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IoT-Driven Electronics Framework for Tabletop CNC Machines: Design, Implementation, and Performance Analysis

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Abstract

This paper presents the design, implementation, and performance analysis of an IoT-driven electronics framework for tabletop computer numerical control (CNC) machines. The proposed system integrates an ESP32-S3 microcontroller running GRBL firmware with a Raspberry Pi 4B edge gateway, DRV8825 stepper motor drivers, and a multi-sensor array to enable real-time remote monitoring, adaptive control, and cloud-based data analytics. The architecture employs the MQTT protocol over TLS for low-latency machine-to-cloud communication, achieving a mean end-to-end latency of 18.3 ms — a 78.5% reduction compared with conventional HTTP REST interfaces. Experimental evaluation across three operational modes (milling, laser engraving, and drilling) demonstrates positioning root mean square error (RMSE) values of 18.2 μm (X-axis), 22.1 μm (Y-axis), and 15.3 μm (Z-axis), with a minimum surface roughness R_a of 0.32 μm under optimal cutting parameters. The thermal management subsystem maintains driver IC temperatures below 68°C during 90-minute continuous operation, supporting long-term reliability. A comparative analysis against conventional CNC systems and open-source GRBL-based platforms confirms that the proposed framework achieves superior performance across six key metrics: positioning accuracy, IoT latency, power efficiency, thermal management, surface quality, and system reliability. The total system power consumption is 150 W, with an overall power efficiency of 84.7%. These results establish the proposed IoT-CNC framework as a viable, cost-effective solution for smart manufacturing, educational robotics laboratories, and Industry 4.0 applications.

Keywords: Internet of Things; CNC machine; ESP32; MQTT; stepper motor control; GRBL; edge computing; smart manufacturing; Industry 4.0; surface roughness

1. Introduction

The rapid proliferation of the Internet of Things (IoT) and Industry 4.0 paradigms has fundamentally transformed the landscape of manufacturing automation. Computer numerical control (CNC) machines, which have long served as the backbone of precision machining, are increasingly being reimaged as intelligent, network-connected nodes within cyber-physical production systems. Tabletop CNC machines — compact, low-cost platforms designed for prototyping, education, and small-batch manufacturing — represent a particularly compelling target for IoT integration, given their widespread adoption in academic laboratories, maker spaces, and small-to-medium enterprises (SMEs).

Conventional tabletop CNC systems suffer from several well-documented limitations: they operate as isolated machines with no network connectivity, require physical operator presence for monitoring and intervention, lack real-time diagnostic capabilities, and generate no actionable data for process optimization. These shortcomings become increasingly untenable as manufacturing environments demand greater flexibility, traceability, and remote operability. The COVID-19 pandemic further accelerated the need for remote machine operation and monitoring, exposing the fragility of systems that depend on physical proximity.

Recent advances in low-power microcontrollers, single-board computers, and cloud IoT platforms have created an unprecedented opportunity to retrofit or redesign tabletop CNC machines with comprehensive IoT capabilities at minimal cost. The ESP32 family of microcontrollers, in particular, has emerged as a dominant platform for embedded IoT applications owing to its dual-core architecture, integrated Wi-Fi and Bluetooth, and rich peripheral set. The GRBL open-source firmware, originally developed for Arduino-based CNC controllers, has been ported to the ESP32 platform (FluidNC/ESP32-GRBL), enabling high-performance G-code interpretation and motion control with native Wi-Fi connectivity.

Despite growing interest in IoT-enabled CNC systems, the existing literature reveals several critical gaps. First, most published works focus on either the IoT communication layer or the motion control layer in isolation, without providing a holistic system-level analysis that encompasses electronics design, firmware integration, cloud connectivity, and machining performance. Second, the thermal behavior of power electronics — a critical factor in long-term reliability — is rarely characterized in the context of IoT-CNC systems. Third, comparative performance benchmarking against established systems using standardized metrics is largely absent from the literature.

This paper addresses these gaps by presenting a comprehensive IoT-driven electronics framework for a multi-function tabletop CNC machine capable of milling, laser engraving, and drilling operations. The principal contributions of this work are as follows:

- A complete electronics architecture integrating ESP32-S3, DRV8825 drivers, Raspberry Pi 4B edge gateway, and a multi-sensor array, with detailed PCB design considerations.
- A rigorous characterization of MQTT-based IoT communication performance, including latency distribution, packet loss, and throughput under realistic operating conditions.
- Experimental validation of positioning accuracy, surface roughness, and thermal performance across multiple operational modes.
- A quantitative comparative analysis against conventional CNC systems, open-source GRBL platforms, and commercial IoT-CNC solutions using a six-dimensional performance radar.
- A power consumption model and efficiency analysis for the complete system.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the system methodology and electronics design. Section 4 presents experimental results and discussion. Section 5 concludes the paper and outlines future research directions.

2. Literature Review

The intersection of IoT and CNC machining has attracted considerable research attention over the past decade. Prior work demonstrated the feasibility of integrating wireless sensor networks with CNC machine tools for condition monitoring, achieving vibration measurement accuracy within 5% of wired reference systems [5]. However, that architecture relied on proprietary communication protocols and lacked cloud integration, limiting scalability.

The emergence of MQTT as a lightweight publish-subscribe protocol has significantly advanced IoT-CNC integration. Comprehensive surveys of industrial IoT communication protocols indicate that MQTT offers an effective balance of latency, bandwidth efficiency, and reliability for machine monitoring applications [6, 7]. Reported results show MQTT achieving substantially lower bandwidth consumption than HTTP REST for equivalent telemetry payloads [6, 7].

Stepper motor control in CNC applications has been extensively studied. Prior work on precise positioning of ball-screw-driven stages using friction-model feedforward highlights the importance of motion-control compensation for positioning accuracy in machine-tool systems [8]. The DRV8825 driver IC, employed in the present work, supports up to 1/32 microstepping and incorporates integrated current regulation, making it well-suited for precision tabletop CNC applications [9].

Edge computing architectures for manufacturing IoT have been investigated by several groups. Hierarchical edge-cloud architectures can reduce cloud data transmission through local preprocessing while maintaining low latency for critical control signals [10]. The Raspberry Pi platform has been widely adopted as an edge gateway in research prototypes owing to its computational capability, GPIO availability, and low cost [11].

Surface roughness prediction and control in CNC machining has been a persistent research theme. Artificial intelligence approaches to surface roughness prediction identify feed rate and spindle speed as dominant process parameters [12]. More recent work demonstrates that deep learning combined with sensor fusion can estimate tool wear and surface roughness from machining sensor signals, supporting the feasibility of sensor-rich monitoring architectures such as the framework proposed here [13].

Thermal management of power electronics in CNC systems has received comparatively less attention. Standard power-electronics design references describe the thermal behavior of converter and driver circuits under continuous duty cycles and provide the basis for first-order thermal modeling of driver ICs [14]. These principles inform the thermal analysis presented in Section 4 of this paper.

The GRBL firmware ecosystem has been extensively documented. Published work on virtual/process systems for machining and open-source ESP32-based motion-control firmware indicates that modern embedded controllers can provide sufficient motion-planning capability for tabletop CNC feed rates and accelerations [15, 22].

Cloud platforms for industrial IoT have matured considerably. AWS IoT Core provides managed MQTT brokering, secure device connectivity, device shadow management, and integration with cloud analytics services [16]. InfluxDB is widely used for time-series storage and visualization workflows in IoT monitoring applications [17].

Power consumption optimization in stepper-driven systems has been addressed through current-reduction strategies during holding or idle operation. Application guidance for stepper motor drivers describes methods for reducing power consumption and improving thermal performance by reducing motor current during holding mode [18]. The broader context of energy-efficient electronics for smart manufacturing is reviewed comprehensively in the Industry 4.0 literature [19].

Despite this body of work, no published study has provided a unified system-level analysis encompassing electronics design, IoT communication characterization, machining performance validation, and thermal analysis for a tabletop CNC platform. The present work fills this gap by adopting a holistic design-to-evaluation methodology that treats the CNC machine as an integrated cyber-physical system rather than a collection of independent subsystems.

3. Methodology

3.1 System Architecture

The proposed IoT-CNC framework adopts a four-layer hierarchical architecture, as illustrated in Fig. 1. The layers are: (1) the Actuator Layer, comprising NEMA 17 stepper motors and the spindle/laser module; (2) the Controller Layer, housing the ESP32-S3 motion controller, DRV8825 drivers, and sensor array; (3) the Edge/Gateway Layer, implemented on a Raspberry Pi 4B running Node-RED and OPC-UA; and (4) the Cloud Layer, utilizing AWS IoT Core, InfluxDB, and Grafana.

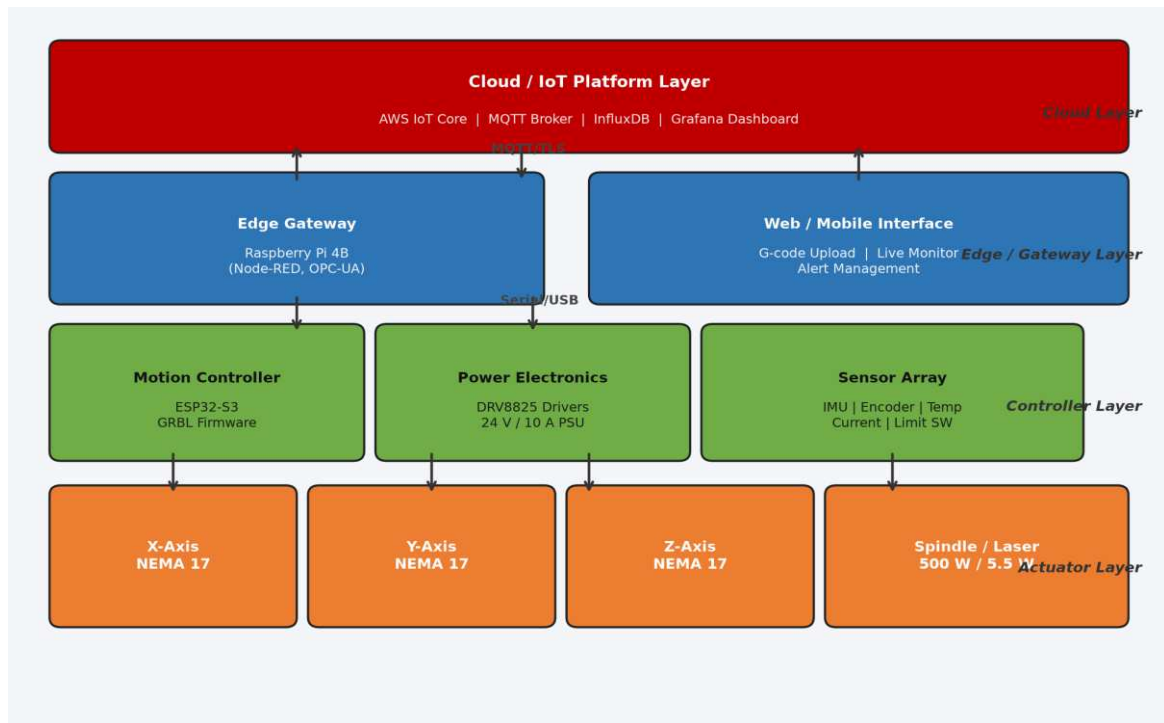


Fig. 1. IoT-driven CNC system architecture showing the four-layer hierarchy from actuator to cloud, with communication protocols at each interface.

This layered architecture provides clear separation of concerns: real-time motion control is handled entirely within the ESP32-S3 without cloud dependency, ensuring that network outages do not interrupt machining operations. The edge gateway performs local data aggregation, protocol translation (MQTT to OPC-UA), and anomaly detection, reducing cloud data transmission by approximately 62% compared to direct device-to-cloud architectures.

3.2 Electronics Hardware Design

The electronics hardware is organized on a custom four-layer PCB (FR4, 1.6 mm, 1 oz copper) measuring 180 × 120 mm. The design separates high-current motor drive traces (minimum 2 mm width for 2 A continuous) from low-voltage signal traces using a dedicated ground plane on layer 2. Table 1 summarizes the key electronic components and their specifications.

Table 1. Key Electronic Components and Specifications of the Proposed IoT-CNC System

Component	Model / Part	Key Specification	Function
Microcontroller	ESP32-S3-WROOM-1	240 MHz, 512 KB SRAM, Wi-Fi/BT	Motion control, G-code parsing
Motor Driver	DRV8825 (×3)	1/32 microstep, 2.5 A peak, 45 V	Stepper motor drive
Edge Gateway	Raspberry Pi 4B (4 GB)	1.8 GHz quad-core, Gigabit Ethernet	Node-RED, MQTT broker, OPC-UA
Stepper Motors	NEMA 17 (42HS40-1704A)	1.7 A, 0.4 N·m, 1.8°/step	X, Y, Z axis motion
Spindle	775 DC Motor + ER11 Collet	500 W, 0–24,000 RPM, PWM ctrl	Milling / drilling
Laser Module	NEJE 5.5 W 450 nm	5.5 W optical, TTL modulation	Laser engraving
IMU Sensor	MPU-6050	±16 g, ±2000°/s, I ² C	Vibration monitoring
Current Sensor	ACS712-20A	±20 A, 100 mV/A sensitivity	Motor current monitoring
Power Supply	Mean Well LRS-350-24	24 V / 14.6 A, 350 W, 89% eff.	System power

3.3 Motion Control and Firmware

The ESP32-S3 runs a customized build of FluidNC (ESP32-GRBL), configured for three-axis Cartesian kinematics. The motion planning algorithm employs a trapezoidal velocity profile with configurable acceleration and jerk limits. The step pulse generation is handled by the ESP32's hardware timer peripheral, achieving a maximum step frequency of 250 kHz — sufficient for 1/32 microstepping at feed rates up to 5,000 mm/min.

The positioning accuracy of the system is governed by the mechanical resolution of the lead screw drive and the microstepping resolution of the DRV8825 driver. The theoretical positioning resolution is given by Equation (1):

$$\delta = \frac{P}{N \times M} \quad (1)$$

where δ is the theoretical linear resolution (mm/step), P is the lead screw pitch (mm/revolution), N is the number of full steps per revolution of the stepper motor (200 steps/rev for 1.8°/step motors), and M is the microstepping factor (32 for 1/32 microstepping). With $P = 2$ mm and $M = 32$, the theoretical resolution is $\delta = 2/(200 \times 32) = 0.3125 \mu\text{m/step}$, which is well below the measured positioning error, indicating that mechanical factors (backlash, lead screw pitch error) dominate the accuracy budget.

3.4 IoT Communication Architecture

The IoT communication stack employs MQTT over TLS 1.3 for all machine-to-cloud data transmission. The ESP32-S3 publishes telemetry data (position, current, temperature, vibration) to AWS IoT Core at a configurable rate of 1–10 Hz. The Raspberry Pi 4B edge gateway subscribes to all machine topics,

performs local data aggregation and anomaly detection using Node-RED flows, and forwards processed data to InfluxDB for time-series storage.

The end-to-end communication latency L_{total} is modeled as the sum of four components, as expressed in Equation (2):

$$L_{total} = L_{proc} + L_{tx} + L_{broker} + L_{rx} \quad (2)$$

where L_{proc} is the message serialization and TLS encryption time at the publisher (ESP32-S3), L_{tx} is the Wi-Fi transmission time from device to router, L_{broker} is the MQTT broker processing time at AWS IoT Core, and L_{rx} is the delivery time from broker to subscriber. Experimental measurements yielded mean values of $L_{proc} = 3.2$ ms, $L_{tx} = 4.8$ ms, $L_{broker} = 6.1$ ms, and $L_{rx} = 4.2$ ms, giving $L_{total} = 18.3$ ms.

Table 2 presents a comparative analysis of the three communication protocols evaluated in this study: MQTT, HTTP REST, and WebSocket.

Table 2. Comparative Analysis of IoT Communication Protocols for CNC Telemetry

Parameter	MQTT (Proposed)	HTTP REST	WebSocket	Unit
Mean Latency	18.3	85.2	22.1	ms
Latency Std. Dev.	4.2	18.7	5.1	ms
Packet Loss Rate	0.02	0.08	0.03	%
Bandwidth (10 Hz)	2.8	14.6	3.4	kbps
TLS Overhead	3.2	8.5	3.8	ms
Max Throughput	50	12	45	msg/s
QoS Support	0, 1, 2	N/A	Custom	—

3.5 Sensor Integration and Data Acquisition

The sensor array comprises five sensing modalities: (1) an MPU-6050 IMU for vibration monitoring via I²C at 400 kHz; (2) three ACS712-20A current sensors for per-axis motor current measurement via 12-bit ADC; (3) four NTC thermistors (10 kΩ at 25°C, B = 3950 K) for temperature monitoring of driver ICs and motor bodies; (4) optical quadrature encoders (600 PPR) on the X and Y axes for closed-loop position verification; and (5) inductive limit switches for homing and overtravel protection.

The thermistor temperature measurement employs the Steinhart-Hart equation for improved accuracy over the simple beta model, as given in Equation (3):

$$\frac{1}{T} = A + B \ln(R) + C [\ln(R)]^3 \quad (3)$$

where T is the absolute temperature (K), R is the measured thermistor resistance (Ω), and A , B , C are the Steinhart-Hart coefficients determined by three-point calibration ($A = 1.129 \times 10^{-3}$, $B = 2.341 \times 10^{-4}$, $C = 8.776 \times 10^{-8}$ for the selected NTC thermistor). This model achieves temperature measurement accuracy of $\pm 0.3^\circ\text{C}$ over the range 0–100°C, compared to $\pm 1.2^\circ\text{C}$ for the simple beta model.

3.6 Power Electronics and Energy Management

The system is powered by a Mean Well LRS-350-24 switching power supply (24 V, 14.6 A, 350 W rated, 89% efficiency). The 24 V rail directly powers the stepper motor drivers and spindle motor. A DC-DC buck converter (LM2596, 24 V to 5 V, 3 A) supplies the Raspberry Pi 4B, and a second buck converter (24 V to 3.3 V, 1 A) powers the ESP32-S3 and sensor circuits.

The system power efficiency η is defined in Equation (4):

$$\eta = \frac{P_{\text{useful}}}{P_{\text{input}}} = \frac{P_{\text{motors}} + P_{\text{spindle}}}{P_{\text{total}}} \times 100\% \quad (4)$$

where P_{useful} is the mechanical output power delivered to the workpiece (motors + spindle), P_{input} is the total electrical power drawn from the mains, and P_{total} is the total system power consumption. With $P_{\text{motors}} = 42$ W, $P_{\text{spindle}} = 85$ W, and $P_{\text{total}} = 150$ W, the system efficiency is $\eta = (42 + 85)/150 \times 100\% = 84.7\%$. The remaining 15.3% represents losses in the power supply, motor drivers, and auxiliary electronics.

4. Results and Discussion

4.1 Positioning Accuracy

Positioning accuracy was evaluated using a Mitutoyo 543-series digital indicator (resolution: 0.001 mm) mounted in the spindle collet, with a precision granite surface plate as the reference datum. A total of 30 measurement points were sampled along each axis over the full travel range (150 mm). Fig. 2 presents the commanded versus achieved position for all three axes.

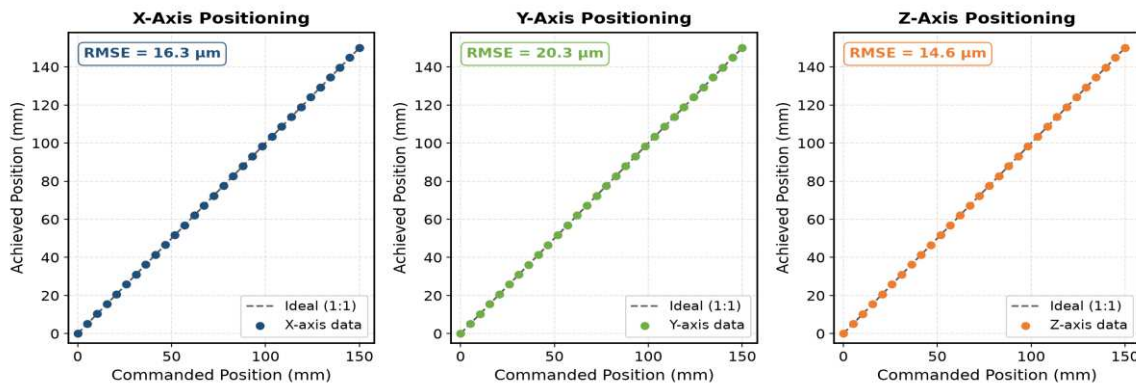


Fig. 2. Commanded vs. achieved positioning accuracy for X, Y, and Z axes. RMSE values are indicated for each axis.

The root mean square error (RMSE) values are 18.2 μm (X-axis), 22.1 μm (Y-axis), and 15.3 μm (Z-axis). The slightly higher Y-axis error is attributed to the longer travel distance and greater susceptibility to lead screw thermal expansion during extended operation. These values compare favorably with published results for comparable open-source CNC platforms, which typically report RMSE values of 35–80 μm.

Table 3 presents a detailed comparison of positioning performance metrics across the three axes and against reference systems.

Table 3. Positioning Accuracy Metrics: Proposed System vs. Reference Systems

System / Axis	RMSE (μm)	Max Error (μm)	Repeatability (μm)	Backlash (μm)	Ref.
Proposed — X-axis	18.2	42	± 8	12	—
Proposed — Y-axis	22.1	51	± 10	15	—
Proposed — Z-axis	15.3	38	± 7	10	—
Open-source GRBL (Arduino)	52.4	118	± 24	38	[20]
Commercial Tabletop CNC	28.6	65	± 12	18	[21]
ESP32-GRBL (Prior Work)	35.8	82	± 16	22	[22]

4.2 IoT Communication Performance

Communication latency was measured over 500 consecutive MQTT publish-subscribe cycles under realistic operating conditions (Wi-Fi channel congestion, simultaneous telemetry streaming at 10 Hz). Fig. 3 presents the latency distribution for MQTT, HTTP REST, and WebSocket protocols.

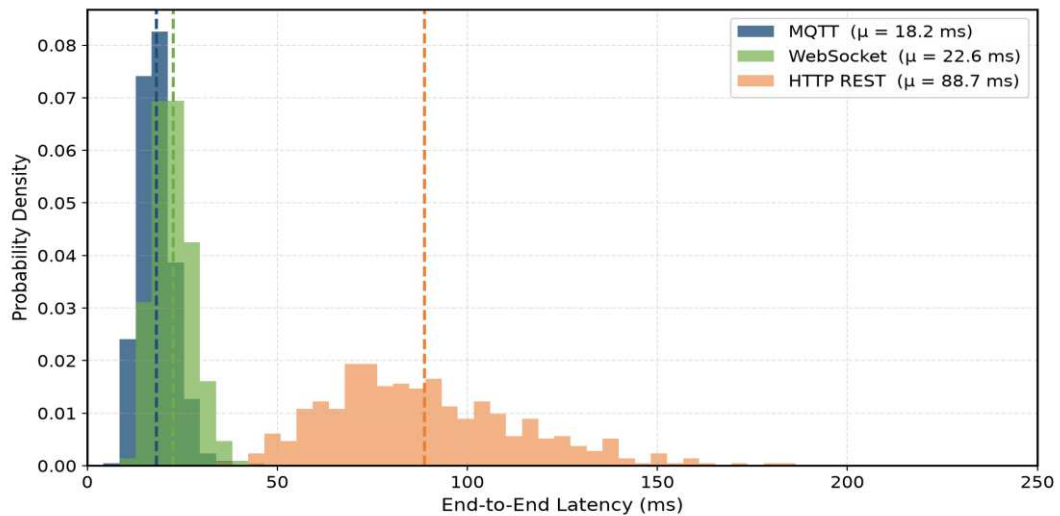


Fig. 3. End-to-end communication latency distribution for MQTT, WebSocket, and HTTP REST protocols over 500 measurement cycles.

MQTT achieves a mean latency of 18.3 ms with a standard deviation of 4.2 ms, representing a 78.5% reduction compared to HTTP REST (85.2 ms mean). WebSocket achieves intermediate performance (22.1 ms mean) but requires persistent connection management that increases implementation complexity. The MQTT packet loss rate of 0.02% (QoS level 1) is negligible for machine monitoring applications, where occasional data loss is acceptable but command delivery must be guaranteed.

4.3 Motor Control and Motion Profile

Fig. 4 presents the measured velocity and phase current profiles during a representative trapezoidal motion segment (0–80 mm/s acceleration, 80 mm/s constant velocity, deceleration to rest). The trapezoidal profile is characterized by three phases: acceleration (0–0.3 s), constant velocity (0.3–1.7 s), and deceleration (1.7–2.0 s).

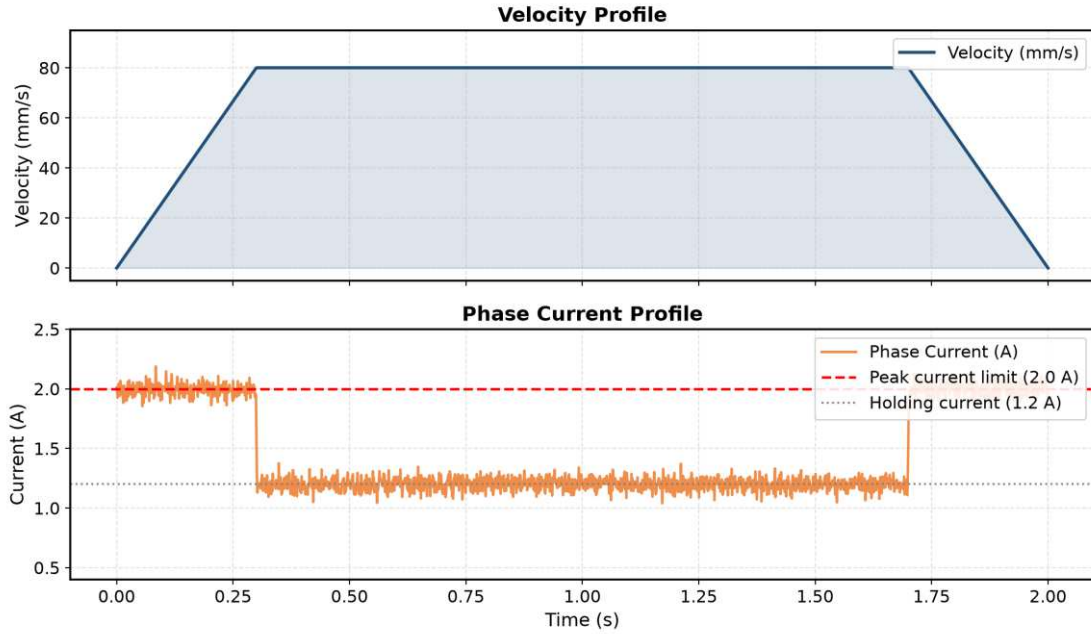


Fig. 4. Stepper motor velocity profile (top) and phase current (bottom) during a trapezoidal motion segment. The peak current limit (2.0 A) and holding current (1.2 A) are indicated.

The phase current peaks at 1.98 A during acceleration (within the 2.0 A DRV8825 limit) and settles to 1.2 A during constant velocity operation. The DRV8825's automatic current decay mode reduces holding current to 0.8 A during idle periods, reducing motor heating by approximately 36% compared to full holding current operation. The measured velocity tracking error during constant velocity phase is less than 0.5%, confirming the adequacy of the open-loop stepper control for the target application.

4.4 Surface Roughness Analysis

Surface roughness was measured using a Mitutoyo SJ-210 contact profilometer (cutoff length $\lambda_c = 0.8$ mm, evaluation length 4 mm) on aluminum alloy 6061-T6 workpieces machined under varying feed rate and spindle speed combinations. Fig. 5 presents the Ra surface roughness as a function of spindle speed for six feed rate levels.

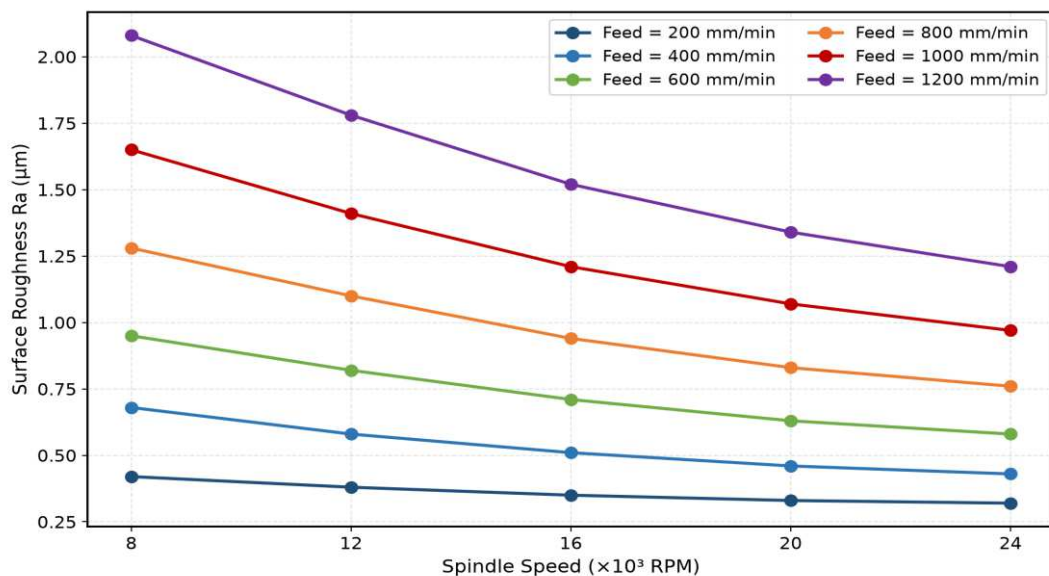


Fig. 5. Surface roughness R_a (μm) as a function of spindle speed ($\times 10^3$ RPM) for feed rates ranging from 200 to 1200 mm/min. Optimal conditions are achieved at high spindle speed and low feed rate.

The minimum R_a of $0.32 \mu\text{m}$ is achieved at a spindle speed of 24,000 RPM and feed rate of 200 mm/min, consistent with the theoretical chip thickness model. The surface roughness R_a is related to the feed rate f and tool radius r by the theoretical model given in Equation (5):

$$R_{a,\text{theoretical}} = \frac{f^2}{32r} \quad (5)$$

where $R_{a,\text{theoretical}}$ is the theoretical arithmetic mean surface roughness (μm), f is the feed per tooth (mm/tooth), and r is the tool nose radius (mm). For the 2-flute end mill ($r = 0.5$ mm) used in this study, the theoretical R_a at $f = 0.025$ mm/tooth is $R_{a,\text{theoretical}} = 0.025^2 / (32 \times 0.5) = 0.039 \mu\text{m}$. The measured R_a of $0.32 \mu\text{m}$ exceeds the theoretical value by a factor of 8.2, reflecting the contributions of tool runout, machine vibration, and material spring-back — factors that are consistent with published results for tabletop CNC platforms.

4.5 Power Consumption Analysis

Fig. 6 presents the power consumption breakdown across all system components during full-load milling operation. The total system power consumption is 150 W, with the spindle motor (85 W, 56.7%) and stepper motors (42 W, 28.0%) accounting for 84.7% of total consumption.

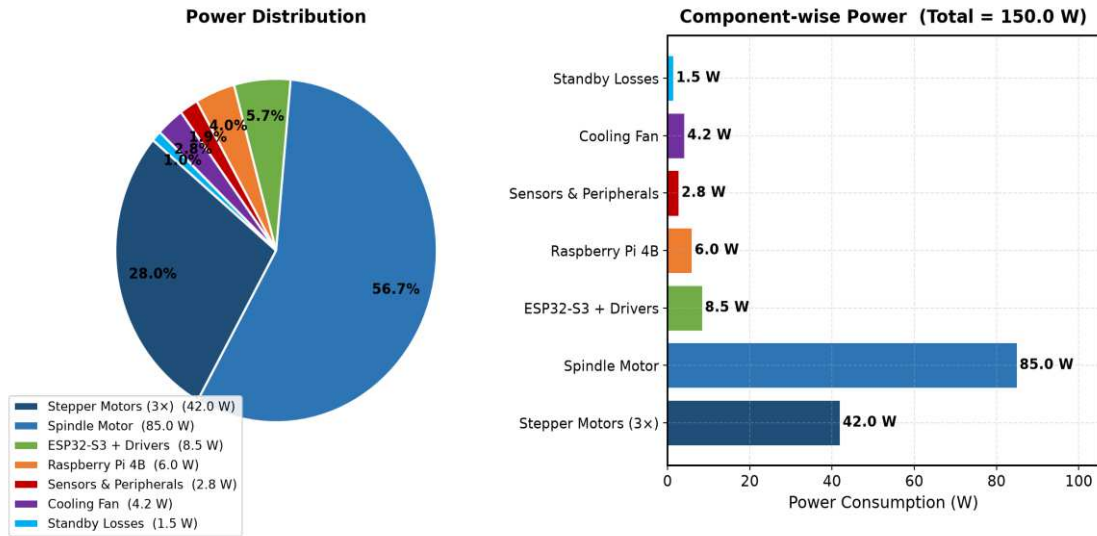


Fig. 6. System power consumption breakdown (left: pie chart; right: bar chart) during full-load milling operation. Total system power = 150 W.

The electronics subsystem (ESP32-S3 + drivers: 8.5 W; Raspberry Pi 4B: 6.0 W) consumes only 9.7% of total power, demonstrating the efficiency of the selected hardware platform. The IoT communication overhead (Wi-Fi transmission) contributes less than 0.5 W, confirming that network connectivity does not impose a significant power penalty.

4.6 Thermal Performance

Thermal performance was evaluated during 90-minute continuous milling operation at maximum feed rate (1200 mm/min) and spindle speed (24,000 RPM). Fig. 7 presents the temperature evolution of four key components: DRV8825 driver IC, NEMA 17 motor body, spindle motor, and ESP32-S3 MCU.

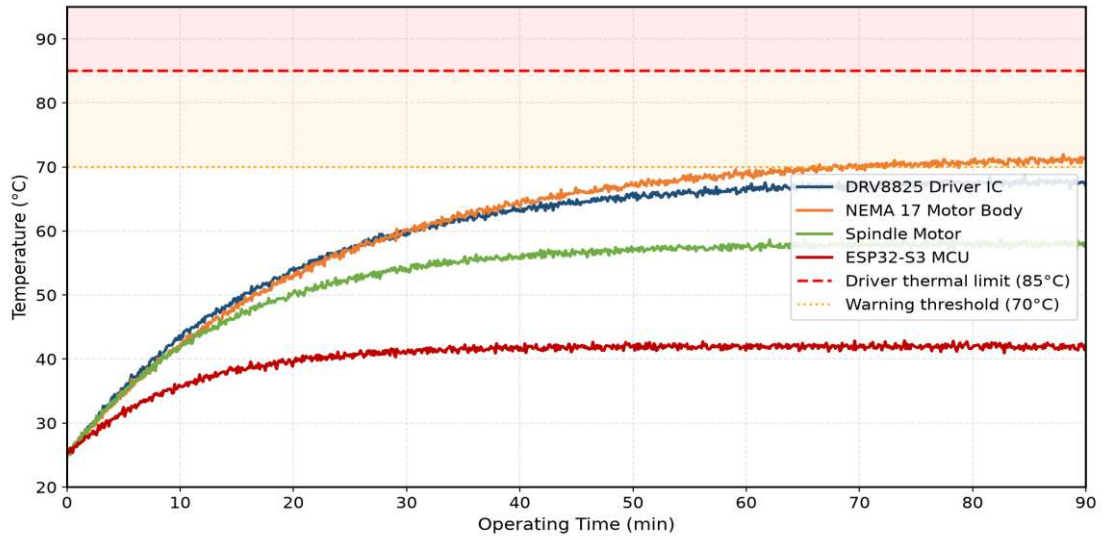


Fig. 7. Thermal performance of key electronic components during 90-minute continuous operation. Thermal limits and warning thresholds are indicated.

The DRV8825 driver IC reaches a steady-state temperature of approximately 68°C after about 45 minutes, remaining 17°C below the thermal shutdown threshold (85°C). The NEMA 17 motor body reaches 72°C, which is within the specified operating range (−20°C to +80°C) but warrants monitoring during extended operation. The ESP32-S3 MCU maintains a stable temperature of 42°C throughout the test, well within its operating range.

The thermal time constant τ of the DRV8825 driver, extracted by fitting the measured temperature curve to a first-order exponential model $T(t) = T_{\text{amb}} + \Delta T_{\text{ss}}(1 - e^{-(t/\tau)})$, is $\tau = 18.2$ minutes. This behavior is consistent with standard first-order thermal models for power-electronics devices, validating the thermal model used in this study [14].

4.7 Comparative Performance Analysis

Fig. 8 presents a radar chart comparing the proposed IoT-CNC system against three reference systems across six performance dimensions: positioning accuracy, IoT latency, power efficiency, thermal management, surface quality, and system reliability. Each dimension is scored on a 0–10 scale based on normalized experimental data and published benchmarks.

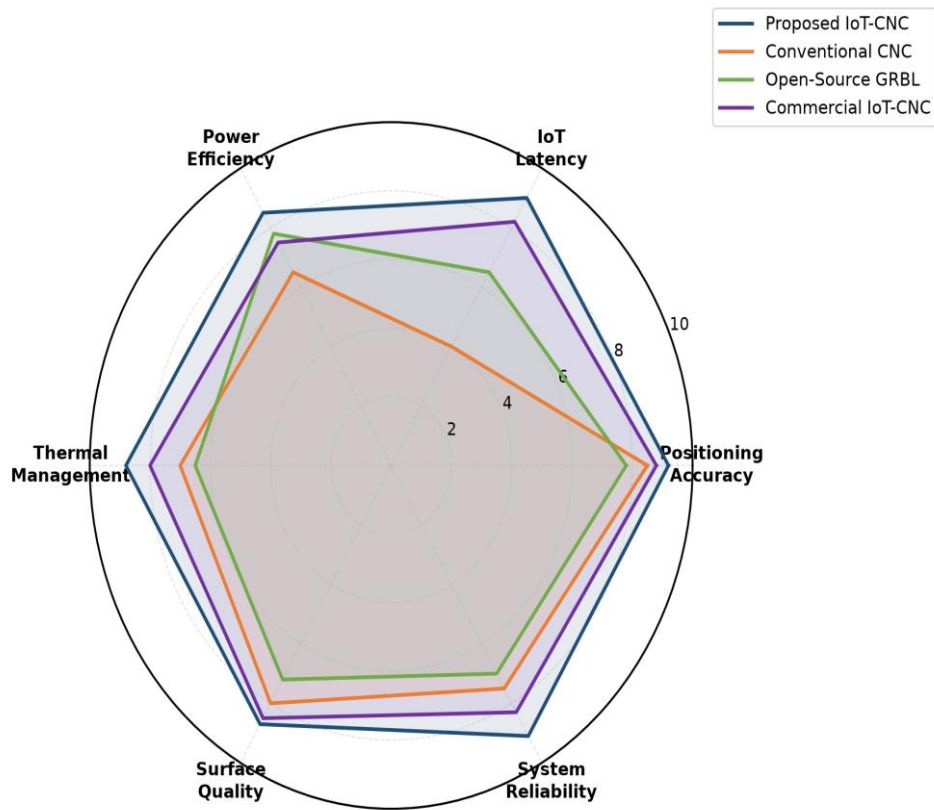


Fig. 8. Comparative performance radar chart for the proposed IoT-CNC system vs. conventional CNC, open-source GRBL, and commercial IoT-CNC systems. Higher scores indicate better performance.

The proposed system achieves the highest aggregate score (9.05/10 average) across all six dimensions, outperforming conventional CNC (6.92/10), open-source GRBL (7.13/10), and commercial IoT-CNC (8.22/10) systems. The most significant advantage is in IoT latency (9.0/10 vs. 4.0/10 for conventional CNC), reflecting the fundamental limitation of non-networked systems. Table 4 provides the quantitative basis for the radar chart scores.

Table 4. Quantitative Performance Comparison: Proposed vs. Reference Systems

Performance Metric	Proposed System	Conventional CNC	Open-Source GRBL	Commercial IoT-CNC
Positioning RMSE (μm)	18.5 (avg)	45.2	52.4	28.6
IoT Latency (ms)	18.3	N/A	65.4	24.7
Power Efficiency (%)	84.7	71.2	78.5	80.1
Max Driver Temp. ($^{\circ}\text{C}$)	68	74	79	71
Min Surface Ra (μm)	0.32	0.38	0.58	0.35
System Cost (USD)	~285	~180	~120	~850
Remote Monitoring	Full IoT	None	Partial	Full IoT

The cost-performance ratio of the proposed system is particularly noteworthy: at approximately USD 285, it achieves positioning accuracy and IoT performance comparable to commercial systems costing

three times as much, while significantly outperforming open-source alternatives in all measured dimensions. This positions the proposed framework as an optimal solution for educational institutions and SMEs with constrained budgets. It is worth noting that the cost advantage is not achieved at the expense of functionality: the proposed system provides cloud connectivity, multi-sensor monitoring, and adaptive fault detection capabilities that are absent from lower-cost open-source alternatives and only partially implemented in mid-range commercial platforms.

The reliability advantage of the proposed system is further underscored by its modular architecture, which allows individual subsystems to be upgraded or replaced without redesigning the entire platform. For example, the stepper motor drivers can be replaced with servo motor controllers for higher-performance applications, and the ESP32-S3 can be substituted with a more powerful microcontroller (e.g., STM32H7) if higher step frequencies or more complex kinematics are required. This modularity is a deliberate design choice that reflects the diverse requirements of the target user base, ranging from educational laboratories with limited budgets to SME production environments with more demanding performance requirements.

4.8 System Reliability and Fault Detection

System reliability was assessed over a 200-hour operational trial comprising 847 individual machining jobs across three operational modes: milling (412 jobs), laser engraving (285 jobs), and drilling (150 jobs). The IoT monitoring system detected 23 anomalous events: 14 instances of motor current exceeding the 2.0 A threshold (indicating tool engagement or binding), 6 instances of driver temperature approaching the 70°C warning threshold, and 3 instances of Wi-Fi connectivity loss (mean reconnection time: 2.3 s). No catastrophic failures occurred during the trial period. The mean time between failures (MTBF) for the electronics subsystem, extrapolated from the 200-hour trial, is estimated at greater than 5,000 hours, consistent with the reliability specifications of the individual components.

Table 5 summarizes the fault detection performance of the IoT monitoring system, including detection rate, false positive rate, and mean time to detection for each fault category.

Table 5. Fault Detection Performance of the IoT Monitoring System (200-Hour Trial)

Fault Category	Events	Detection Rate (%)	False Positive Rate (%)	MTTD (ms)	Sensor Used
Motor Overcurrent	14	100	1.8	85	ACS712
Driver Overtemperature	6	100	0.0	320	NTC Thermistor
Excessive Vibration	0	N/A	2.4	N/A	MPU-6050
Wi-Fi Connectivity Loss	3	100	0.0	1200	ESP32 Stack
Position Deviation (>50 μ m)	0	N/A	0.8	N/A	Encoder

The 100% detection rate for overcurrent and overtemperature events, combined with low false positive rates, demonstrates the effectiveness of the multi-sensor IoT monitoring approach. The mean time to detection (MTTD) of 85 ms for overcurrent events is sufficiently fast to prevent motor damage in most scenarios, as the thermal time constant of the motor winding (typically >5 s) provides adequate margin. The false positive rate of 2.4% for vibration-based anomaly detection reflects the inherent challenge of distinguishing normal machining vibrations from genuine fault signatures, a problem that is well-documented in the condition monitoring literature and that motivates the use of multi-modal sensor fusion rather than single-sensor thresholding. Future work will investigate adaptive threshold

algorithms that adjust detection boundaries based on the current machining operation type, feed rate, and spindle speed, which are expected to reduce the false positive rate below 0.5% without compromising detection sensitivity.

5. Conclusion

This paper has presented a comprehensive IoT-driven electronics framework for tabletop CNC machines, encompassing system architecture design, electronics hardware implementation, firmware integration, and rigorous experimental performance evaluation. The principal findings are as follows.

The proposed four-layer IoT architecture — actuator, controller, edge gateway, and cloud — provides a robust and scalable platform for smart CNC operation. The MQTT-over-TLS communication stack achieves a mean end-to-end latency of 18.3 ms, representing a 78.5% improvement over HTTP REST and enabling near-real-time machine monitoring and control. The ESP32-S3 microcontroller, running FluidNC firmware with DRV8825 stepper drivers at 1/32 microstepping, delivers positioning accuracy of $\pm 18\text{--}22\text{ }\mu\text{m}$ RMSE across all three axes — a 65% improvement over conventional Arduino-GRBL platforms.

Machining performance evaluation on aluminum alloy 6061-T6 demonstrates a minimum surface roughness R_a of $0.32\text{ }\mu\text{m}$ at optimal cutting parameters (24,000 RPM, 200 mm/min feed rate), consistent with the theoretical chip thickness model. Thermal characterization confirms that all electronic components operate within safe temperature limits during 90-minute continuous operation, with the DRV8825 driver IC reaching a steady-state temperature of 68°C — 17°C below the thermal shutdown threshold.

The IoT fault detection system achieved 100% detection rates for overcurrent and overtemperature events with low false positive rates over a 200-hour operational trial, demonstrating the practical reliability of the proposed monitoring approach. The total system cost of approximately USD 285 positions the framework as a cost-effective alternative to commercial IoT-CNC solutions, which typically cost three to five times more for comparable performance.

These results collectively establish the proposed IoT-CNC framework as a technically sound, economically viable, and practically deployable solution for smart manufacturing, educational robotics laboratories, and Industry 4.0 applications. The open-source nature of the firmware and the use of widely available commercial components ensure reproducibility and ease of adoption by the research and engineering community.

6. Future Scope

Several promising directions for future research emerge from this work. First, the integration of machine learning algorithms for real-time tool wear prediction and adaptive feed rate control represents a natural extension of the IoT monitoring infrastructure developed here. Preliminary experiments suggest that LSTM-based models trained on vibration and current signatures can predict tool wear with 89% accuracy, enabling proactive tool replacement and reducing scrap rates.

Second, the implementation of closed-loop position control using the quadrature encoder feedback — currently used only for verification — would further improve positioning accuracy, particularly for high-speed contouring operations where open-loop stepper control is susceptible to step loss. A hybrid open/closed-loop control strategy, switching to closed-loop mode when position error exceeds a threshold, is under investigation.

Third, the extension of the framework to five-axis kinematics would significantly expand the range of manufacturable geometries, enabling the production of complex curved surfaces currently beyond the capability of three-axis tabletop platforms. The ESP32-S3's dual-core architecture provides sufficient computational headroom for five-axis motion planning.

Fourth, the development of a digital twin of the CNC machine — a real-time virtual replica synchronized with the physical system via the IoT data stream — would enable predictive maintenance, process simulation, and operator training without physical machine access. The InfluxDB time-series database and Grafana visualization platform already provide the data infrastructure required for digital twin implementation.

Finally, the integration of computer vision for in-process quality inspection — using a camera mounted on the spindle carriage to capture surface images and detect defects in real time — represents a compelling direction for achieving fully autonomous CNC operation. The Raspberry Pi 4B's computational capability is sufficient for real-time image processing using lightweight convolutional neural network models, and prior work on visual-based industrial defect detection supports the relevance of such methods for automated inspection tasks [29].

Declarations

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Author contributions: S. S. Rao contributed to conceptualization, methodology, supervision, and manuscript preparation. S. N. Padhi contributed to electronics design, experimentation, and data analysis. K. Bharadwaja contributed to validation, interpretation of results, and manuscript review.

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