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Hybrid IoT-Cloud Control Framework for Human-Robot Collaboration in Cartesian Storage Robots: Design, Implementation, and Statistical Performance Improvement

Engelbert Harsandi Erik Suryadarma [a,1,*], F. Edwin Wiranata [a,2], Twin Yoshua R. Destyanto [a,3], Lenny Halim [a,4], Fredrikus Suarezsaga [b,5]

[a] Universitas Atma Jaya Yogyakarta, Jl. Babarsari No. 44, Yogyakarta 55281, Indonesia
[b] Universitas Widya Dharma Pontianak, Jl. Hos Cokroaminoto No. 445, Pontianak 78243, Indonesia
[1] engelbert.harsandi@uajy.ac.id; [2] edwin.wiranata@uajy.ac.id; [3] twin.destyanto@uajy.ac.id; [4] lenny.halim@uajy.ac.id;
[5] suarezsaga@widyadharma.ac.id
* Corresponding Author

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ABSTRACT

Autonomous robots demonstrate high efficiency and precision in repetitive and structured tasks; however, their flexibility is often limited in dynamic or unstructured environments. Conversely, manually controlled systems allow human adaptability and situational awareness but tend to suffer from slower operation and inconsistent performance. To address this imbalance, this study evaluates the viability of a Firebase-based IoT–cloud architecture for real-time Cartesian robot control within a human–robot collaboration framework. The framework was implemented on a Cartesian robot prototype using an ESP32-based controller, with task commands synchronized through Firebase Realtime Database to support hybrid switching between autonomous execution and human teleoperation. Experimental evaluation involving 576 trials demonstrates that the hybrid framework achieves a perfect task success rate of 100%, outperforming manual operation (99.65%). It also reduces the average task completion time by 12.02%, with improvements ranging from 4.93% to 23.43% across individual tasks. Critically, the hybrid system significantly enhances operational consistency, reducing performance variability by 54% to 161% compared to manual control, as confirmed by statistical tests (Bonett and Levene's tests, $p < 0.05$). Cloud communication latency remains stable below 200 ms, ensuring reliable real-time operation. Despite the promising results, the experimental evaluation is limited to a single-robot setup under controlled network conditions, which may not fully represent large-scale or highly dynamic industrial environments. This work demonstrates that the proposed hybrid framework effectively combines human flexibility with robotic efficiency and consistency, offering a scalable and robust solution for adaptive warehouse automation that can be extended to broader warehouse and logistics applications involving remote supervisory control.

1. Introduction

Warehouse and storage automation have become a cornerstone of modern logistics and manufacturing systems, driven by the growing need for efficiency, accuracy, and reliability in material handling operations. Autonomous robots have been extensively deployed in industrial environments for tasks such as pick-and-place, sorting, and palletizing due to their precision and repeatability [1]-[6]. Cartesian robots offer advantages in positional accuracy and mechanical stability, making them suitable for repetitive linear motions in storage applications [7]-[11]. However, most autonomous warehouse systems are designed under structured and predictable environmental assumptions. When faced with dynamic or unstructured conditions, such as unexpected object positions, occlusions, or hardware variability, their performance tends to degrade significantly [12], [13]. This limitation highlights a fundamental weakness in the concept of full autonomy when dealing with real-world uncertainty.

Several studies have attempted to address these limitations through enhanced autonomy and adaptive control techniques. Machine learning–based control [14]-[16], reinforcement learning [17]-[19], and vision-based perception systems [20]-[23] have been integrated into robotic architectures to improve adaptability. Although these methods enhance autonomous capability, they still struggle in unpredictable or novel conditions where contextual human judgment is essential [24]. Purely autonomous systems often fail to generalize beyond their training environments and require human intervention for anomaly handling or unexpected events. Thus, the existing challenge is not solely to increase autonomy but to achieve a balance between robotic efficiency and human adaptability [25]-[27]. Human–robot collaboration (HRC) has emerged as a promising paradigm that enables functional cooperation between humans and robots at the control and decision level, including remote and cloud-mediated interaction scenarios where physical co-presence is not required [28]-[34]. Teleoperation systems, where human operators directly control robot motion through communication interfaces, provide flexibility and decision-making capabilities in complex scenarios such as dynamic storage layouts or uncertain object configurations [35]-[38]. However, conventional teleoperation approaches are constrained by communication latency, limited situational awareness, and operator fatigue during prolonged operation [39]-[44]. Furthermore, purely manual systems cannot achieve the consistency and speed of autonomous operation, highlighting the need for hybrid control frameworks that seamlessly integrate both capabilities.

Unlike mobile or articulated robots, Cartesian storage robots operate in highly structured environments that demand precise, repeatable linear motion and consistent timing across repetitive tasks. In such settings, purely autonomous systems lack adaptability to dynamic operational changes, while manual or conventional teleoperation often introduces variability and inefficiency. This creates a specific need for a hybrid IoT–Cloud framework that can preserve the deterministic execution required by Cartesian mechanisms while enabling human intervention through cloud-mediated supervision. Recent developments in cloud robotics and the Internet of Things (IoT) have created new opportunities for distributed intelligence and data-driven control in robotic systems [45]-[52]. Cloud-based architecture allows robots to offload computation [53], [54], share sensory data [55], [56], and synchronize tasks across multiple devices [57]-[59], while IoT connectivity enables real-time monitoring and bidirectional communication [60], [61]. Several studies have implemented cloud–IoT infrastructures for robotic monitoring [62]-[64], task coordination [65]-[67], and predictive maintenance [68]-[70]. Nevertheless, most existing works focus on data synchronization and offline coordination rather than real-time human–robot collaboration for operational control.

Most existing IoT-based teleoperation systems rely on direct socket communication or lightweight publish–subscribe protocols, such as MQTT, to achieve low-latency command transmission. While these approaches are practical for tightly coupled point-to-point control, they typically lack persistent state management, built-in synchronization, and resilience to transient network disruptions. Direct Wi-Fi socket connections require continuous peer-to-peer availability and manual session handling. In contrast, MQTT-based systems depend on external broker management and additional application-layer logic to ensure command consistency and historical traceability. In contrast, the proposed Hybrid IoT–Cloud framework utilizes Firebase Realtime Database as a cloud middleware, providing persistent state synchronization, automatic client reconnection, multi-device scalability, and integrated data logging. These characteristics are particularly advantageous for human-in-the-loop teleoperation in warehouse environments, where operational robustness, consistency, and scalability are more critical than minimal end-to-end latency. To the best of our knowledge, existing studies have not explicitly examined the integration of teleoperation and autonomous control through cloud-based middleware in Cartesian robots for warehouse applications. This absence highlights a significant research gap in developing hybrid frameworks that combine the efficiency of autonomous systems with the flexibility of human teleoperation in real-world storage environments.

Despite the growing adoption of IoT- and cloud-enabled robotic systems, existing IoT-based teleoperation frameworks commonly face several limitations, including sensitivity to network latency, a lack of persistent state synchronization, limited scalability for multi-client supervision, and a tight coupling between communication and low-level motion control. Moreover, prior studies have rarely focused on Cartesian warehouse robots, where repetitive structured motion must coexist with flexible remote human supervision under variable network conditions. The novelty of this work lies in the integration of cloud-based control as a supervisory layer for IoT-based teleoperation, enabling robust and scalable remote control while preserving deterministic local motion execution in Cartesian storage robots. To overcome these limitations, this study proposes a hybrid IoT–Cloud control framework for Cartesian storage robots that combines autonomous task execution with human teleoperation via a web-based interface. The proposed architecture enables seamless mode transition between autonomous and manual operation, supported by a cloud synchronization layer that maintains real-time communication with low latency. This system design ensures that human operators can immediately intervene when autonomous routines encounter unstructured or uncertain conditions, thereby enhancing flexibility without compromising efficiency. Unlike conventional teleoperation systems, the proposed method utilizes a cloud-mediated control loop that leverages the Firebase Realtime Database, offering low-overhead, bidirectional communication and persistent data logging for task management.

The contribution of this research is threefold. First, it presents a novel hybrid human–robot collaboration framework that integrates IoT-based connectivity and cloud control to enable adaptive teleoperation in storage environments. Second, it introduces a dual-mode task scheduling mechanism that dynamically coordinates autonomous and teleoperated control inputs while ensuring task continuity and timing efficiency. Third, the paper provides a quantitative performance evaluation of the proposed system through experimental validation, measuring task completion rate, average completion time, and network latency as key performance indicators. The results demonstrate that the hybrid framework improves the task completion rate by 0.35% and reduces average completion time by 12.02% compared to fully manual operation, confirming the feasibility of real-time collaborative control for warehouse automation.

Based on the identified research gap, this study is guided by the following research objectives: (1) to evaluate the feasibility of a hybrid IoT–Cloud control framework for Cartesian storage robots; (2) to quantitatively assess its impact on task success rate, execution time, and operational consistency compared to manual control; and (3) to analyze whether cloud-mediated supervisory control can improve reliability without compromising real-time performance.

2. Method

A structured research workflow was adopted to ensure that the proposed IoT-based teleoperation framework was designed, implemented, and evaluated in a systematic and reproducible manner. Fig. 1 presents an overview of the research methodology in the form of a flowchart, outlining the sequential stages followed throughout the study. The flowchart provides a high-level representation of the logical progression from system design to result interpretation, enabling readers to clearly understand how each phase contributes to the overall research objectives.

The initial stage, System Design and Development, focuses on the construction and integration of hardware and software components. In this phase, the Cartesian robot prototype is developed and connected to an IoT infrastructure. The ESP32 microcontroller is programmed to execute motion commands, manage cloud communication, and handle basic safety conditions. This stage establishes the technical foundation required for reliable remote operation.

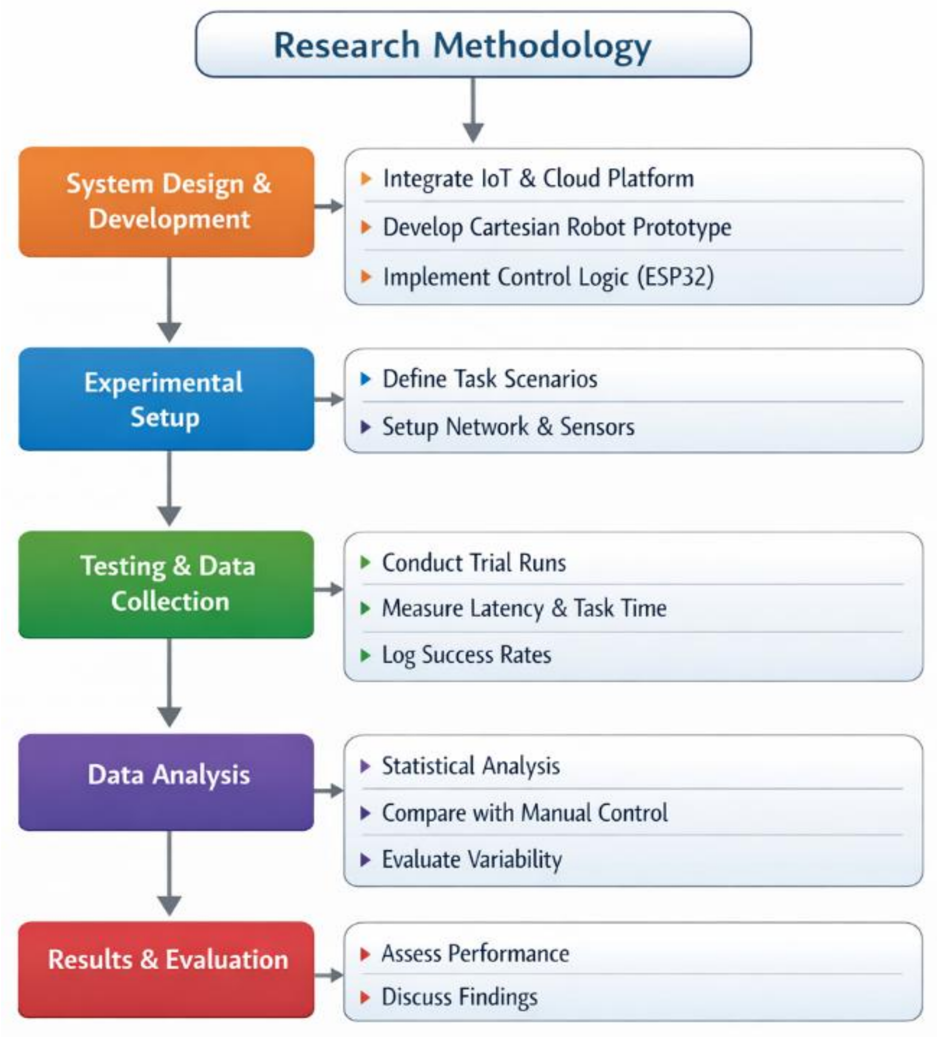

Fig. 1. System architecture

The Experimental Setup stage defines the operational conditions under which the system is evaluated. Representative warehouse-related tasks are designed, and the network configuration is established to enable real-time data exchange between the human interface, cloud platform, and robot controller. This phase ensures that the experiments are conducted under controlled yet realistic conditions. The Testing and Data Collection stage involves executing multiple experimental trials to obtain quantitative performance metrics. During each trial, task completion time, success rate, and cloud communication latency are recorded. Repeated testing allows the study to capture performance variability and assess the consistency and reliability of the proposed teleoperation framework. The final stage, Data Analysis and Evaluation, focuses on interpreting the collected data and drawing meaningful conclusions. Statistical analyses are performed to compare the proposed system with manual operation, with an emphasis on efficiency, operational consistency, and reliability. The outcomes of this stage inform the discussion and conclusions, supporting the practical applicability of the proposed framework in warehouse automation contexts.

2.1. System Architecture

The overall system architecture is organized into two main domains: the Human Interference layer and the Autonomous Control System, as illustrated in Fig. 2. The Human Interference layer includes the human operator and a web-based Human–Machine Interface (HMI) that enables remote teleoperation, monitoring, and task supervision. Through this interface, operators can issue motion commands, visualize robot feedback, and adjust control parameters in real time using any internet-connected device. This layer provides the flexibility to intervene during uncertain or complex situations that exceed the autonomous controller's predictive capability.

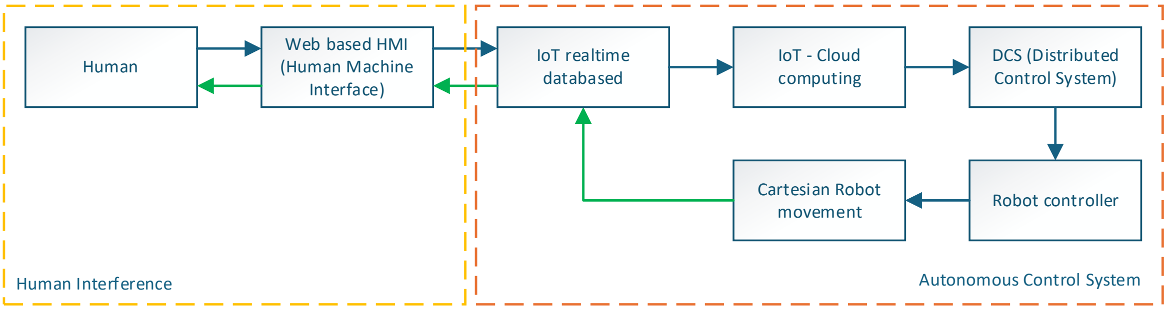

Fig. 2. System architecture

The experimental platform utilizes a hybrid embedded control architecture that combines an ESP32 microcontroller and an Arduino Uno. The ESP32 is responsible for cloud communication and real-time data exchange with the Firebase Realtime Database, while the Arduino Uno handles low-level motion execution and actuator coordination. This separation enables reliable real-time control while maintaining stable cloud connectivity.

The Cartesian robot is activated using closed-loop stepper motors (Nema 23, type 57HSE) driven by HBS57H hybrid servo drivers. Each motor provides a rated torque of 3.0 Nm, operates at a phase current of 3.5 A, and has a step angle of 1.8°. The motor drivers support an input voltage range of 24–70 VDC, current above 3 A, and micro-stepping resolution up to 1/256, enabling smooth and precise linear motion. The average operating speed of the motion system is approximately 1000 RPM, corresponding to a linear motion speed of 6.5 cm/s under experimental conditions. The system is designed to handle a maximum payload of 2000 g, which reflects typical loads in small-scale warehouse storage tasks. Object manipulation is performed using a two-finger servo clamp gripper, selected for its simplicity, reliability, and compatibility with repetitive pick-and-place operations.

The Autonomous Control System domain comprises the IoT real-time database, cloud computing layer, distributed control system (DCS), and robot controller. The IoT real-time database implemented using Firebase Realtime Database acts as a communication bridge between the human interface and the autonomous subsystem. It allows bidirectional data exchange in lightweight JSON format with update intervals of approximately 100–200 milliseconds, providing low-latency communication suitable for hybrid teleoperation scenarios. At the cloud computing layer, data synchronization and command processing are performed to ensure consistent coordination between the human interface and the robot controller. All communication between layers occurs through secure HTTPS protocols to maintain data integrity and reliability over public networks.

No explicit latency compensation or predictive control algorithms are implemented at the cloud or ESP32 level. Instead, cloud communication is intentionally restricted to high-level motion commands and task state updates. Once a command is received, all low-level trajectory execution, step generation, and motor timing are handled locally by the distributed microcontroller-based control system. This architectural separation ensures that network-induced latency and jitter affect only command update timing rather than continuous motion execution, thereby preventing direct disturbance of the robot's physical trajectory. In the event of an internet connection loss during task execution, the robot continues to execute the currently active motion command using locally stored trajectory parameters. Since low-level motor control and timing are handled entirely by the embedded controller, ongoing motion is not interrupted by cloud disconnection. However, no new commands or task updates can be received until connectivity is restored. After completing the current motion, the robot enters an idle and safe state, awaiting further instructions. This design ensures deterministic behaviours and prevents unstable or unintended motion under intermittent network conditions.

The distributed control system (DCS) is implemented using multiple Arduino-based microcontrollers, which execute control tasks deterministically in near real time. Each Arduino module is responsible for a specific motion axis or subsystem, enabling modularity and distributed processing. These controllers interpret high-level commands received from the cloud database and translate them into precise pulse-width modulation (PWM) and digital control signals for the stepper motor drivers. This distributed configuration reduces processing load on a single controller and enhances system responsiveness during multi-axis movement.

The physical implementation of the proposed system is shown in Fig. 3, which depicts the Cartesian robot and warehouse storage unit. The robot structure is built using an aluminum extrusion frame with three orthogonal linear axes (X, Y, and Z) driven by stepper motors through timing belts and lead screws. The end-effector comprises a gripper mechanism that enables both autonomous and teleoperated pick-and-place operations. The storage rack is composed of multiple grid compartments that emulate a warehouse inventory system, where objects of different sizes and weights are organized in labeled bins.

Fig. 3. Cartesian robot and warehouse storage

2.2. System Modeling

To rigorously analyze and control the Cartesian robot within the proposed hybrid framework, a mathematical model is developed that captures the dynamics of the multi-axis system. The robot is modeled as a three-degree-of-freedom (3-DOF) system moving along the X, Y, and Z axes. In Equations (1)-(10), all variables are defined explicitly, with position expressed in millimeters, velocity in millimeters per second, and time in seconds. The model assumes rigid linear axes, negligible backlash, and bounded acceleration consistent with the physical constraints of the implemented Cartesian robot. The equations of motion are derived using the Euler–Lagrange formulation. The Lagrangian L is defined as the difference between the kinetic energy T and potential energy U of the system:

$$L = T - U \tag{1}$$

The kinetic energy of the system is given by:

$$T = \frac{1}{2}m_x\dot{x}^2 + \frac{1}{2}m_y\dot{y}^2 + \frac{1}{2}m_z\dot{z}^2 \tag{2}$$

where m_x, m_y, m_z represent the effective masses along each axis, and $\dot{x}, \dot{y}, \dot{z}$ are the respective velocities.

Assuming negligible potential energy variation in the horizontal plane, the Euler–Lagrange equations yield the following dynamic model:

$$\frac{d}{dt}\left(\frac{\partial L}{\partial \dot{q}_i}\right) - \frac{\partial L}{\partial q_i} = \tau_i - F_{d,i}, \quad i = x, y, z \tag{3}$$

where $q = [x, y, z]^T$ is the generalized coordinate vector, $\tau = [\tau_x, \tau_y, \tau_z]^T$ is the torque input vector, and $F_d = [F_{d,x}, F_{d,y}, F_{d,z}]^T$ represents the viscous damping forces:

$$F_{d,i} = b_i\dot{q}_i \tag{4}$$

with b_i as the damping coefficient for each axis. The resulting dynamic equations are:

$$\begin{aligned} m_x\ddot{x} + b_x\dot{x} &= \tau_x \\ m_y\ddot{y} + b_y\dot{y} &= \tau_y \\ m_z\ddot{z} + b_z\dot{z} &= \tau_z \end{aligned} \tag{5}$$

These equations are discretized and implemented in the distributed control system for real-time trajectory tracking and state estimation. The hybrid control strategy integrates autonomous and human-operated modes through a state-dependent switching rule. Let $u_a(t)$ denote the autonomous control input and $u_h(t)$ the human-generated input via the web interface. The combined control input $u(t)$ is defined as:

$$u(t) = \sigma(t).u_a(t) + \big(1 - \sigma(t)\big).u_h(t) \tag{6}$$

where $\sigma(t) \in \{0,1\}$ is a switching signal determined by:

$$\sigma(t) = \begin{cases} 1 & if \|e(t)\| \le \epsilon \text{ } and \text{ } autonomous \text{ } mode \text{ } active \\ 0 & otherwise \end{cases} \tag{7}$$

Here, $e(t) = q_d(t) - q(t)$ is the tracking error, $q_d(t)$ is the desired trajectory, and ϵ is a predefined tolerance threshold. The autonomous controller $u_a(t)$ is designed as a proportional-derivative (PD) controller with gravity compensation:

$$u_a(t) = K_p e(t) + K_d \dot{e}(t) \tag{8}$$

where K_p and K_d are positive definite gain matrices.

The communication between the human operator and the robot is modeled as a delayed feedback system due to network latency. Let τ_c represent the cloud-induced delay. The human input received by the robot at time t is:

$$u_h(t) = \hat{u}_h(t - \tau_c) \tag{9}$$

where $\hat{u}_h$ is the command sent by the operator. Because motion trajectories are executed locally after command reception, the effect of cloud-induced delay τ_c manifests as a bounded input delay at the supervisory control level rather than as continuous feedback delay within the actuator control loop. The system stability under variable delay is ensured by selecting controller gains that satisfy the following sufficient condition derived from the Lyapunov–Krasovskii functional:

$$K_d > \frac{\tau_{max}}{2} \|K_p\| \tag{10}$$

where $\tau_{\max}$ is the maximum expected delay.

The control strategy was validated through staged functional testing before experimental evaluation. Local motion execution was first verified in standalone mode to ensure deterministic trajectory generation and step timing. Integrated validation was then performed under cloud-mediated command delivery by repeatedly issuing identical high-level commands and confirming consistent local execution. This process ensured that observed performance variations during experiments were attributable to communication effects rather than control instability.

2.3. Experimental Setup

The experimental setup was designed to evaluate the operational reliability and timing performance of the proposed hybrid IoT–Cloud control framework implemented on a Cartesian storage robot. The evaluation focused on two primary performance indicators: task completion and task completion time. The term completion task refers to the robot's ability to successfully execute and finalize a motion sequence between two predefined coordinates. In contrast, completion time denotes the total duration required for each task, measured from the initiation of motion (the first stepper-motor pulse) until the successful placement of the object in the designated bin. Together, these two parameters provided a quantitative assessment of the system's reliability and efficiency under various control modes.

Before experimentation, the robot axes were calibrated to predefined reference positions to ensure repeatable motion. Safety limits were enforced in software by constraining workspace boundaries, maximum speed, and payload thresholds. In the event of communication loss or invalid commands, the system defaults to a safe stop state to prevent unintended motion. Communication latency was monitored throughout the experiments using timestamped command transmission and reception events recorded at both the client interface and the embedded controller. Round-trip latency values were derived from cloud database logs and local serial records, allowing continuous observation of latency variations during task execution. These measurements serve as the basis for the latency analysis presented in the Results section.

The experiment was conducted on a 10×5 rack structure representing a warehouse storage grid, where rows 1–10 were indexed from top to bottom, and columns A–E were arranged from right to left. Each grid cell, such as 5-C, corresponded to a unique coordinate position accessible to the robot's end-effector. The robot's home position was located at coordinate 10-E, situated at the lower-left corner of the workspace. From this reference point, the robot executed a motion sequence consisting of twelve tasks arranged as follows: 10-E → 5-C → 2-E → 2-C → 2-A → 5-A → 8-A → 8-C → 8-E → 5-E → 5-C → 2-E → 8-A. The corresponding rack layout trajectories illustrating these motions are shown in Fig. 4.

During testing, two control modes were compared: a manual operation mode and the proposed hybrid IoT–Cloud mode. In manual operation, the operator entered coordinate commands directly into the local controller, without interacting with the cloud. In contrast, the hybrid mode employed a cloud-based control scheme in which motion commands were transmitted through the Firebase Realtime Database, and the operator interacted with the system using a web-based Human–Machine Interface (HMI). The HMI, implemented as an HTML dashboard (see Fig. 5), provided a visual grid of the rack, start and home buttons, and a live command log that confirmed real-time synchronization between the robot controller and the cloud server.

The experimental design follows a repeated-measures approach, where each participant performs multiple tasks under both control conditions. The total of 576 trials provides sufficient statistical power for within-subject comparison of performance metrics such as task success rate, completion time, and variability, which is appropriate for evaluating system-level performance rather than human population differences.

A within-subjects comparative study was conducted where the same eight participants (N = 8) performed identical warehouse manipulation tasks under both control modalities: manual physical button operation and the proposed hybrid IoT–Cloud framework. This repeated-measures design eliminated inter-participant variability, with each participant contributing 36 trials per condition (12 tasks × 3 repetitions), resulting in 288 trials per control mode and a total of 576 trials across the study. To mitigate learning, fatigue, and order effects, the sequence of task execution and control modes was counterbalanced across participants. Participants were given rest periods between task blocks, and task order was randomized to prevent systematic bias due to learning or fatigue accumulation.

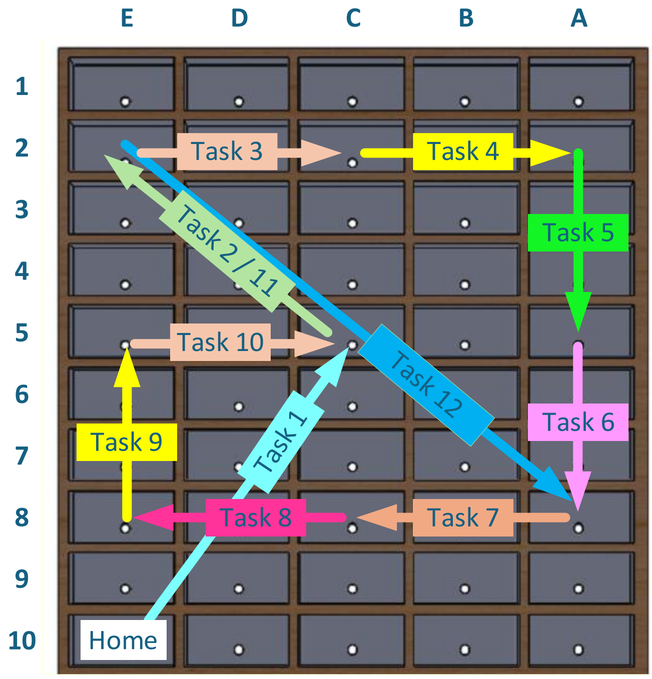

Fig. 4. Rack layout trajectories

The experimental protocol commenced with system calibration and participant orientation. Each testing session employed counterbalancing to control for order effects, with participants randomly assigned to complete either the manual or hybrid condition first. In the manual physical button condition, operators used a dedicated control panel positioned adjacent to the robot, executing commands through direct tactile button presses without any cloud connectivity or autonomous assistance. Conversely, the hybrid IoT–Cloud condition utilized a web-based Human-Machine Interface (HMI) with real-time visual feedback, where commands were synchronized via Firebase Realtime Database, enabling remote operation with cloud-mediated control and latency compensation mechanisms.

3. Results

The experimental evaluation provides a quantitative assessment of the proposed hybrid IoT–Cloud control framework against a conventional manual control mode. The results, summarized in Table 1, and visualized through Normal probability plots (Fig. 6 and Fig. 7), collectively demonstrate the superior efficacy of the hybrid system across all critical metrics: task success rate, operational efficiency, and performance consistency.

A primary finding is the flawless task execution achieved by the hybrid control framework. As detailed in Table 1, the manual control mode recorded a single failure in Task 4, resulting in a 99.65% success rate (287 out of 288 trials). In stark contrast, the hybrid mode achieved a perfect 100% success rate across all twelve tasks (288 out of 288 trials). This improvement, though numerically small, is critical in industrial settings where reliability is paramount. It indicates that the cloud-mediated interface enhances operational robustness by standardizing the command input and potentially mitigating the occasional errors inherent in direct manual operation.

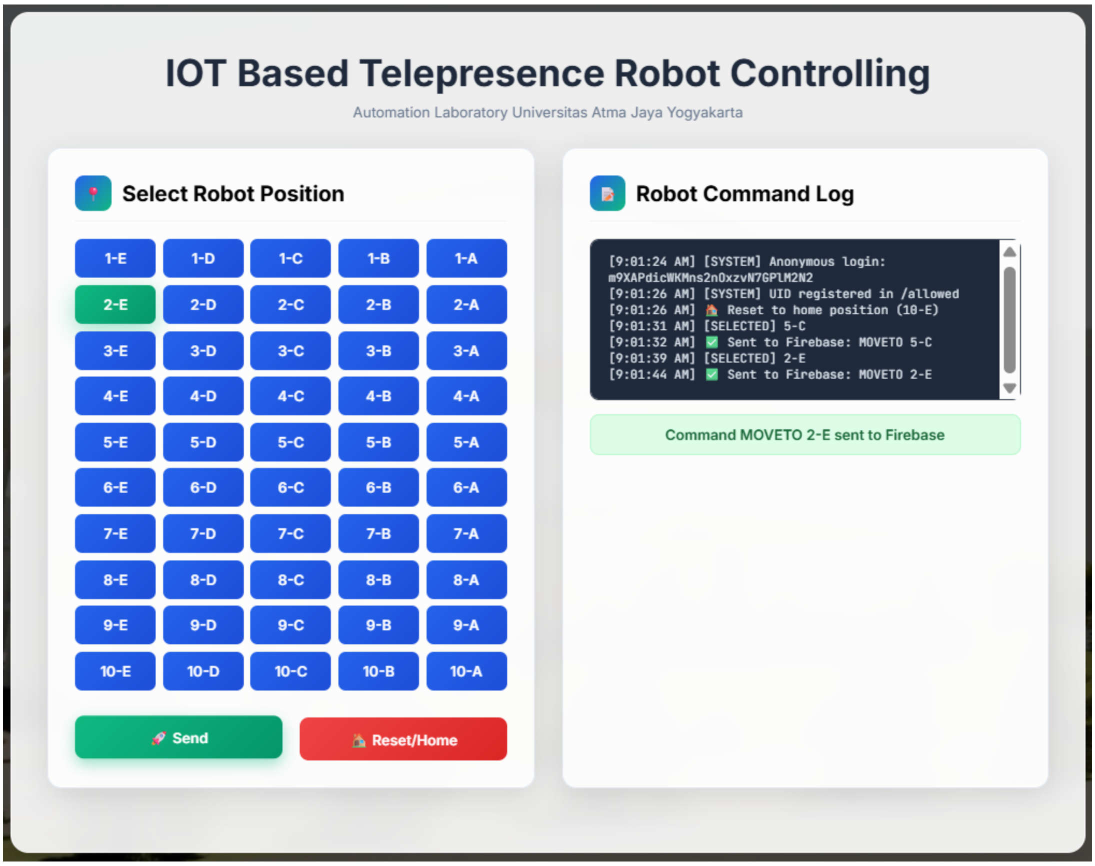

Fig. 5. HTML dashboard

Table 1. Manual control vs hybrid control statistic descriptive

Task No	Manual Control				Hybrid Control				Mean diff
	Completion task		Completion time (s)		Completion task		Completion time (s)		
	Succeed	Fail	Mean	StDev	Succeed	Fail	Mean	StDev	
Task 1	24	0	21.18	0.33	24	0	20.00	0.16	1.19
Task 2	24	0	9.52	0.31	24	0	8.49	0.12	1.04
Task 3	24	0	7.10	0.34	24	0	5.98	0.13	1.11
Task 4	23	1	7.12	0.30	24	0	6.03	0.12	1.10
Task 5	24	0	5.12	0.36	24	0	3.99	0.16	1.13
Task 6	24	0	5.11	0.29	24	0	3.99	0.19	1.12
Task 7	24	0	6.98	0.26	24	0	5.93	0.12	1.05
Task 8	24	0	7.21	0.32	24	0	5.90	0.15	1.31
Task 9	24	0	5.20	0.34	24	0	3.98	0.14	1.22
Task 10	24	0	7.13	0.36	24	0	6.03	0.15	1.09
Task 11	24	0	9.59	0.36	24	0	8.49	0.17	1.10
Task 12	24	0	21.02	0.27	24	0	19.98	0.14	1.04
SUM	**287**	**1**			**288**	**0**			

The reported task success rates were obtained under stable and representative network conditions typical of laboratory and campus Wi-Fi environments. No explicit network stress testing, such as artificial packet loss, bandwidth limitation, or forced disconnection, was performed during the experiments. Consequently, the reported 100% success rate reflects operational reliability under nominal connectivity rather than worst-case network degradation. It is important to note that, due to the proposed architecture, cloud communication is limited to high-level command transmission, while motion execution is handled locally. As a result, transient network delays primarily affect command update timing and do not interrupt ongoing task execution; however, prolonged connectivity loss may still delay task initiation.

Furthermore, the hybrid framework yielded a significant and consistent reduction in task completion time. For all twelve tasks, the mean completion time was lower under hybrid control, resulting in an average decrease of 12.02% compared to the manual mode. This enhancement in speed is statistically reinforced by the consistently lower standard deviations (StDev) observed for the hybrid control across all tasks in Table 1. The probability plots visually corroborate this marked improvement in consistency. The data points for manual control in Fig. 5 show a noticeable scatter from the theoretical normal line, particularly in the tails, indicating greater variability and the presence of outliers. Conversely, the data for hybrid control in Fig. 6 exhibits a much tighter alignment with the central trend, signifying a more predictable and stable performance profile.

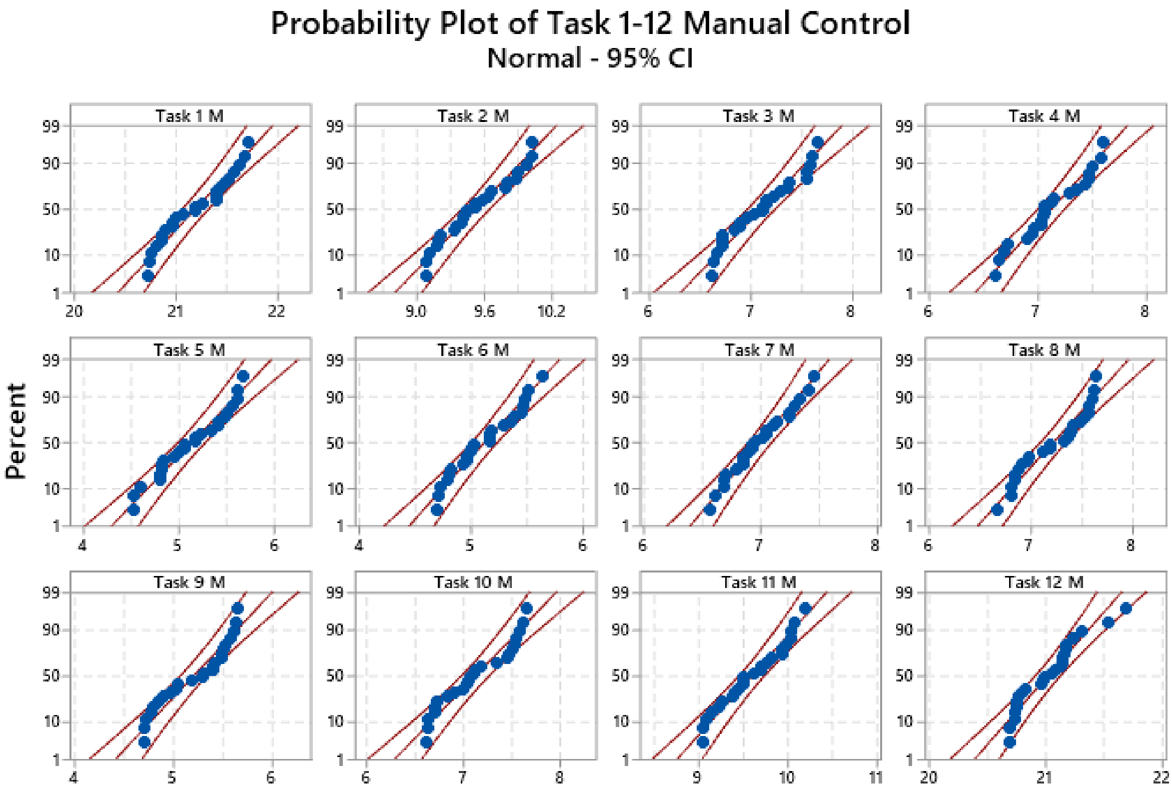

Fig. 6. Probability plot of task 1-12 manual control

4. Discussion

To substantiate the overarching trends with rigorous statistical evidence, a detailed analysis was conducted for each task, beginning with Task 1. The statistical comparison relies on two key methods: Bonett and Levene's tests, as well as Analysis of Variance (ANOVA). The Bonett and Levene's tests are robust methods for comparing the variability (variances) between two groups. Their key advantage is that they are valid for any continuous data distribution, making them highly reliable for real-world performance data that may not perfectly follow a normal distribution. On the other hand, Analysis of Variance (ANOVA) is used to determine if there is a statistically significant difference between the means of two or more groups. In this context, a one-way ANOVA determines whether the difference in average completion time between manual and hybrid control is genuine and not due to random chance.

The Bonett and Levene's tests for Task 1. H_0 is the null hypothesis and H_1 is the alternative hypothesis at the significance level $\alpha = 0.05$.

$$H_0: \frac{\sigma_1}{\sigma_2} = 1 \tag{11}$$

$$H_1: \frac{\sigma_1}{\sigma_2} \neq 1 \tag{12}$$

Where σ_1 is standard deviation of Task 1 manual control and σ_2 is standard deviation of Task 1 hybrid control.

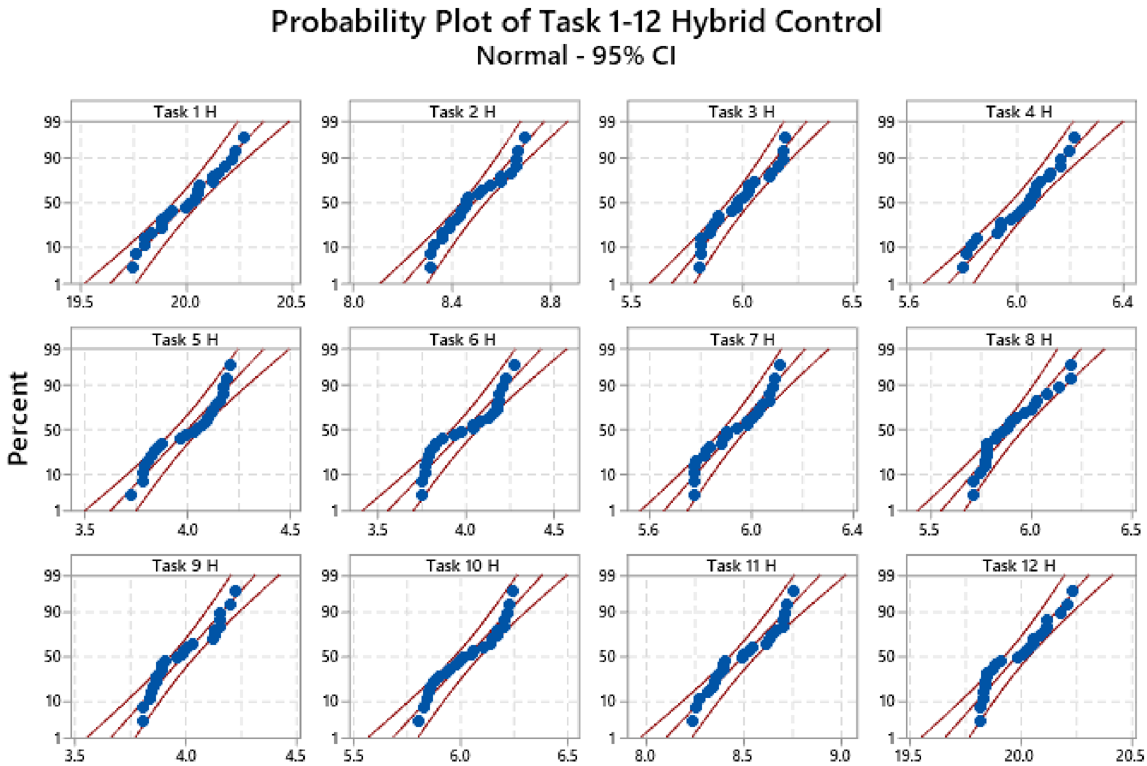

Fig. 7. Probability plot of task 1-12 hybrid control

Based on the result in Table 2, Bonett and Levene's tests for equality of variances decisively rejected the null hypothesis (H_0: $\sigma_1/\sigma_2 = 1$), with both methods producing exceptionally low p-values ($p < 0.001$). The estimated ratio of standard deviations stood at 2.11, indicating that the manual control's variability was more than double that of the hybrid system. This substantial difference in consistency is further substantiated by the non-overlapping 95% confidence intervals for the population standard deviations: (0.283, 0.415) for manual control versus (0.129, 0.204) for hybrid control. The application of Bonett's and Levene's tests assumes independent task trials and approximately comparable distribution shapes across control modes, which are appropriate for assessing differences in performance variability between manual and hybrid control conditions.

Table 2. Bonett and levene test result for task 1

Method	Test statistic	DF1	DF2	*P*-Value
Bonett	18.33	1		0.000
Levene	20.24	1	46	0.000

The statistical analysis presented in Fig. 8 provides compelling visual evidence of the hybrid control system's superior consistency in performance. The 95% confidence interval for the ratio of standard deviations (σ(Task 1 M) / σ(Task 1 H)) is entirely positioned above the null value of 1, confirming that the manual control's process variability is statistically greater than that of the high-control process. This is further substantiated by highly significant p-values ($p < 0.001$) from both

Bonett's and Levene's tests, which unequivocally reject the null hypothesis of variance equality. The corresponding boxplots offer a stark visual contrast: the distribution for Task 1 H demonstrates a markedly more compact interquartile range and narrower whiskers compared to Task 1 M. This illustrates that hybrid control not only achieves a faster central tendency but also produces a significantly tighter clustering of completion times, thereby affirming its enhanced reliability and operational predictability.

The ANOVA tests for Task 1. H_0 is that all means are equal, and H_1 is that not all means are equal at the significance level $\alpha = 0.05$. Based on the results in Table 3, ANOVA revealed a statistically significant difference in mean completion times ($F(1,46) = 256.11$, $p < 0.001$). The hybrid control demonstrated a marked reduction in average completion time, achieving 19.99 seconds compared to 21.18 seconds for manual operation, representing a 5.6% improvement in execution speed for Task 1. The effect size was particularly substantial, with the model explaining 84.77% of the variance in completion times ($R^2 = 0.85$). The clear separation between the 95% confidence intervals for the population means-(21.08, 21.29) for manual versus (19.89, 20.10) for hybrid-provides compelling evidence that the performance enhancement is not merely statistically significant but practically meaningful (see Fig. 9).

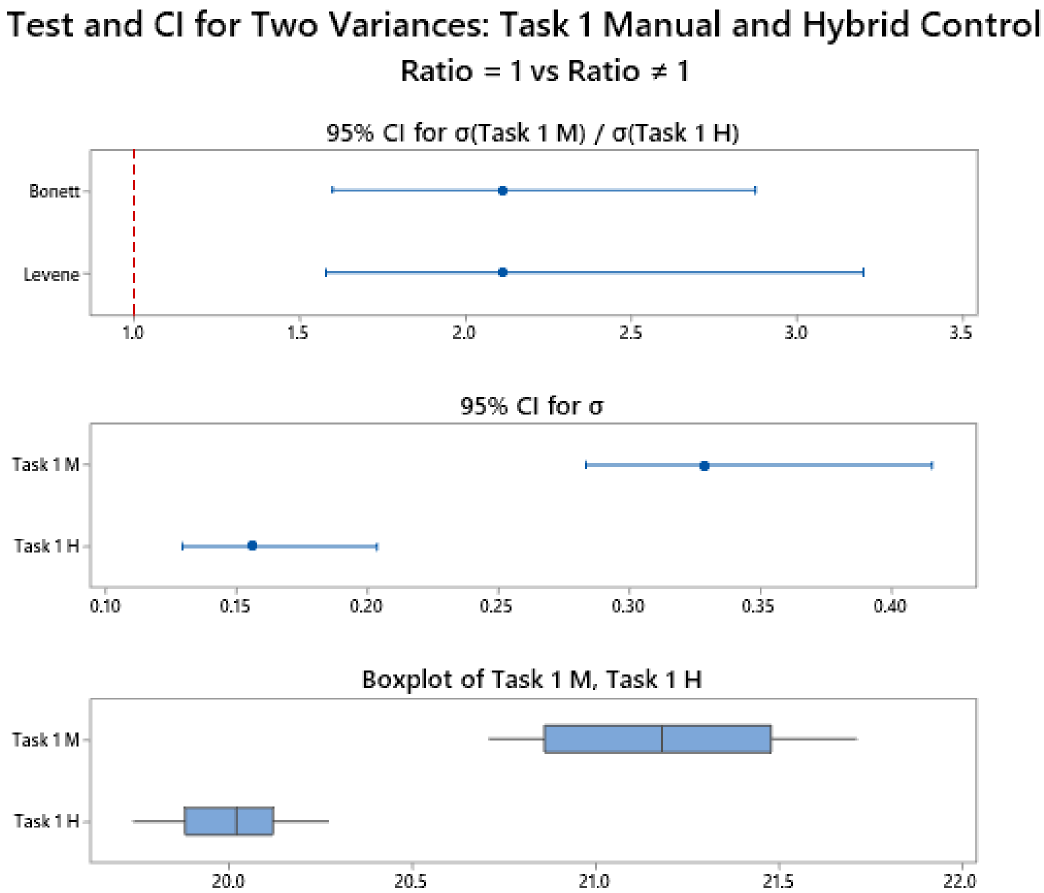

Fig. 8. Probability plot of task 1-12 hybrid control

The superior performance consistency observed in Task 1 establishes a definitive pattern that persists across the entire spectrum of operational tasks (Tasks 2-12). Statistical analysis using Bonett and Levene's tests reveals that the hybrid control system consistently produces significantly lower variability in completion times compared to manual control across all subsequent tasks. As summarized in Table 4, the estimated ratio of standard deviations (Manual/Hybrid) ranges from 1.54 (Task 6) to 2.61 (Task 3), with all 95% confidence intervals excluding the null value of 1. The associated p-values are consistently below the 0.05 significance threshold, providing robust evidence to reject the null hypothesis of equal variances in every instance.

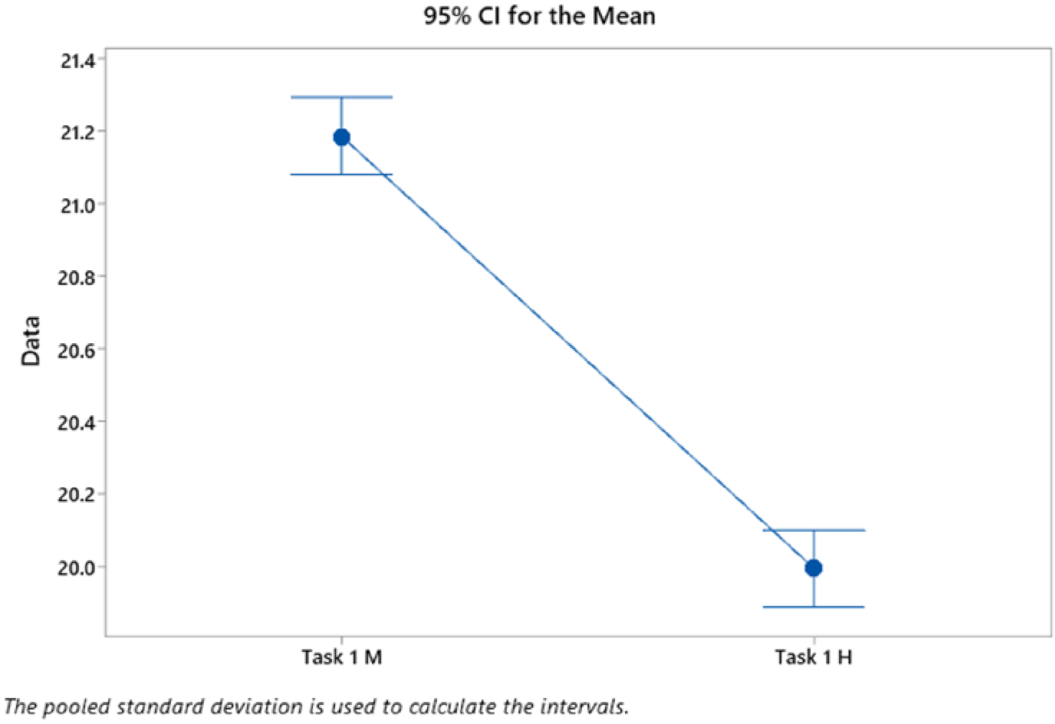

Fig. 9. Interval plot 95% confidence interval of task 1

Table 3. ANOVA test result for task 1

Source	DF	Adj SS	Adj MS	*F*-Value	*P*-Value
Factor	1	16.946	16.9456	256.11	0.000
Error	46	3.044	0.0662		
Total	47	19.989			

Table 4. Statistical summary of variance comparison for all Tasks (1-12)

Task	Estimated Ratio (σ_1/σ_2)	95% CI (Bonett)	95% CI (Levene)	*P*-Value (Bonett)	*P*-Value (Levene)
1	2.11	(1.598, 2.876)	(1.579, 3.201)	0	0
2	2.52	(1.839, 3.442)	(1.710, 3.961)	0	0
3	2.61	(1.936, 3.533)	(1.794, 3.855)	0	0
4	2.5	(1.762, 3.698)	(1.547, 4.222)	0	0.001
5	2.26	(1.680, 2.956)	(1.544, 3.196)	0	0
6	1.54	(1.153, 1.970)	(1.054, 1.953)	0.007	0.025
7	2.14	(1.533, 2.837)	(1.325, 2.797)	0	0.003
8	2.14	(1.578, 3.221)	(1.637, 3.538)	0	0
9	2.45	(1.887, 3.205)	(1.733, 3.470)	0	0
10	2.4	(1.844, 3.105)	(1.623, 3.192)	0	0
11	2.12	(1.586, 2.787)	(1.472, 2.861)	0	0
12	1.96	(1.186, 2.789)	(1.211, 2.541)	0.015	0.007

Notably, while Tasks 6 and 12 exhibit relatively lower variance ratios (1.54 and 1.96, respectively), they still maintain statistical significance, with p-values of 0.007 and 0.025 for Bonett and Levene's tests, respectively, confirming the hybrid system's consistent advantage even in tasks where the performance gap is narrower. The stability of these results across different task complexities and durations underscores the robustness of the hybrid control framework. The reduction in variability translates directly to enhanced process capability and operational predictability. The hybrid system's ability to maintain tighter control over task execution times demonstrates its effectiveness in mitigating the inherent uncertainties of human-operated systems. This consistency improvement, coupled with the previously established reduction in mean completion times, presents a compelling case for implementing hybrid IoT–Cloud control systems in warehouse automation environments, where both efficiency and reliability are critical performance metrics.

The analysis of variance (ANOVA) results for Tasks 2-12 provide compelling evidence of the hybrid control system's superior efficiency in terms of mean completion times. As summarized in Table 5, the one-way ANOVA reveals statistically significant differences between manual and hybrid control across all tasks, with exceptionally high F-values ranging from 183.71 (Task 11) to 335.18 (Task 7) and all p-values < 0.0001.

The magnitude of these differences is substantial and practically significant. The percentage improvement in mean completion time ranges from 4.93% (Task 12) to 23.43% (Task 9), demonstrating that the hybrid system consistently outperforms manual control across various task durations and complexities. Particularly noteworthy are Tasks 5, 6, and 9, which show improvements exceeding 21%, indicating that the hybrid framework is efficient for shorter-duration tasks. The high R-squared values (ranging from 79.97% to 87.93%) indicate that the control method (manual vs. hybrid) explains a substantial proportion of the variance in completion times. This strong explanatory power underscores the fundamental impact of the control system on operational efficiency. The non-overlapping 95% confidence intervals for the means in all tasks further reinforce the reliability of these findings.

Table 5. ANOVA result summary for all tasks (1-12)

Task	F-Value	P-Value	R-sq (%)	Manual Mean (s)	Hybrid Mean (s)	Mean Difference (s)	Improvement (%)
1	256.11	0	84.77	21.185	19.996	1.1884	5.61
2	234.45	0	83.60	9.5238	8.4879	1.0359	10.88
3	224.83	0	83.02	7.0958	5.9813	1.1145	15.70
4	269.52	0	85.69	7.1204	6.0254	1.0950	15.38
5	195.23	0	80.93	5.1225	3.9921	1.1304	22.07
6	255.15	0	84.73	5.1117	3.990	1.1217	21.94
7	335.18	0	87.93	6.9829	5.9292	1.0537	15.09
8	329.39	0	87.75	7.2108	5.8992	1.3116	18.19
9	263.05	0	85.12	5.2029	3.9838	1.2191	23.43
10	190.65	0	80.56	7.1262	6.0333	1.0929	15.34
11	183.71	0	79.97	9.5908	8.4933	1.0975	11.44
12	276.86	0	85.75	21.020	19.984	1.0367	4.93

The comprehensive experimental results presented in this study demonstrate unequivocally that the proposed hybrid IoT–Cloud control framework significantly outperforms conventional manual control across all performance metrics. The integration of cloud-based synchronization with a web-based Human-Machine Interface (HMI) has yielded systematic improvements in both operational consistency and efficiency that transcend specific task characteristics. Statistical evidence reveals a robust pattern: the hybrid system not only achieves faster task completion but does so with remarkably greater consistency, effectively addressing the fundamental limitations of human-operated systems while preserving human adaptability for complex decision-making scenarios.

The magnitude of improvement is both statistically significant and practically meaningful. The hybrid system reduced average completion time by 12.02% across all tasks, with individual task improvements ranging from 4.93% to 23.43%. Notably, the shorter-duration tasks (Tasks 5, 6, and 9) exhibited the most substantial improvements, indicating that the cloud-mediated control loop effectively minimizes the cognitive and physical latency associated with human response times. This reduction in execution time, coupled with the perfect task success rate (100% vs. 99.65% for manual control), demonstrates the hybrid system's capacity to enhance both speed and reliability simultaneously-a combination rarely achieved in human-robot collaboration systems.

From a practical perspective, the observed average reduction of 12.02% in task completion time implies a meaningful improvement in operational throughput for repetitive warehouse storage tasks.

In continuous pick-and-place operations, even modest reductions in cycle time can accumulate substantial efficiency gains over extended operating periods. More importantly, the reduction in performance variability ensures more predictable task execution, which is crucial for scheduling, synchronizing with other automated systems, and maintaining overall warehouse reliability.

The variance analysis reveals the most compelling advantage of the hybrid control framework. The consistently significant results from both Bonett and Levene's tests across all twelve tasks ($p < 0.05$ in all cases, with most p-values < 0.001) demonstrate that the reduction in variability is not task-specific but systemic. The estimated ratios of standard deviations ranging from 1.54 to 2.61 indicate that the manual control system produced 54% to 161% more variability than the hybrid system. This substantial reduction in performance dispersion has profound implications for warehouse automation, where predictable cycle times are essential for efficient system planning and throughput optimization.

The practical significance of this consistency improvement extends beyond statistical metrics. In industrial applications, reduced variability translates directly to higher process capability indices (Cpk), improved resource allocation, and more reliable throughput estimation. The hybrid system's ability to maintain tight control over task execution times, regardless of task complexity or duration, suggests that the cloud-based architecture effectively mitigates the cognitive and motor variability inherent in human operators. This finding addresses a critical challenge in human-robot collaboration: maintaining human flexibility while achieving robotic consistency.

Despite the improvements demonstrated in efficiency and reliability, several limitations should be acknowledged. The experimental evaluation was conducted under representative but controlled network conditions. While latency variations were monitored and analyzed, extreme network congestion or large-scale multi-client scenarios were not explicitly tested. Additionally, the current implementation focuses on a single Cartesian robot operating under supervisory IoT-based teleoperation. Scaling the framework to larger warehouse environments involving multiple robots, heterogeneous tasks, and shared cloud resources may introduce additional communication overhead and coordination challenges. Future work will therefore focus on large-scale deployment studies, network-aware scheduling strategies, and systematic evaluation under more diverse operational and network conditions.

The performance advantages observed in this study can be attributed to several key architectural features of the proposed hybrid framework. The cloud-mediated control loop, implemented through Firebase Realtime Database, provides a standardized communication channel that eliminates the variability associated with direct human-machine interaction. The web-based HMI offers a structured interface that reduces cognitive load and decision latency, while the distributed control system ensures deterministic execution of motion commands. This architectural approach effectively disappoints the human decision-making process from physical execution, allowing each component to operate at its optimal capacity.

The system's ability to maintain low communication latency (below 200 ms) while achieving these performance improvements validates the feasibility of cloud-based control for real-time applications. The fact that these benefits were consistent across tasks of varying durations and complexities suggests that the hybrid framework is robust and scalable. Furthermore, the perfect task success rate in hybrid mode, in contrast to the single failure in manual mode, indicates that the cloud-based interface may reduce error rates by providing clearer feedback and more structured interaction patterns. The results of this study have significant implications for the design of next-generation warehouse automation systems. The demonstrated ability to combine human adaptability with robotic consistency addresses a fundamental challenge in flexible automation: maintaining efficiency in dynamic, unstructured environments. The hybrid framework enables human operators to intervene when necessary while ensuring that routine operations benefit from the speed and repeatability of automated execution.

This research contributes to the evolving paradigm of human-robot collaboration by demonstrating that cloud-based architecture can effectively bridge the gap between fully manual and fully autonomous systems. The performance improvements achieved—ranging from a 12.02% reduction in completion time to over 100% improvement in consistency—represent substantial operational advantages that can be directly translated into increased throughput, reduced operational costs, and enhanced system reliability in real-world warehouse applications.

The performance of the proposed IoT–Cloud teleoperation framework was further analyzed by comparing it with results reported in related studies on cloud robotics and IoT-based teleoperation systems. Previous works have shown that teleoperated warehouses or mobile robots typically experienced reduced operational consistency and increased task completion time due to network latency and communication variability, particularly when using direct Wi-Fi or broker-based protocols under dynamic conditions [71]-[76]. In comparison, the present study demonstrates a higher task success rate and improved temporal consistency, which can be attributed to the separation of cloud-based supervisory control and local execution on the robot controller. Unlike earlier approaches that rely on continuous low-level command streaming, the proposed architecture minimizes the impact of network fluctuations by delegating motion execution to the local controller once commands are received. As a result, the observed performance aligns favorably with, and in several aspects surpasses, previously reported results in similar warehouse teleoperation scenarios, highlighting the practical advantages of the proposed hybrid IoT–Cloud control framework.

A key strength of the proposed IoT–Cloud teleoperation framework is its ability to improve operational consistency and reliability by separating cloud-based supervisory control from local motion execution. This design reduces the sensitivity of robot motion to short-term network fluctuations while preserving human-in-the-loop flexibility. Nevertheless, the system remains dependent on network availability and cloud connectivity, which may limit its performance in highly critical or large-scale deployment scenarios. These limitations indicate potential directions for future research, including latency-aware control strategies, edge–cloud offloading, and scalability analysis in more diverse warehouse environments.

Future work will extend the evaluation to include systematic network stress testing under degraded communication conditions, such as increased latency, packet loss, and intermittent connectivity. Such experiments will enable a more comprehensive assessment of system robustness and provide quantitative bounds on acceptable network performance for cloud-mediated human–robot collaboration.

5. Conclusion

This study has successfully designed, implemented, and validated a hybrid IoT–Cloud control framework for Cartesian storage robots, effectively bridging the critical gap between the rigid efficiency of full autonomy and the adaptive but inconsistent nature of manual control. The proposed system integrates teleoperation, IoT connectivity, and cloud-based control through a web-based interface synchronized with Firebase Realtime Database, enabling seamless transitions between autonomous and human-controlled modes while maintaining low communication latency (<200 ms).

The experimental results provide compelling evidence of the framework's superiority. The hybrid system achieved a perfect task success rate of 100%, outperforming manual control's 99.65%, demonstrating enhanced operational reliability. More significantly, it reduced average completion time by 12.02% across all tasks, with individual task improvements ranging from 4.93% to 23.43%. The most substantial improvements were observed in shorter duration tasks (Tasks 5, 6, and 9), with an average improvement exceeding 21%. This suggests that the cloud-mediated control loop effectively minimizes cognitive and physical latency in human response times.

The most substantial advantage lies in the improvement of consistency. The variance analysis demonstrated that the hybrid system reduced performance variability by 54% to 161% across different tasks, with all Bonett and Levene's tests showing statistical significance ($p < 0.05$). This major reduction in performance dispersion, combined with the speed enhancement, proves the system's capacity to simultaneously deliver both efficiency and reliability combination rarely achieved in human-robot collaboration systems.

This research makes three significant contributions to warehouse automation. First, it presents novel hybrid architecture that effectively combines human adaptability with robotic consistency. Second, it provides rigorous quantitative validation through comprehensive statistical analysis of both mean performance and variability. Third, it demonstrates the practical feasibility of cloud-based real-time control for industrial applications.

Despite the promising results, the current study is limited to a single-robot experimental setup under controlled network conditions, with a relatively minor participant sample that may not fully represent large-scale or highly dynamic industrial environments. Future work will focus on integrating artificial intelligence techniques for predictive mode switching, enabling the system to anticipate when human supervision or autonomous execution is most appropriate based on task context and network conditions. Key challenges to be addressed include system scalability in multi-robot warehouse deployments, robustness under variable and unstable network conditions, and integration with existing warehouse management and automation systems. In addition, edge–cloud computational offloading strategies will be investigated to dynamically distribute control and perception workloads between embedded controllers and cloud services, thereby enhancing responsiveness and improving deployment scalability.

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