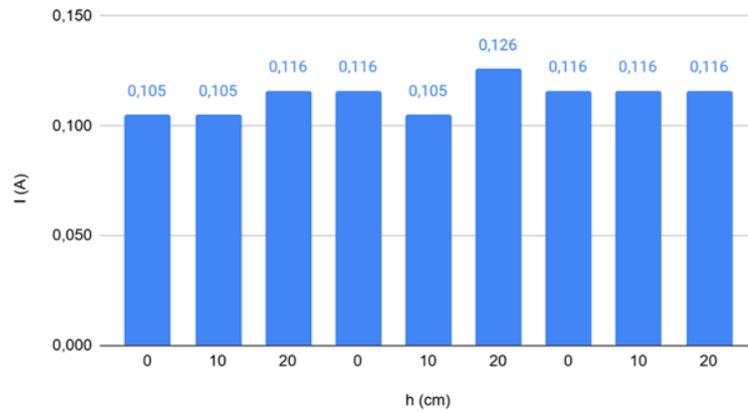


Fig. 7. Height (h) versus current intensity (I) in the pick-and-place scenario.

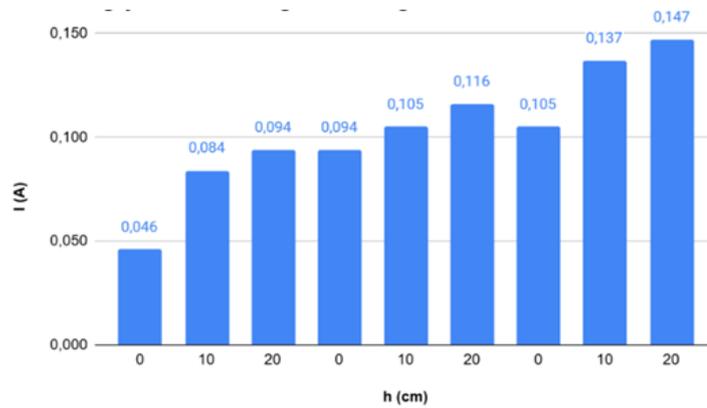


Fig. 8 Lifting height (h) versus current intensity (I) in the 90° lift scenario

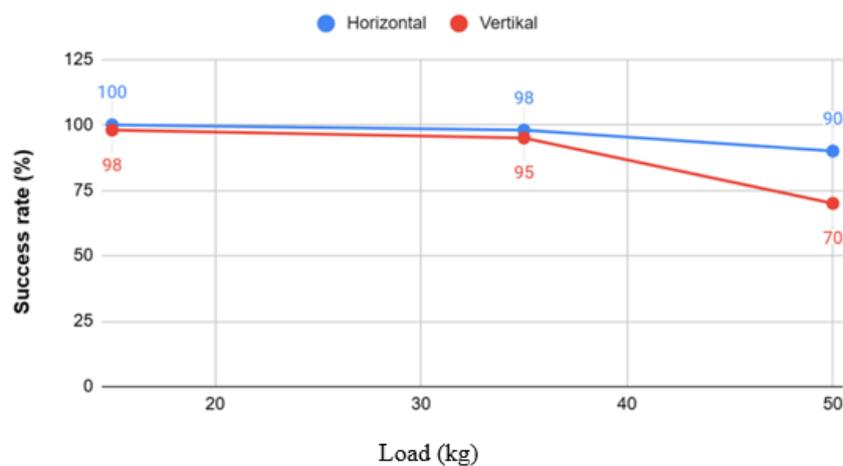


Fig 9. Success rate graph of horizontal and vertical payload lifting.

### CONCLUSION

An IoT-based 3-DOF robotic arm control system was successfully implemented using the ESP32 microcontroller and the Blynk platform. The robotic arm demonstrates a relatively brief response time, ranging from 0.5 to 0.9 seconds, under stable Wi-Fi conditions and close operational proximity. However, system performance is highly contingent upon network quality. Latency increases significantly beyond 1 second, and command execution failures occur when the distance reaches 5 meters or when physical obstructions are present. These limitations are attributed to the current system design, which utilizes an open-loop control mechanism without feedback sensors. The study concludes that this prototype is optimal for lightweight applications, such as the displacement of small objects.

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