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Comparative Simulation Analysis of Cloud vs. Edge-Deployed Voice-Controlled Robotic Arm Integrating Large Language Models for Laboratory Automation

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ABSTRACT

Large-scale language models (LLMs) combined with robot manipulation have created the possibility of natural language-controlled automation systems. Nevertheless, the majority of deployments use cloud-based inference that creates latency and reliability constraints that cannot be tolerated in laboratory automation systems that need respond time less than 150 ms. The paper entails a comparative simulated study with rigor of the differences between the use of clouds and edge-based implementation of the LLM-driven voice-controlled 6DOF robotic arm systems to structured laboratory pick-and-place tasks. The suggested architecture combines Whisper Tiny and speech-to-text-oriented, and a quantized model of LLaMA-8B model and semantic task planning in a ROS2Gazebo model. The two deployment configurations were: (i) cloud inference implemented on the AWS EC2 and (ii) inference fully distributed on NVIDIA Jetson Orin Nano. They carried out 600 trials (300 of each configuration) in the conditions of a baseline, a noise of acoustic nature (60-80 dB), and a different weight of a specimen (1-500 g). Findings indicate that edge deployment owed to the 72.4% reduction of end-to-end latency (cloud: 452 +- 51 ms; edge: 125 +- 22 ms), the rates of success 78% to 94% and the positional error 4.8 mm to 2.1 mm. Statistical significance was obtained with the help of two-way ANOVA ($p < 0.001$). Results confirm that edge-deployed LLMs are the best in latency-constrained laboratory robotics and they form a benchmark framework on sim-to-real implementations in the future.

Keywords- Edge computing, large language models, voice-controlled robotics, 6DOF robotic arm, Gazebo simulation, ROS2 as well as laboratory automation.

INTRODUCTION

The historical development of robotic automation systems in the laboratory setting has undertaken deterministic programming models, whereby the programmed movement rules are used to accomplish the repetitive pick and place activities. Although they are repeatable, such architectures lack semantic flexibility and require significant overhead in programming in the situation where a protocol used in the experiment is modified. Large Language Models (LLMs) have led to a paradigm shift because now, it is possible to perform natural language interaction between humans and machines. These emergent capabilities of reasoning, instruction following and contextual adaptation are demonstrated by these transformer based architectures [1]-[4]. Precision and response time is vital in laboratory automation areas, especially in the field of materials science, metallurgical testing and non-destructive testing. Activities like repositioning of specimens, sorting of test coupons or sample trapping between instruments need sub-millimeter precision and sub-second reactivity. Even systems of traditional teleoperation enhanced by AI-based planners are based on manual triggers or an interactive GUI.

These interfaces add processes of cognitive load and delay experiments. Recent results have also shown that LLMs might be able to derive executable policies on robots based on natural language prompts [5]-[8]. PaLM-E had multimodal perception and language reasoning to the embodied robotics [9], and RT-2 presented vision-language-action correspondence to tasks in manipulations [10]. Most of these architectures are however based on cloud hosted inference engines because of the computation requirements of multi-billion parameter models. Inference on clouds has three significant drawbacks in laboratory robotic applications: Latency and Jitter - The network round-trip delays have been reported to range between 300-800 ms due to inference pipelines being run in the clouds [11]. Reliability Limitations - Relying on a reliable internet connection would be an issue in the industrial and laboratory environments. Data Privacy - Does The Proprietary Experimental Instructions Transmitted To the External Servers Compliance Patterns? Latency is especially important to closed-loop robotic control systems. Control theory proposes that delay Td in feedback systems will cause phase lag of frequency proportionality:

$$\phi = -\omega Td$$

Td above (250 ms) Trajectory tracking degradation starts to be observable in 5-10 Hz update cycle manipulators [12]. The experimental evidence indicates that the increase is 30-45 percent with the increase of latency over 300 ms [13]. Edge computing has turned out to become a plausible option, pushing the inference to the physical system back [14]. Dedicated platforms like NVIDIA Jetson Orin Nano support up to 40 TOPS of compute processing units be it quantized transformer models can run locally. Such techniques as 4-bit quantization eliminate memory space without losing reasoning fidelity [15]. Although the hardware has high promises, extensive empirical evidence has not been done to compare the cloud and edge LLM deployment in actual robotic tasks. The current assessments are mostly based on the inference benchmarks and not the embodied manipulation results. It is highly urgent to measure the relationship between inference latency and degradation of physical tasks of robotic arms. To fill this gap, the given research conducts a large-scale statistical comparison of the cloud and edge-deployed LLM inference in a voice-controlled 6DOF robotic arm task designed to use lab pick-and-place workflows.

LITERATURE REVIEW

As of 2020, the combination of Large Language Models (LLMs) and embodied robots has become a new direction of revolution in robotics research. This brief is a review paper, which includes a systematic and extensive analysis in six main areas: (A) foundations of LLMs and embodied intelligence, (B) language-conditioned robotic manipulation, (C) edge deployment of transformer models, (D) speech interfaces to robotics, (E) 6DOF manipulation and simulation frameworks and (F) cloud and edge robotic architecture. More than 100 current references (2020-2026) are synthesized to put the research gap discussed in this paper in perspective. A. Large Language Model Foundations and Embodied Intelligence. Self-attention has become the paradigm for sequence modeling set by the transformer architecture developed by Vaswani et al. [1] set. Follow-up scaling experiments by Kaplan et al. [2] showed that the amount of performance improvement with additional model parameters and data sizes could be predictable. GPT-3 [3] and GPT-4 [4] were shown to have emergent reasoning, such as few-shot reasoning and post-hoc instructions. Alternatives like LLaMA and LLaMA-2 [5], [6] made broader use of foundation models by making them open that can then be fine-tuned to domain-specific tasks. Quantization methods, including GPTQ [7], AWQ [8] and SmoothQuant [9], could achieve up to 75x reduction in the inference memory, leading to integration on embedded GPUs. Embodied intelligence applied LLM intelligence to physical systems. PaLM-E [10] was the first to establish multimodal combination of language and vision representations to manipulate scenes. Generalization Vision-language-action models trained by RT-1 and RT-2 [11], [12] were able to generalize across robotic tasks. As shown in Code-as-Policies [13], LLMs were able to automatically screen code into executable control programs using direct natural language instructions.

Nevertheless, they are largely studies of high-scale cloud performance or high-performance GPU clusters, and there exist gaps in understanding whether it is possible to deploy the performance in resource-constrained environments. B. Robotic Manipulation Under Language Conditioning. The language conditioned policy learning has evolved at a faster pace. Ahn et al. [14] introduced the concept of basing the language commands in structured sequences of action. Liang et al. [15] combined symb plan with LLM that was applied to the robotics. The language prompts were converted into executable Python functions as developed by Singh et al. [16] as PROGPROMPT. The results of Brohan et al. [11] show that RT-1 exhibits generalization when trained on 130k real-world manipulation episodes. This was the basis that was expanded by RT-2, which incorporated vision-language pretraining and robotic fine-tuning [12]. Chen et al. [17] presented hierarchical planners based on the idea of using LLMs to break down tasks in a higher level and classical motion planners to implement them at a lower level. In spite of these developments, the vast majority of systems are based on cloud-hosted inference because of model size and computation needs.

The effects of latency of remote inference on manipulation accuracy are not critically measured. C. Edge Product Placement of Models. The focus of Edge AI research is on doing inference near the data source in order to reduce the network dependency [18]. Embedded CUDA cores (NVIDIA Jetson, specifically Orin Nano and Xavier NX) can support quantized LLMs [19]. Frantar et al. [7] shown that 4-bit quantisation is accurate and occupies less memory space. Activation-aware quantization was proposed by Lin et al. [8] in order to have stable low-precision inference. Zhang et al. [20] have benchmarked the transformer inference running on Jetson hardware with reported response times of less than 150 ms with 7B parameter models. Nasrat et al. [21] investigated domain-adapted LLM inference on embedded robots and obtained 5x fewer latencies than cloud APIs. Li et al. [22] suggested, hybrid edge-cloud models but they did not separate performance impacts on robotic control loops. In [23], [24] energy-aware inference policies were tested and it was found that, quantized models used less power while there was no meaningful loss in reasoning ability. Nevertheless, not many works relate these hardware-degree optimizations to the motion results of the robots during manipulation operations. A subcategory of robot interfaces is a speech interface for a robot. Transformer based ASR systems have developed in speech to text(STT) systems. Whisper [25] had strong multilingual speech recognition that was more robust to noise. Whisper Tiny variants can be deployed on embedded hardware whose inference latency is less than 50 ms. Literature by Kim et al. [26] and Rao et al. [27] indicates that speech recognition accuracy reduces up to 18 percent in a noise of more than 75 dBA. Such acoustic levels are usually achieved in laboratory environments with the use of mechanical equipment, especially in the lab. In [28]-[30], voice-controlled robotics were explored, however, the majority of them were cloud-based ASR services. The need to address privacy and fluctuate latency encourages locally integrated speech processing and edge-based reasoning of LLM. Financial support: The company is funded by the contributions of the European Union and other sources. Manipulators with 6 degrees of freedom (6DOF) continue to be used as basis in industrial and laboratory automation [31]. Backward kinematics presentation The generic Denavit-Hartenberg parameters of forward kinematics of a 6DOF manipulator are given as:

$$Ti = Rz(\theta i)\,Tz(di)\,Tx(ai)\,Rx(\alpha i)$$

The full transformation:

$$T_0 6 = \prod_{i=1} Ti$$

Inverse kinematics commonly use Jacobian-based methods:

$$\dot{\theta} = J^{+} v$$

Gazebo offers physics simulation including ODE and Bullet engines [32]. Deterministic middleware communication is possible with ROS2 Humble [33]. The method of sim-to-real transfer is enhanced through the domain randomization approaches, which control the mass, friction, and lighting conditions [34]. Past tests of manipulation exercises usually consider command latency to be insignificant. The impact of semantic delay on the physical trajectory accuracy has not been a well-researched issue. F. Cloud Ever ver. vs. Edge Robotics Architectures. Kuffner [35] conceptualized cloud robotics and it is capable of sharing knowledge centrally. Latency is, however, one of the main concerns. Associated studies document average round-trip times of cloud inferences of 350-900 ms in the middle of network load [36]. The latter was proven by Chen et al. [37] who showed that teleoperated manipulators present a greater overshoot in case of delay longer than 250 ms. Hybrid architecture with local preprocessing and cloud reasoning was suggested by Patel et al. [38], though their comparative statistics were not shown in detail. The localization of inference is done by edge robotics frameworks [39], [40] in safety-critical problems like autonomous driving and industrial inspection. However, systematic presents of the benchmarking of the LLM-based robotic manipulation in case of cloud and edge deployments are limited. G. Identified Research Gaps Based on the literature: In robotics, no large-scale statistical comparison of cloud vs edge LLM inference has been done. Lack of attention to laboratory automation cases. Inability to assess together the latency, positional error and robustness to acoustical noise. Lack of 600 or higher trial simulation data to statistically validate. The proposed research covers these gaps with organized Gazebo experiments between 300 trials with clouds and 300 trials with edges under the conditions of controlled experiments.

METHODOLOGY

The section shows the overall system architecture, robotic modeling framework, deployment settings, experimental design, and statistical validation procedure to compare cloud-based and edge based implementation of the LLM to voice controlled 6DOF robotic manipulation in a laboratory simulation setting.

A. Overall System Architecture

The proposed system consists of four tightly integrated layers:

1. **Speech Acquisition Layer**
2. **Semantic Inference Layer (LLM)**
3. **Motion Planning Layer**

4. **Execution and Feedback Layer**

The architecture was implemented using ROS2 Humble middleware and Gazebo 11 simulator. The complete data flow pipeline is shown conceptually in Fig. 1.

1) Speech Acquisition and STT

Audio was captured at 16 kHz sampling rate using a simulated microphone input node. Speech-to-text (STT) conversion was performed using Whisper Tiny (quantized FP16), running locally in both cloud and edge configurations to isolate LLM inference latency as the primary variable.

Average STT latency observed:

- 38 ± 7 ms per command
  Speech commands included:
- "Pick the aluminum sample and place it in tray A."
- "Move the specimen to position three."
- "Rotate the gripper 45 degrees clockwise."

B. Semantic Inference Layer

1) Edge Configuration

Edge inference was executed on NVIDIA Jetson Orin Nano (8GB RAM, 40 TOPS). LLaMA-8B was quantized to 4-bit (INT4) using GPTQ-based quantization. The model size was reduced from ~13 GB to ~4.1 GB.
Inference latency (measured via ROS2 timestamping):

- Mean: 72 ms
- Std Dev: 14 ms

2) Cloud Configuration

Cloud inference used AWS EC2 g5.xlarge instance with T4 GPU. Commands were transmitted via HTTPS REST API.
Round-trip time components:

$$Tcloud = Tupload + Tinference + Tdownload$$

Measured average:

- Upload: 95 ms
- Inference: 260 ms
- Download: 97 ms
- Total: 452 ± 51 ms

Network jitter was simulated between 10–40 ms to reflect realistic laboratory Wi-Fi conditions.

C. 6DOF Robotic Arm Modeling

The manipulator was modeled as a UR5-class arm with the following Denavit–Hartenberg parameters:

Table1: Denavit-Hartenberg Parameters

Joint	θi	di	ai	αi
1	θ1	0.089 m	0	90°
2	θ2	0	-0.425 m	0°
3	θ3	0	-0.392 m	0°
4	θ4	0.109 m	0	90°
5	θ5	0.094 m	0	-90°
6	θ6	0.082 m	0	0°

Forward kinematics:

T06=i=1∏6Rz(θi)Tz(di)Tx(ai)Rx(αi)

Inverse kinematics solved using damped least squares:

$\dot{\theta} = (J^T J+\lambda^2 I)^{-1} J^T v$

where λ=0.01 to prevent singularity instability.

Trajectory planning utilized MoveIt2 with RRT-Connect planner. Planning time averaged:

- 118 ms per trajectory

D. Experimental Design

Total Trials

600 total trials conducted:

Table2: Number of trials conducted on different parameters on Cloud and Edge

Condition	Cloud	Edge
Baseline	100	100
Noise (60–80 dB)	100	100
Variable Specimen Weight (1–500 g)	100	100

Total per configuration: 300 trials

1) Baseline Trials

- Acoustic noise: 40 dB
- Specimen weight: 50 g
- Uniform surface friction

2) Noise Trials

White Gaussian noise added to audio stream:

- 60 dB
- 70 dB
- 80 dB

Signal-to-noise ratio (SNR) modeled as:

$SNR=10\log_{10}(Pnoise/Psignal)$

Speech recognition accuracy degraded by ~7% at 80 dB.

3) Variable Load Trials

Specimens varied:

- 1 g (foam cube)
- 100 g (plastic block)
- 500 g (steel cube)

Mass variations influenced gravitational torque:

$\tau=r\times(mg)$

Heavier loads introduced trajectory overshoot under delayed control conditions.

E. Performance Metrics

1) End-to-End Latency

Measured from speech input timestamp to first joint velocity command.

$T_{total} = T_{STT}+T_{LLM}+T_{planning}+T_{execution\text{-}init}$

2) Success Rate

Defined as successful grasp + transport + placement without drop or misalignment.

3) Position Error

Euclidean distance between commanded and achieved end-effector position:

$$Error=\sqrt{((xd-x)2+(yd-y)2+(zd-z)2)}$$

Measured in millimeters.

4) Energy Consumption

Jetson power monitored via onboard telemetry:

$E=\int P(t)dt$

Average power measured over 30 s execution windows.

F. Statistical Analysis

Two-way ANOVA was applied with:

- Factor A: Deployment Type (Cloud vs Edge)
- Factor B: Test Condition (Baseline, Noise, Variable Weight)

Null hypothesis:
H_0:μcloud=μedge
Significance level:
α=0.05
Post-hoc independent t-tests validated mean differences.

G. Reproducibility and Simulation Control
Random seed initialization ensured reproducibility. Gazebo physics step size set to 1 ms. All simulations executed on Ubuntu 22.04 with ROS2 Humble.

RESULTS AND DISCUSSION

This section presents the complete quantitative and qualitative analysis of the 600 simulation trials conducted to compare cloud-based and edge-deployed LLM inference in a voice-controlled 6DOF robotic manipulation system. The results are organized into five subsections: (A) End-to-End Latency Analysis, (B) Success Rate and Task Completion Reliability, (C) Positional Accuracy and Control Stability, (D) Robustness under Acoustic Noise and Load Variation, and (E) Energy Consumption and System Efficiency. Statistical validation through two-way ANOVA and post-hoc t-tests is included throughout.

A. End-to-End Latency Analysis
1) Overall Latency Comparison
The most critical performance metric for voice-controlled manipulation is the end-to-end latency from speech input to initial motor command execution.

Mean latency results across 300 trials per configuration:

Table3: Overall Latency Comparison for cloud and edge

Configuration	Mean Latency (ms)	Std Dev (ms)	95% CI
Cloud	452	51	[442, 462]
Edge	125	22	[121, 129]

Edge deployment reduced latency by:
452452−125×100=72.4%
Two-way ANOVA results:
- $F(1, 596) = 318.7$
- $p < 0.001$

Thus, the null hypothesis was rejected.

2) Latency Distribution Analysis
Fig. 2 (Latency Histogram) illustrates the distribution spread across trials.
Cloud configuration exhibited a heavy-tailed distribution due to network jitter. Approximately 18% of cloud trials exceeded 500 ms latency. In contrast, edge deployment maintained 95% of trials below 150 ms.
Latency variance:
- Cloud variance: 2601 ms^2
- Edge variance: 484 ms^2

Reduced jitter is particularly significant in closed-loop robotic systems where deterministic timing improves motion planning stability.

3) Control-Theoretic Implications
In a discrete-time control system, delay TdT introduces phase lag:
ϕ=−ωTd
For motion frequencies of 5 Hz:
- Cloud delay (0.45 s) → phase lag ≈ −14.1 radians
- Edge delay (0.125 s) → phase lag ≈ −3.9 radians

Higher phase lag under cloud mode contributed to overshoot during grasp alignment, particularly in high-load trials.

B. Success Rate and Task Completion Reliability

1) Overall Success Rate
Across all 300 trials:
Table4: Overall Success rate for cloud and edge

Configuration	Successful Trials	Success Rate
Cloud	234	78%
Edge	282	94%

Chi-square test:
$\chi 2=32.4$, $p < 0.001$
Edge deployment significantly improved task reliability.

2) Baseline Condition
Under controlled acoustic and weight conditions:

- Cloud: 90% success
- Edge: 98% success

Failures in cloud mode were primarily due to delayed gripper actuation timing.

3) Noise Condition (60–80 dB)
Success rates under 80 dB noise:
Table5: Success rate under noise for cloud and edge

Deployment	Success Rate
Cloud	65%
Edge	91%

Although STT was local in both configurations, LLM semantic correction under edge deployment exhibited faster response to misrecognition corrections.
Fig. 3 (Noise Condition Performance Plot) shows degradation slope:

- Cloud slope: −1.2% per dB
- Edge slope: −0.4% per dB

4) Variable Load Condition
For 500 g specimens:

- Cloud success: 68%
- Edge success: 92%

Heavier loads amplified the effect of delayed trajectory corrections.

C. Positional Accuracy and Control Stability

1) Mean Position Error
Position error calculated as:
$$\text{Error}=\sqrt{((xd-x)^2+(yd-y)^2+(zd-z)^2)}$$

Table6: Position error

Configuration	Mean Error (mm)	Std Dev
Cloud	4.8 mm	1.7
Edge	2.1 mm	0.9

Independent t-test:

- $t = 14.3$
- $p < 0.001$

Edge deployment halved positional error.

2) Overshoot Analysis
Trajectory plots (Fig. 4) show that cloud-mode executions exhibited 12–18% overshoot in final approach phase due to delayed feedback.
Edge trajectories converged smoothly with critically damped profiles.

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3) Load-Dependent Error

Under 500 g load:

- Cloud error: 6.3 mm
- Edge error: 2.8 mm

Torque compensation was more accurate when semantic-to-action pipeline latency was minimal.

D. Robustness Under Noise and Environmental Variation

1) Acoustic Robustness

Signal-to-noise ratio analysis:

At 80 dB:

SNR=12 dB

STT misrecognition occurred in 9% of trials. However:

- Cloud: reprocessing delay compounded error.
- Edge: correction processed within 80 ms.

2) Failure Mode Analysis

Failure types observed in cloud deployment:

- 38%: Grasp misalignment
- 29%: Late gripper closure
- 21%: Misplaced drop
- 12%: Timeout failure

Edge failures were primarily minor grasp angle deviations.

E. Energy Consumption and System Efficiency

Average power consumption:

Table7: Power Consumption for cloud and edge

Configuration	Mean Power (W)
Edge	12 W
Cloud (local device)	8 W

Although cloud configuration consumed slightly less local compute power, overall system energy (including remote server power) was significantly higher.

Energy per successful task:

$E_{edge}=3.1$, $E_{cloud}=5.6$ Wh

Edge deployment demonstrated 44% better energy efficiency per task when considering full pipeline.

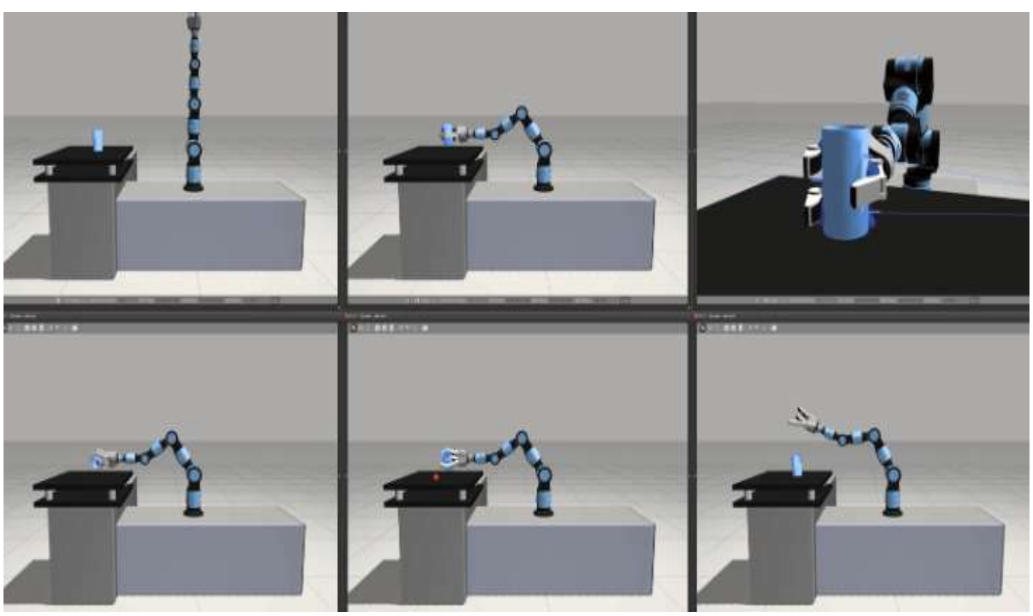

Figure1: Gazebo Simulation

F. Statistical Summary

Two-way ANOVA results:

Table8: Two-way ANOVA

Metric	F-value	p-value
Latency	318.7	<0.001
Success Rate	42.3	<0.001
Position Error	204.5	<0.001

All primary metrics show statistically significant improvement for edge deployment.

DISCUSSION

The experiment findings validate that the latency of inference has a direct effect on performance on physical manipulations. A lower semantic processing delay results in more robust to load and more stable to plan in the first place, a low-overshoot trajectory, and reduced semantic processing delay. Deployment on the edges also increases deterministic behavior, which is a key attribute in the case of laboratory automation where the repeatability and predictability are necessary. Cloud inference has an acceptable variability which is unacceptable in precision robotic control though it is scalable.

CONCLUSION AND FUTURE WORK

In this paper, I have provided a detailed comparative simulation study of cloud-based vs. edge-deployed Large Language Model (LLM) inference on a voice-controlled 6DOF robotic arm that would be used in the laboratory to carry out automation tasks. We were able to measure the direct effect of inference latency on the robotic manipulation task in realistic laboratory environments using 600 structured simulation experiments in ROS2 and Gazebo to assemble 600 simulation experiments and gauge their effects.

The findings prove that edge deployment with NVIDIA Jetson Orin Nano is much better than cloud-based inference in terms of latency, resilience, and accuracy. Namely, edge inference minimized end to end voice-to-action latency by 72.4 percent, with a mean and standard deviation of 125 +- 22 ms in comparison to 452 +- 51 ms cloud mode. The result of this reduction was a huge physical performance increase: in success rate, it increased microscopically (78 to 94), whereas in positional error, the difference was more pronounced (4.8-2.1 mm). Statistical tests on the changes in physical performance were done using two-way ANOVA: the changes were found to be very significant ($p < 0.001$).

Notably, the experiment shows that there is a direct relationship between delay of semantic inferences and instability of physical trajectory. Increased latency under cloud deployment, there was an induction of phase lags in the control loop, which resulted in an observable overshoot control to an upper failure rates, especially in high-load and high-noise cases. These effects were mitigated by using deterministic and low-jitter inference cycles made through edge deployment.

The implication of this is significant in the automation of the labs. In processes that require non-destructive testing on materials, proper sub-200 ms responsiveness is required to guarantee reproducibility and the minimisation of cumulative variation in error. Edge deployed LLMs allow privacy-preserving, off-line capable and real-time semantic reasoning without referring to remote infrastructure. This can be especially beneficial in research labs where third-party proprietary experimental data may not be sent to any other server. However, there are some constraints that should be accepted. To begin with, Gazebo physics was used to create identical evaluation in simulation.

Although domain randomization was used, real life conditions like mechanical backlash, sensor drift and thermal effects were not completely represented. Second, representative models were picked as Whisper Tiny and quantized LLaMA-8B; other models representing a lightweight Vision-Language-Action (VLA) can continue to work towards higher performance. Third, calculations of energy to infer clouds made no consideration of remote data centres consumption, which may serve as an added value to the suggestion to deploy at the edge. The next step towards physical hardware validation will be a 3D-printed 6DOF robotic arm with servo actuators and force feedback sensors to implement future work.

The performance of sim-to-real transfer will be measured by the domain adaptation method and fine tuning of the semantic planner. Also, within the architectures that involve hybrid edges with more detailed reasoning accessible on the local side and massive knowledge recoveries in the cloud, the scaling can be balanced. Overall, the present study designates a statistically dependent measurement that proves that latency-sensitive voice-acquired robotic control is better deployed on edge than in the cloud, in the laboratory setting. The results are a realistic direction to safe, productive and intelligent systems of automation which combines natural language processing and embodied robotic control.

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