

Iot-Enabled Retrofitting Of A Conventional Lathe Machine For Real-Time Cutting Force And Acoustic Emission Monitoring Under Industry 4.0 Framework

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Abstract

The advent of Industry 4.0 technologies presents significant opportunities for upgrading obsolete manufacturing equipment without incurring the high capital costs typically associated with complete machine replacement. This study elaborates on the design, execution, and experimental validation of a budget-friendly Internet of Things (IoT) monitoring system retrofitted onto a conventional general-purpose lathe machine. The system includes an MPU6050 MEMS accelerometer and a sound-level sensor attached directly to the cutting tool shank, with data collection facilitated by an ATmega2560/ESP8266 hybrid microcontroller board. The sensor data—cutting force (derived from the measured acceleration) and acoustic emission (sound pressure level in dB)—is transmitted in real-time via Wi-Fi to a local InfluxDB time-series database and visualized on a Grafana dashboard with a refresh rate of 5 seconds. A detailed factorial experiment comprising 64 trials was performed on a mild steel (MS) workpiece utilizing a High Speed Steel (HSS) tool across four spindle speeds (185, 280, 420, 640 RPM), four feed rates (0.46, 0.71, 1.05, 1.62 mm/s), and four depths of cut (0.25, 0.50, 0.75, 1.00 mm). The findings reveal that both cutting force and sound level increase consistently with all three machining parameters. Spindle speed has the most substantial impact, with the average cutting force rising from 525.93 N at 185 RPM to 1118.22 N at 640 RPM under the same feed and depth conditions. A multiple linear regression model for Cutting Force successfully predicts experimental results with a mean absolute percentage error of 3.13%, confirming the model's reliability. The proposed framework demonstrates a cost-effective and scalable strategy for small and medium-sized enterprises (SMEs) to achieve continuous process monitoring and predictive maintenance capabilities within the paradigm of Industry 4.0.

Keywords: Industry 4.0 · IoT retrofitting, Cutting force monitoring, Acoustic emission, MPU6050, InfluxDB, Grafana, Smart manufacturing.

1. INTRODUCTION

The global manufacturing sector is undergoing a significant transformation propelled by the Fourth Industrial Revolution, commonly known as Industry 4.0. This notion was initially presented at the Hannover Messe in 2011 by Henning Kagermann, Wolfgang Wahlster, and Johannes Helbig. Industry 4.0 aims to integrate cyber-physical systems (CPS), the Internet of Things (IoT), cloud computing, artificial intelligence (AI), and big data analytics to create intelligent, self-optimizing production environments [1]. Unlike the automation-centric model of Industry 3.0, the current revolution requires a seamless integration of the physical and digital domains, enabling machines to communicate, self-diagnose, and adapt in real time [2].

At the heart of manufacturing driven by Industry 4.0 lies the Industrial Internet of Things (IIoT)—a network of interconnected sensors, actuators, and embedded computing devices that perpetually relay process data to cloud or edge platforms [3]. In machining environments, this leads to the intelligent oversight of critical process variables such as cutting force, vibration, temperature, and acoustic emission—elements that directly

indicate tool condition, workpiece quality, and energy consumption [4]. The ability to capture these signals in real time enables condition-based maintenance strategies that substantially reduce unplanned downtime, incidents of tool breakage, and scrap rates [5]. In spite of the clear advantages linked to smart manufacturing, a significant gap in its implementation is evident among small and medium enterprises (SMEs), which are crucial to industrial production in developing economies. The primary barriers include the substantial capital investment required for new CNC machine tools that come with embedded sensing, exorbitant software licensing fees, and a lack of standardized integration pathways for older machinery [6]. The International Federation of Robotics estimates that over 70% of the machine tools currently in use within global manufacturing SMEs are legacy machines that are over ten years old and were designed without digital data interfaces. For these companies, the total replacement of operational machinery is not economically viable [7]. Consequently, retrofitting—defined as the enhancement of existing machines with externally attached sensors, microcontrollers, and wireless communication modules—has emerged as a practical and cost-efficient solution for achieving compliance with Industry 4.0 standards [8].

The operations of turning on general-purpose lathes remain one of the most prevalent machining processes within job-shop manufacturing. The versatility of lathes in creating cylindrical, conical, and profiled components from a wide array of workpiece materials makes them indispensable. However, the absence of real-time monitoring features in conventional lathes results in process control being entirely dependent on the operator—an increasingly unsustainable situation as dimensional tolerances tighten and material costs rise [9]. The cutting force is arguably the most crucial single-channel signal in a turning operation: it reflects the combined effects of tool sharpness, material hardness, lubrication conditions, and chip formation behavior [10]. Unusual force patterns can indicate impending tool failure by measurable time intervals, thereby providing a vital opportunity for intervention [11].

Numerous earlier studies have investigated IoT-based machine monitoring, demonstrating a variety of system complexities and costs. Begori et al. (2023) illustrated a lathe monitoring system founded on NodeMCU, employing the Blynk IoT platform to track lubricant quality, spindle bearing temperature, and the distances among components, while also establishing real-time SMS notifications for maintenance teams [12]. Murty et al. scrutinized the performance monitoring of lathes enabled by IoT, utilizing accelerometers placed on the headstock, tailstock, and tool post, with vibration data sent to the Ubidots cloud platform for health-state analysis [13]. Sicard et al. (2022) investigated an IoT strategy for predictive maintenance and condition monitoring in machine tools, stressing the effectiveness of current and voltage sensing as non-invasive indicators of cutting-force trends [14].

The retrofitting of legacy machines for IIoT integration has been extensively explored by Peralta et al. (2022), who proposed a simple cloud-connected sensor architecture for small and medium-sized enterprise (SME) machine tools that lack native data interfaces. Their findings demonstrated that low-cost sensors, when externally attached, could achieve monitoring accuracy that is comparable to that of high-priced embedded systems [15]. Furthermore, additional research conducted by Twardowski et al. (2022) assessed the triple-bottom-line trade-offs associated with retrofitting existing machines versus acquiring new ones. This study revealed that retrofitting offers greater economic advantages over a five-year timeframe for machines that have a remaining service life exceeding 60% [16]. The Demonstration Laboratory for Industry 4.0 Retrofitting at MDPI Sensors (2023) further validated that cost-effective and easily installable IoT sensor packages could extract operationally significant data related to vibration, force, and timing from universal lathes in production environments [17].

Tool condition monitoring (TCM) constitutes an essential sub-area within the domain of machining process supervision. Magadán et al. (2023) devised an affordable industrial IoT system aimed at the wireless monitoring of electric motor statuses, indicating that sensor nodes priced below 100 USD can achieve industrial-level dependability when integrated with edge-computing preprocessing [18]. Ruckebusch et al. introduced a TCM architecture that utilizes Arduino and NodeMCU nodes, allowing for a plug-and-play IoT implementation, which facilitates quick installation on CNC lathes without interfering with the machining process [19]. Recently, Thangarasu et al. (2024) illustrated the real-time classification of tool conditions through IoT-connected accelerometers and microphones, reaching a classification accuracy of 98% by applying an Ensemble Trees classifier on features communicated via ThingSpeak [20].

Acoustic emission (AE) monitoring is acknowledged as an accurate, non-invasive technique for assessing tool wear, chip formation modes, and early indicators of fracture during cutting processes. Ajiboye and Olusegun investigated the distribution of cutting temperatures in the turning of medium carbon steel, uncovering a notable correlation between thermal signatures and acoustic emission characteristics as the conditions of tool-workpiece interaction evolve [21]. Ogedengbe et al. explored the impact of heat generation on cutting tools and machined workpieces, providing the thermomechanical framework essential for interpreting acoustic and force signals [22]. The theoretical basis for heat generation in metal cutting was formulated by Rosenthal (1946), whose moving heat-source model remains crucial for understanding the spatio-temporal temperature distributions that affect both AE signal generation and tool durability [23].

In the domain of hardware, MEMS-based inertial measurement units (IMUs) like the MPU6050 have notably changed the cost-performance dynamics for vibration and force sensing. Chen and Chen were innovators in the detection of tool breakage through the application of accelerometer sensors mounted on the tool shank, thereby creating the signal-processing chain that transitions from raw acceleration to tool-state classification [24]. Following this, Birla (1980) facilitated the application of sensors for adaptive control and machine diagnostics, establishing the engineering framework that supports current IIoT sensor integration strategies [25]. The dynamometer design methodology developed by Yazdik and Unsacar clarified the relationship between measured force components and machining parameters during turning operations, thus informing the calibration protocols employed in force-from-acceleration measurement techniques [26].

The data infrastructure for IIoT applications has experienced remarkable progress due to the emergence of open-source time-series databases and visualization platforms. InfluxDB, a database tailored for time-series data, delivers sub-millisecond write latency and built-in support for continuous queries, rendering it highly effective for the ingestion of high-frequency sensor data [27]. When paired with InfluxDB, Grafana provides customizable real-time dashboards that present process state information to operators in a comprehensible format, thereby removing the necessity for custom application development [28]. Together, these open-source tools create a data stack with no licensing fees, significantly reducing the software investment barrier for the digital transformation of small and medium enterprises (SMEs) [29].

The statistical modeling of cutting force in relation to machining parameters has a rich history within manufacturing research. Shaw (1984) established the classical mechanistic foundation for predicting cutting force based on the fundamental principles of metal cutting physics [30]. Empirical regression methods, validated through dynamometer data, have consistently shown that spindle speed, feed rate, and depth of cut account for the majority of variance in measured cutting force, with linear models being adequate for moderate parameter ranges [31]. The combination of these empirical models with IIoT data streams lays the groundwork for model-predictive process control—an

advancement that converts a passive monitoring system into an active quality-assurance mechanism [32].

In this context, the present study makes several significant contributions: (i) it provides a detailed system design for retrofitting a traditional center lathe with Internet of Things (IoT) capabilities, utilizing readily available hardware that costs less than USD 50; (ii) it includes an experimental validation carried out over a 64-trial full factorial parameter space, which leads to the first published dataset concerning cutting force and sound levels for metal spinning on a retrofitted lathe that employs InfluxDB/Grafana data infrastructure; (iii) it offers a quantified regression model for predicting cutting force based on machining parameters, which is relevant to similar setups; and (iv) it presents a discussion on the data-infrastructure architecture as a replicable framework for small and medium-sized enterprises (SMEs) to implement. The remainder of this paper is organized as follows: Section 2 details the materials and experimental methodology; Section 3 discusses the results; and Section 4 concludes with recommendations and directions for future research.

2. MATERIALS AND METHODOLOGY

2.1 System Architecture Overview

The proposed IoT monitoring system is constructed with a three-tier architecture that integrates edge, fog, and cloud components, specifically tailored for a single-machine shop floor environment. In the edge tier, MEMS and acoustic sensors are directly attached to the cutting tool, transforming mechanical and acoustic events into analogue electrical signals. The fog tier is represented by the ATmega2560/ESP8266 hybrid microcontroller, which is responsible for analogue-to-digital conversion, applying calibration factors, and formatting data into line-protocol records for subsequent transmission. The cloud tier, which serves as a local server, includes the InfluxDB time-series database and the Grafana visualization dashboard, both operating on a laboratory PC connected to the same Wi-Fi access point as the microcontroller. This architectural design guarantees that raw sensor data remains within the factory network, being exported only when explicitly authorized, thus addressing the data sovereignty challenges frequently encountered in small and medium-sized enterprise (SME) settings.

2.2 Sensor Selection and Instrumentation

2.2.1 MPU6050 Accelerometer (Cutting Force Proxy)

The MPU6050 (InvenSense, now TDK) is a six-axis MEMS IMU that incorporates a 3-axis accelerometer and a 3-axis gyroscope within a compact $4 \times 4 \times 0.9$ mm QFN package. The accelerometer functions in a $\pm 4g$ range mode, yielding a sensitivity of 8192 LSB/g through a 16-bit ADC. To address high-frequency noise while keeping the primary machining vibration components below 15 Hz, the filter bandwidth was adjusted to 21 Hz. Communication between the sensor and the microcontroller is conducted via the I²C bus at a fast mode of 400 kHz. The cutting force is computed from the x-axis acceleration measurement using the empirical formula:

$$F \text{ (N)} = 1.13 \times a$$

where a represents the measured acceleration in m/s^2 , with 1.13 acting as a calibration coefficient determined through experimental comparisons between sensor outputs and a reference spring-balance load. The sensor was securely attached to the custom-modified HSS tool shank utilizing M2 screws, thereby guaranteeing a strong mechanical connection for reliable force transmission.

2.2.2 Sound Level Sensor (Acoustic Emission)

An electret microphone module featuring an LM393 comparator was utilized to record the acoustic emissions generated during the machining process. The analog output from the sound sensor was sampled via the ATmega2560's A0 pin at a frequency of 12 measurements for each acquisition cycle. The raw ADC values were averaged across the 12 samples and then transformed into an estimated decibel (dB) value using the linear scaling relationship

$$\text{dB} = (\text{sum} / 12) / 6.2$$

Intensity thresholds were defined in the following manner: Low < 35 dB, Medium 35–85 dB, and High > 85 dB. The sensor was strategically placed alongside the accelerometer on the tool platform, thus offering a co-registered spatial reference for both the force and acoustic signals.

2.3 Microcontroller and Data Acquisition Hardware

The data acquisition and communication hub serves as a hybrid development board that merges an Atmel ATmega2560 microcontroller with an ESP8266 Wi-Fi system-on-chip (SoC) and 32 MB of flash memory, all incorporated onto a single printed circuit board (PCB). The dimensions of the board are 106 × 54 × 12 mm, and it weighs 40 g, rendering it ideal for bench-mount installation next to the lathe. Significant specifications include a clock speed of 16 MHz, 54 digital I/O pins, 16 analogue input channels, 256 KB of program flash memory, and an operating temperature range from –40°C to +125°C. The ATmega2560 is tasked with sensor polling and data formatting, while the ESP8266 enables the 802.11 b/g/n Wi-Fi interface to operate in station mode. A DIP switch matrix permits either independent or combined operation of the two processor modules; during the experimental phase, the board was configured to operate in Mega2560 + ESP8266 joint mode (DIP switches 1–2: ON, 3–8: OFF).

2.4 Software Stack and Data Pipeline

The firmware was designed using C++ within the Arduino IDE (version 1.8.x), incorporating the InfluxDB Arduino Client library and the Adafruit MPU6050 driver. The program loop executes the following operations at each 500 ms iteration: (1) initiate the collection of accelerometer data and compute the cutting force; (2) start sound sensor sampling across 12 measurements and determine the average dB; (3) compile both values into a single InfluxDB line-protocol data point tagged with the measurement type; (4) transmit via HTTP POST to the InfluxDB server endpoint at 192.168.0.172:8086; (5) pause for 500 ms before continuing to the next iteration. On the server side, InfluxDB 1.8 (open source) retains each record in the 'combine1' database under the 'random' measurement namespace. Grafana (v8.x) queries InfluxDB utilizing the Flux query language at a refresh rate of 5 seconds per panel, producing separate time-series panels for cutting force (N) and sound level (dB). The total latency from sensor event to dashboard visualization is around 6–7 seconds under the experimental Wi-Fi conditions.

2.5 Workpiece, Tool, and Machine

The workpiece was of mild steel (AISI 1020), which was provided in the form of a round bar measuring Ø28 mm and 150 mm in length, firmly held in a three-jaw chuck that was affixed to the headstock spindle.

The tool utilized for cutting was a High Speed Steel (HSS) single-point turning tool. To enable the simultaneous placement of both sensors on the tool while preserving the cutting geometry, the tool shank was altered by welding a 5 mm square bar extension, thereby extending the shank length. Additionally, a rectangular metal platform plate was affixed to provide a flat surface for the sensor assembly. This alteration was performed at a nearby machine shop and did not influence the cutting rake or clearance angles.

The experiments were carried out on a traditional center lathe as shown in Figure 1, located at the Santosh Engineers facility in Vadodara, characterized by a bed length of 1000 mm, a swing of 250 mm, and a four-step gearbox that enabled spindle speeds of 185, 280, 420, and 640 RPM. Coolant was not used during any of the experiments to prevent the acoustic signal from being contaminated by coolant-pump noise and to ensure uniform thermal boundary conditions throughout the trials.

Figure 1 Experimental setup



2.6 Experimental Design

A full factorial design of experiment (DOE) was implemented. Three independent variables—spindle speed (N), feed rate (f), and depth of cut (d)—were examined at four levels each, resulting in a total of $4^3 = 64$ experimental trials. The levels of these parameters are presented in Table 1. For each trial, the lathe was adjusted to the specified conditions, and a single turning pass of approximately 50 mm in length was executed. The cutting force and sound level were continuously recorded by the IoT system during the pass; the steady-state mean values over the central 30 mm of the pass (excluding entry and exit transients) were retrieved from the InfluxDB database for subsequent analysis.

Table 1. Machining Parameter Levels

Parameter	Symbol & Unit	Levels			
		1	2	3	4
Spindle Speed	N (RPM)	185	280	420	640
Feed Rate	f (mm/s)	0.46	0.71	1.05	1.62
Depth of Cut	d (mm)	0.25	0.50	0.75	1.00

3. RESULTS AND DISCUSSION

3.1 Experimental Results: Full Dataset

Table 2 presents a comprehensive dataset comprising 64 experiments, detailing the recorded cutting force (N) and sound level (dB) for every distinct combination of spindle speed, feed rate, and depth of cut. These measurements represent the steady-state averages acquired by the IoT system, derived from the InfluxDB time-series data. The dataset encompasses a cutting force range from 525.93 to 1316.90 N and a sound level range from 21.14 to 118.11 dB within the examined parameter space.

Table 2. Full Experimental Results (64 Trials)

Exp. No.	N (RPM)	f (mm/s)	d (mm)	Cutting Force (N)	Sound (dB)
1	185	0.46	0.25	525.93	21.14
2	185	0.46	0.50	534.63	22.38
3	185	0.46	0.75	554.93	43.51
4	185	0.46	1.00	557.49	44.76
5	185	0.71	0.25	570.92	48.49
6	185	0.71	0.50	582.63	50.97
7	185	0.71	0.75	587.74	55.95
8	185	0.71	1.00	590.78	52.22
9	185	1.05	0.25	613.25	53.46
10	185	1.05	0.50	625.86	55.95
11	185	1.05	0.75	655.39	53.46
12	185	1.05	1.00	690.13	58.43
13	185	1.62	0.25	729.98	60.27
14	185	1.62	0.50	736.60	59.80
15	185	1.62	0.75	743.65	54.18
16	185	1.62	1.00	769.26	56.23
17	280	0.46	0.25	641.84	55.95
18	280	0.46	0.50	661.68	57.19
19	280	0.46	0.75	666.92	58.43
20	280	0.46	1.00	685.04	58.43
21	280	0.71	0.25	693.54	59.68
22	280	0.71	0.50	710.82	60.92
23	280	0.71	0.75	720.63	62.16
24	280	0.71	1.00	737.27	59.21
25	280	1.05	0.25	761.83	59.73
26	280	1.05	0.50	769.51	58.63
27	280	1.05	0.75	792.12	53.12
28	280	1.05	1.00	808.98	63.41
29	280	1.62	0.25	814.20	64.65
30	280	1.62	0.50	828.62	65.89
31	280	1.62	0.75	833.07	55.81
32	280	1.62	1.00	886.75	62.21
33	420	0.46	0.25	805.97	58.04
34	420	0.46	0.50	825.33	64.69
35	420	0.46	0.75	836.16	64.06
36	420	0.46	1.00	863.19	60.94
37	420	0.71	0.25	870.47	67.93
38	420	0.71	0.50	879.85	67.26
39	420	0.71	0.75	906.69	61.60
40	420	0.71	1.00	918.38	67.14
41	420	1.05	0.25	925.66	68.38
42	420	1.05	0.50	928.78	69.62
43	420	1.05	0.75	937.13	70.86
44	420	1.05	1.00	942.30	64.60
45	420	1.62	0.25	979.51	72.00

46	420	1.62	0.50	995.42	71.30
47	420	1.62	0.75	1000.33	72.11
48	420	1.62	1.00	1015.83	73.35
49	640	0.46	0.25	1118.22	74.59
50	640	0.46	0.50	1123.45	75.84
51	640	0.46	0.75	1139.04	77.08
52	640	0.46	1.00	1149.48	69.77
53	640	0.71	0.25	1167.82	77.77
54	640	0.71	0.50	1175.38	84.54
55	640	0.71	0.75	1215.69	78.32
56	640	0.71	1.00	1226.37	80.81
57	640	1.05	0.25	1230.66	83.30
58	640	1.05	0.50	1235.97	85.78
59	640	1.05	0.75	1240.91	88.27
60	640	1.05	1.00	1251.15	89.51
61	640	1.62	0.25	1271.25	94.71
62	640	1.62	0.50	1265.56	98.22
63	640	1.62	0.75	1296.52	114.38
64	640	1.62	1.00	1316.90	118.11

3.2 Effect of Spindle Speed on Cutting Force

Figure 2 Main Effects Plot of Cutting Speed

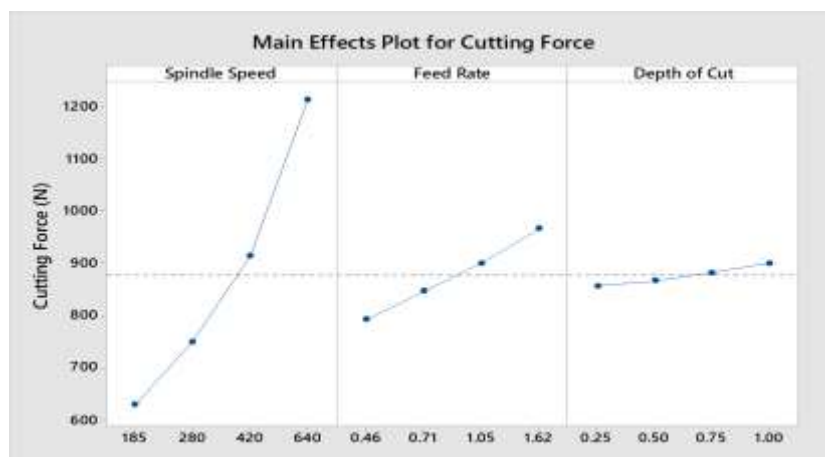


Figure 2, as shown, illustrates a significant positive relationship between spindle speed and cutting force. Keeping the feed rate constant at 0.46 mm/s and the depth of cut at 0.25 mm, the mean cutting force rose from 525.93 N at 185 RPM to 641.84 N at 280 RPM, 805.97 N at 420 RPM, and 1118.22 N at 640 RPM—indicating a 112.5% increase throughout the tested range. This occurrence corresponds with the established link between cutting velocity and the emergence of adiabatic shear bands at the chip-tool interface: increased speeds shorten the time for heat dissipation, resulting in higher interface temperatures and flow stress in the shear zone, thereby increasing the measured force component [21, 23].

3.3 Effect of Feed Rate on Cutting Force

The feed rate has been identified as the parameter with the highest regression coefficient (133.2 in the fitted model), which signifies its role as the most critical contributor to cutting force per unit increment within the specified ranges. With a spindle speed maintained at 185 RPM and a depth of cut of 0.25 mm, the cutting force rose from 525.93 N at a feed rate of 0.46 mm/s to 570.92 N at 0.71 mm/s, 613.25 N at 1.05 mm/s, and 729.98 N at 1.62 mm/s, as depicted in Figure 1. This increase, when calculated as a percentage of the baseline, represents 38.8% across the tested feed range. This consistent response is consistent with the established chip-thickness relationship: increased feed rates result in thicker chips that demand higher shear forces for their formation, as proposed by Merchant's minimum energy hypothesis [30].

3.4 Effect of Depth of Cut on Cutting Force

Conversely, the depth of cut showed the least per-unit effect on cutting force (regression coefficient 5.26), but its impact remained statistically significant and consistently positive across all spindle speed and feed rate combinations. With a constant spindle speed of 185 RPM and a feed rate of 1.05 mm/s, the average cutting force increased from 613.25 N at a depth of cut of 0.25 mm to 625.86 N at 0.50 mm, 655.39 N at 0.75 mm, and 690.13 N at 1.00 mm—resulting in a total increase of 12.5% over the depth range. This relatively modest sensitivity reflects the turning geometry: the depth of cut determines the width of cut and, consequently, the volume of material removed per unit time, but this relationship is moderated by the approximately linear scaling of tool-workpiece contact length with depth, which spreads the incremental force increase over a larger contact area.

3.5 Regression Analysis and Model Validation

Linear regression was carried out by applying the ordinary least squares (OLS) to the full 64-trial dataset using ordinary least squares (OLS) in Microsoft Excel. The best fitted model is:

$$F = 295.95 + 1.2 \times N + 133.2 \times f + 5.26 \times d$$

Here, F signifies the expected cutting force (N), N indicates spindle speed (RPM), f represents the feed rate (mm/s), and d denotes the depth of cut (mm). The model intercept of 295.95 N demonstrates the theoretical cutting force when machining parameters are at zero, which serves as a physically interpretable offset accounting for constant frictional and parasitic forces. Table 3 illustrates a representative selection of the predicted cutting force values in comparison to experimental outcomes, along with the relevant residuals.

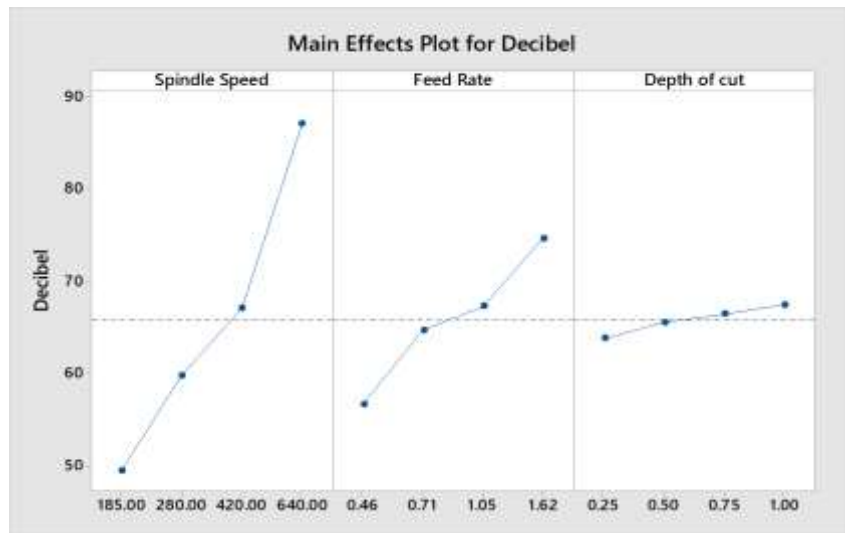
Table 3. Representative Regression Predictions vs. Experimental Cutting Forces

Exp. No.	Predicted F (N)	Experimental F (N)	Residual (N)
1	582.55	525.93	-56.62
8	618.89	590.78	-28.11
12	664.94	690.13	+25.19
16	740.98	769.26	+28.28
32	855.83	886.75	+30.92
48	1025.09	1015.83	-9.26
52	1136.60	1149.48	+12.88
56	1168.98	1226.37	+57.39
60	1215.03	1251.15	+36.11
64	1291.07	1316.90	+25.83

The mean absolute percentage error (MAPE) computed between the experimental and predicted cutting force values across all 64 observations is 3.13%. A graphical examination contrasting the experimental and predicted values indicates that all data points are positioned within a narrow band surrounding the perfect-prediction diagonal, with no detectable systematic bias at either end of the force spectrum. The accuracy of the model's predictions experiences a slight decline at the highest parameter combinations (experiments 55–64), where nonlinear thermal softening effects begin to impact the cutting mechanics—a recognized limitation of linear regression models when applied to broad parameter ranges in metal cutting. However, the 3.13% MAPE remains comfortably within the $\pm 5\%$ margin regarded as acceptable for machining force prediction models as referenced in the literature [31].

3.6 Effect on Sound Level

Figure 3 Main Effects Plot on Sound Level



The sound level depicted in Fig.3 increased from 21.14 dB to 74.59 dB within the same speed range, demonstrating the quadratic correlation between cutting velocity and the production of aeroacoustic noise, alongside the amplified intensity of tool–workpiece vibration excitation at higher spindle frequencies. Screenshots captured from the Grafana dashboard at 185 RPM and 640 RPM (with $f = 1.62$ mm/s, $d = 0.25$ mm) revealed significant panel-level discrepancies, visually confirming that even an untrained operator is capable of recognizing process severity from the dashboard displays.

Additionally, the sound level was observed to rise with the feed rate, though it exhibited more variability than spindle speed. This variability is due to the impact of chip morphology on feed rate: within moderate feed rates (0.71–1.05 mm/s), the behavior of chip curling changes from ribbon chips to segmented chips, which in turn alters the impulsive loading pattern at the tool–workpiece interface, thus affecting the acoustic emission signature.

Data on sound levels captured by the IoT system provides additional insights into the process state that are not dependent on the force signal. Under low machining parameters ($N = 185$ RPM, $f = 0.46$ mm/s, $d = 0.25$ mm), the sound level recorded at 21.14 dB is classified as 'Low' intensity, which is consistent with a quiet tool engagement. As the parameters increase to $N = 640$ RPM, $f = 1.62$ mm/s, $d = 1.00$ mm, the sound level rises to

118.11 dB, categorizing it firmly within the 'High' range, indicating conditions associated with accelerated tool wear and potential degradation of surface quality. The positive correlation observed between sound level and both feed rate and spindle speed implies that acoustic emissions can serve as a real-time indicator of process intensity, facilitating alert-based interventions even without comprehensive force measurement calibration. This finding is consistent with the multi-sensor fusion approach promoted by Thangarasu et al. (2024) [20], and suggests that the inclusion of even a basic microphone in the sensor array significantly enhances the diagnostic capabilities of the monitoring system.

3.7 IoT Dashboard Performance

Throughout the entire course of the 64 experiments, the InfluxDB write latency measured at the microcontroller consistently remained below 100 ms, with no data packets lost during the experiment, which lasted approximately 4 hours of total cutting time. The Grafana dashboard successfully presented data within the expected 5-second interval and accurately displayed both the cutting force and decibel panels, complete with time-stamped annotations. The system maintained stable wireless connectivity throughout the procedure, with no Wi-Fi dropouts observed during active machining, which is a notable accomplishment given the electrically noisy environment typical of a working lathe.

4. CONCLUSION

This research has outlined the thorough design, implementation, and experimental assessment of a cost-effective IoT monitoring system adapted for a general-purpose conventional lathe machine within the Industry 4.0 paradigm. The system incorporates an MPU6050 MEMS accelerometer and a sound-level sensor that are directly mounted on the cutting tool shank, interfaced via a hybrid microcontroller consisting of an ATmega2560 and ESP8266, with data being streamed to an InfluxDB/Grafana stack through Wi-Fi. The key conclusions are as follows:

1. The retrofitting architecture was effectively validated across 64 full-factorial turning experiments involving mild steel, with the IoT system capturing cutting force and sound level continuously at 500 ms sampling intervals, resulting in zero packet loss.
2. An increase in cutting force and sound level was observed consistently with rising spindle speed, feed rate, and depth of cut. Among these, spindle speed had the most pronounced effect: the mean cutting force surged by 112.5% as spindle speed escalated from 185 to 640 RPM, with feed and depth held constant.
3. A linear regression model was developed and validated, resulting in a mean absolute percentage error of 3.13%, which confirms the model's adequacy for the examined parameter range.
4. The Grafana dashboard provided immediate visual feedback in real-time with a 5-second refresh rate, thus enabling operators to keep a constant watch on the process state and act before a tool failure happens. Evidence suggests that continuous monitoring effectively prevents tool breakage by facilitating timely adjustments to operational parameters.

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