Available online at www.sciencedirect.com

Manufacturing Letters

Manufacturing Letters 41 (2024) 200–207

52nd SME North American Manufacturing Research Conference (NAMRC 52, 2024)

Feasibility of 5G-Enabled Process Monitoring in Milling Operations

Liwen Hu[a,b], Baihui Chen[a,b], ElHussein Shata[a,b], Shashank Shekhar[c], Charif Mahmoudi[c]

Ivan Seskar[d], Qingze Zou[a,b], Y.B. Guo[a,b,*]

[a]*Department of Mechanical and Aerospace Engineering, Rutgers University-New Brunswick, Piscataway, NJ 08854, USA*
[b]*New Jersey Advanced Manufacturing Initiative, Rutgers University-New Brunswick, Piscataway, NJ 08854, USA*
[c]*Siemens Corporation Technology, Princeton, NJ 08540, USA*
[d]*Wireless Information Network Laboratory, Rutgers University-New Brunswick, NJ 08902, USA*

* Corresponding author. Tel.: +001-848-445-2225; fax: +001-732-445-3124. *E-mail address:* yuebin.guo@rutgers.edu

Abstract

5G monitoring holds immense potential for revolutionizing manufacturing processes by enabling real-time data transmission, remote control, enhanced quality control, and increased efficiency. However, it also presents challenges related to 5G monitoring infrastructure. To explore 5G's potential for process monitoring, this study introduces a novel 5G-enabled architecture designed to address the challenges, enhancing the process monitoring's efficiency, accuracy, and reliability in the case of milling operation. To investigate the feasibility of this sophisticated 5G network for process monitoring, two testbeds, i.e., the 5G robotic milling testbed and the 5G CNC milling testbed, have been developed. An accelerometer and a laser scanner have been retrofitted with 5G communications capability to capture critical process signals in the testbeds, respectively. It has shown that the sensor data can be upstreamed to a 5G edge server for data analytics and visualization in ultra-low latency. This work highlights the transformative impact of 5G communication on process monitoring for time-critical manufacturing.

Keywords: 5G network, 5G-enabled sensor, Process monitoring, Edge computing, Machining

1. Introduction

1.1 Background

The manufacturing industry has witnessed significant advancements in recent years, with the integration of cutting-edge technologies to enhance efficiency and productivity. One such technology that holds immense promise for manufacturing processes is the fifth-generation (5G) wireless network. 5G offers high-speed, low-latency communication, making it an ideal candidate for real-time monitoring and control of manufacturing operations. The ultra-low latency of 5G networks enables real-time data transmission, allowing manufacturers to collect and analyze data from various sensors and devices in real-time. This capability enhances decision-making processes and enables rapid responses to change in the production environment. 5G networks also enable remote monitoring and control of manufacturing processes, reducing the need for physical presence on the factory floor. This not only improves safety but also allows experts to remotely troubleshoot and optimize production processes, reducing downtime and maintenance costs.

Several notable developments have been achieved to assess the feasibility and benefits of 5G in manufacturing. These studies provide valuable insights into the potential practical applications of 5G technology. This study focuses on the application of 5G technology in advanced manufacturing, specifically examining 5G-enabled process monitoring in milling operations through detailed case studies.

Milling is a common technology for fabricating high-value components, such as turbine blades, engine blocks, and molds [1], with numerous industrial applications. Despite its widespread applications and extensive studies [2-4], milling remains a complex process influenced by numerous factors, including tool conditions [5], machining parameters [6], workpiece material characteristics [7], etc. The milled surface quality is critical for its functionalities, including friction, wear resistance, and fatigue life [8]. Therefore, real-time milling process monitoring is imperative to identify and mitigate potential process abnormalities. The prevalent method for process monitoring employs various online sensors, such as accelerometers [9], dynamometers [10], acoustic emission (AE) sensors [11], and microphones [12], to capture the milling process signals. Multi-sensor monitoring systems are also often used [13, 14] to simultaneously harness data from different sensors to track different process aspects. The rich sensor dataset facilitates a comprehensive analysis for applications like tool life estimation [5], stability studies [13, 14], and surface finish prediction [15, 16], ultimately driving cost reduction and enhancing product quality. The growing demand for process efficiency has also spurred the development of adaptive control strategies to mitigate chatter and other detrimental phenomena during milling [17-19].

1.2. 5G-based process monitoring

Real-time monitoring of the milling process is fraught with challenges, primarily due to the complexity of the process and the high-speed dynamics involved. The volume of data generated by sensor systems necessitates robust and fast communication networks to transmit, process, and analyze the information in real-time [20, 21]. Conventional communication technologies often fail to meet these demands, leading to long-latency issues and potential loss of critical data [22-24]. Additionally, the harsh manufacturing environment poses another layer of difficulty, where sensors and communication equipment must withstand extreme conditions while maintaining accuracy and reliability. Moreover, the prevalent use of wire-based sensors in manufacturing settings introduces practical challenges, particularly in installation (e.g., the rotating blades in milling) and maintenance. The manufacturing space is often constrained and densely packed with machinery, complicating the task of deploying wired devices and potentially hindering their optimal placement for precise monitoring. These challenges underscore the necessity of a paradigm shift in the monitoring approach, setting the stage for integrating 5G technology to address these bottlenecks and unlock the full potential of real-time milling process monitoring.

5G, advancing over the previous generation of wireless communications, represents the fifth-generation technology standard for broadband cellular networks. Given the advancements in broadband cellular networks, the 5G protocol outlined by the 3rd Generation Partnership Project (3GPP) is widely accepted within the industry as the prevailing standard for 5G technology. The advent of 5G technology has opened new possibilities for the manufacturing industry [25, 26], enabling faster, more reliable wireless connectivity and real-time communication [27, 28] between machine tools, sensors, and control units. 5G applications in manufacturing include the development of smart factories [29], remote monitoring and control of equipment, augmented reality [30], and real-time tracking of goods and materials in the supply chain. These applications have the potential to significantly improve efficiency, productivity, and cost-effectiveness in manufacturing operations. The 5G manufacturing research trend can be observed in Fig. 1, which depicts the results of a Scopus analysis using "5G" and "manufacturing" as keywords. The search provides insight into the increasing interest and activity in the field of 5G-enabled manufacturing, as the research interests have been steadily growing since 2016.

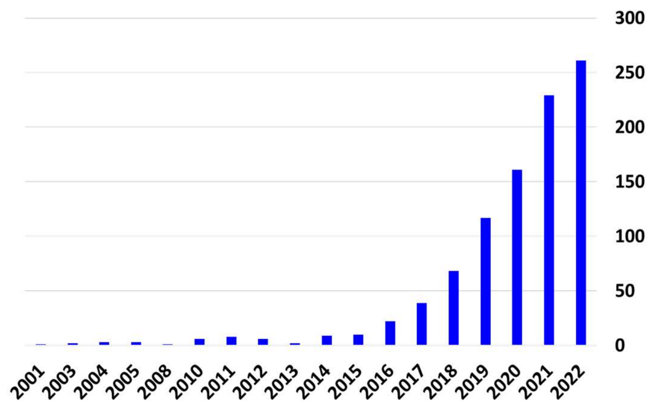

Fig. 1. 5G Manufacturing publications trend since 2001.

The comparative analysis of different wireless communication protocols is summarized in Table 1. References [22-24, 31] elucidate the superiority of 5G, which excels with its impressive data rate ranging from 1 to 10 Gbps and latency as low as one millisecond, catering perfectly to real-time applications such as monitoring a dynamic milling process. 4G/LTE and Wi-Fi 6 provide reasonable alternatives but surpass 5G in speed and responsiveness. Bluetooth and Zigbee are more suited for short-range, low-data-rate applications, with Zigbee catering to ultra-low power scenarios. LoRa/LoRAWAN stands out for its long-range capabilities, though at the expense of data rate and latency. Overall, 5G's high data rate and ultra-low latency offer a transformative potential for real-time industrial monitoring, outperforming other protocols in process monitoring.

Table 1. Comparative analysis of wireless communication protocols.

Communication Protocol	Data Rate	Latency	Range	Frequency
5G*	~ 20 Gbps	< 10 ms	~ 200 m	30 GHz to 300 GHz, < 6 GHz
4G/LTE	~ 100 Mbps	< 50 ms	~ 200 m	< 6 GHz
WLAN (Wi-Fi 6)	~ 9.6 Gbps	< 50 ms	~ 100 m	2.4 GHz, 5 GHz
Bluetooth	2 ~ 3 Mbps	> 10 ms	~ 100 m	~ 2.4 GHz
Zigbee	~ 250 Kbps	Few ms ~ seconds	~ 100 m	868 MHz, 915 MHz, 2.4 GHz
LoRa/ LoRAWAN	~ 21.9 Kbps	~ seconds	2 ~ 15 Km	< 1 GHz

*Note:
1. The data rate for 5G is approximately 20 Gbps for downlink and 10 Gbps for uplink.
2. The range of 200m is specific to millimeter-wave (mmWave). The sub-6 GHz frequencies offer a significantly higher range.

Numerous 5G applications have been developed to address challenges inherent in traditional communication protocols. Table 2. highlights several leading research groups working on 5G applications. Fraunhofer IPT has initiated 5G applications for the manufacturing industry in Germany. Mohanram et al. [32] introduced a 5G-based multi-sensor platform for monitoring workpieces and machine status. Equipped with diverse sensors, multiple data types (e.g., vibration, temperature, torque, etc.) were collected from workpieces and machines and wirelessly connected to the factory cloud using 5G. Kehl et al. [33] proposed a 5G-enabled Time-Sensitive Network (TSN) and assessed its performance on an edge-controlled mobile robot. The results revealed the communication latency is as low as 1 ms. Ansari et al. [28] conducted 5G trials using an FPGA-based tool to generate data traffic simulating industrial protocol traffic. The findings demonstrated that traffic latencies remained below 1.09-1.12 ms when utilizing the proposed network structure. Ericsson and Fraunhofer IPT collaborated on a case study examining 5G-enabled milling vibration monitoring during the blisk milling process [34]. The report suggested that 5G-enabled real-time monitoring and control could result in annual savings of Euro 360 million on blisk production. Gundall et al. [35] enumerated several 5G-enabled Industry 4.0 use cases, including 5G-enabled cooperative goods transportation, 5G remote control, and industrial campus applications. Huawei Wireless X Labs published a white paper [36] investigating a 5G-enabled cloud robot. The cloud provides advanced control software, while 5G ensures rapid and secure communication between the cloud and the robot.

Table 2. 5G applications in manufacturing research.

Research Group	Key Features	Ref
Fraunhofer IPT	5G-based sensor platform for workpiece and machine monitoring	[32]
	5G-enabled edge-controlled robot	[33]
	5G network performance review with automation traffic	[28]
Ericsson	Milling vibration monitoring using a 5G network	[34]
Bell Labs	5G-enabled Industry 4.0 use cases	[35]
Wireless X Labs	5G-enabled cloud robot	[36]

1.3 Research objectives

This literature analysis assesses the current state of research and developments in 5G monitoring for manufacturing processes and highlights the potential of 5G technology in addressing various manufacturing challenges, including the lack of 5G monitoring infrastructure to realize its potential. This study aims to create a 5G network with 5G-enabled sensors for milling process monitoring and demonstrate the unique capabilities of ultra-low latency sensing and visualization in real time. Specifically, this study aims to demonstrate the capabilities of a novel 5G-enabled monitoring system architecture and implementation, focusing on retrofitting sensors with 5G communications capability, precisely measuring the workpiece geometrical characteristics and process signatures, 5G edge computing, and visualization. The paper is structured as follows: Section 2 presents the system architecture and testbeds setup. Section 3 demonstrates 5G measurement, edge computing, and visualization. Section 4 summarizes the key results of this work.

2. 5G-Enabled Process Monitoring Approach

2.1. Monitoring System Architecture

The schematic of the 5G-based monitoring system (Fig. 2) demonstrates the integral components of the 5G-enabled monitoring system designed for sensing the milling process signature and visualizing the data in real time. The 5G NR (New Radio) transceiver captures raw data from the sensor(s), which monitor the milling process in real-time. This transceiver acts as the initial contact point to bridge the gap with legacy equipment, as commercial sensors and machinery have yet to integrate native 5G support. Once the data is transmitted over 5G, it is received by the 5G Remote Radio Unit. This unit is a powerful router designed to send data over a long distance within the network to a 5G edge server for analysis. The edge analysis plays a crucial role in swiftly processing the raw data, extracting essential features and relevant information that would be used for real-time data visualization. Post-edge analysis sends the processed data back through the 5G network to the 5G NR-Transceiver again. This transceiver feeds the data to a remote PC, enabling data visualization in an edge device (e.g., on-site PC). This visualization assists experts and technicians in understanding the milling process's dynamics and helping in better decision-making.

The entire monitoring system seamlessly integrates advanced 5G technology with traditional sensors and milling processes. The primary objective is to capture raw data, transmit it in real-time over 5G networks, analyze it at the edge, and visualize the processed data to provide actionable insights.

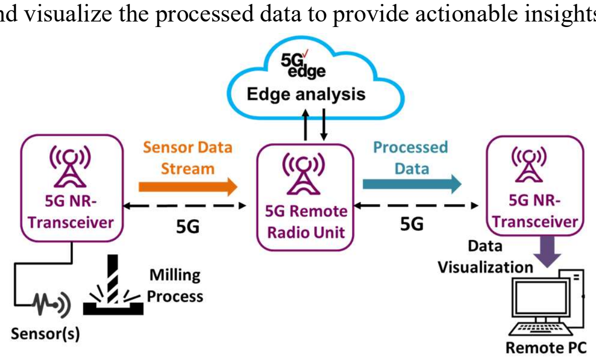

Fig. 2. 5G-Enabled milling monitoring system architecture.

2.2. 5G Communication Network

The 5G Network in this study has been developed and managed using the Orbit-Lab platform. Fig. 3 illustrates the configuration of the 5G communication system. The 5G network is rooted in the COSMOS wireless testbed [37], which leverages an architecture that facilitates dynamic programming. This permits distinct layers tailored for various applications managed by the Software Defined Radio (SDR) [38].

The 5G yellow node acts as a user equipment endpoint (UE) and features a SIMCOM SIM 8200-M2 5G Module, interfaced via PCI-Express (PCIe) and USB 3.0. The SIM8200-M2 is a multi-band 5G modem capable of supporting high data transfer speeds up to 2.4 Gbps. One of its key strengths is the ability to utilize a large number of supported bandwidth configurations across various frequencies, making it highly effective for experiments involving RF space congestion and network behavior under diverse conditions. This module is paired with a Linux-based Quad Core i7 PC, which is used to implement various UE adaptation strategies and to provide the necessary local processing power for sensors and actuators that are attached to it. The flexibility and computational capability of this Linux platform are crucial for handling complex processing tasks and for real-time algorithmic adjustments.

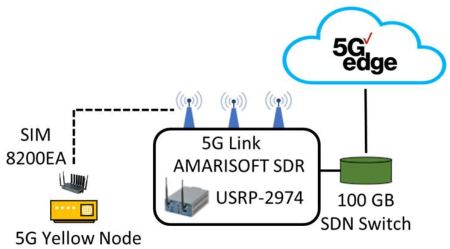

Fig. 3. 5G communication system setup.

At the other end of the 5G link, the SDR-based setup employs the USRP-2974, a unit that integrates an embedded X86 PC with an X310 USRP. This powerful combination provides an effective platform for advanced SDR applications including running the Amarisoft SDR-based gNodeB software and the 5G core [39, 40]. This setup supports the high-speed, low-latency communication that is crucial for edge computing applications in the 5G ecosystem. The SDR-based implementation with the USRP-2974 and Amarisoft enables us to interact with all segments of the 5G spectrum in the sub-6 GHz range (FR1). This capability provides extensive flexibility in exploring and manipulating various aspects of radio functionalities, enhancing our control and understanding of network dynamics for smart manufacturing deployments.

Complementing the USRP-2974, we use high-performance backend servers powered by Xeon processors, primarily for edge processing. These servers are tasked with handling the significant computational demands required for advanced data processing and network functions at the edge of the 5G network. A notable feature of our setup is the connectivity between the USRP-2974 and the edge servers, which is facilitated through a 10 Gbps Ethernet link. This high-speed connectivity is vital for ensuring swift and efficient data transfer, allowing for real-time processing and responsiveness within the network.

3. 5G-Enabled Milling Testbeds

Two testbeds were developed to demonstrate the capability of the proposed 5G-enabled milling monitoring system described in the previous sections.

3.1. 5G robotic milling testbed

The architecture of the 5G robotic milling testbed is illustrated in Fig. 4. Within this setup, an industrial robot is placed next to a rotary table that securely holds the workpiece. This workpiece is meticulously examined by a laser camera integrated with the 5G yellow node. The camera transmits the measure data cloud (a stream of large image data) to the 5G yellow node, relaying the data to the 5G link. A remotely situated 5G edge provides the capability to access and process the data. This testbed excels at performing detailed robotic milling tasks to rectify defective regions. It is worth mentioning that while the intricacies of the 5G-empowered robotic control for milling are noteworthy, they will be explored in a different study as they are not the primary focus of this research.

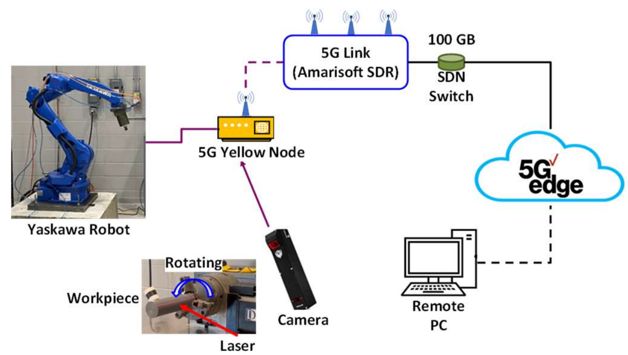

Fig. 4. 5G Robot Testbed Architecture.

The implemented testbed (Fig. 5) is equipped with a Yaskawa GP25, a 6-axis industrial robot, with a Pushcorp SM1503 end milling effector. The sensor is a Gocator 2180 laser camera with a measurement resolution of up to 92 micrometers. It is set up next to a workbench where the workpiece is held by a rotary table (VH-6). The robot and camera have TCP/IP interfaces connected to the 5G yellow node to enable 5G communications. The yellow node is wirelessly connected to a 5G Link for long-distance data transmission. A 5G edge is located remotely and can access the components through the 5G network. The testbed is equipped with the “yellow node” UE acting as the endpoint of the 5G link.

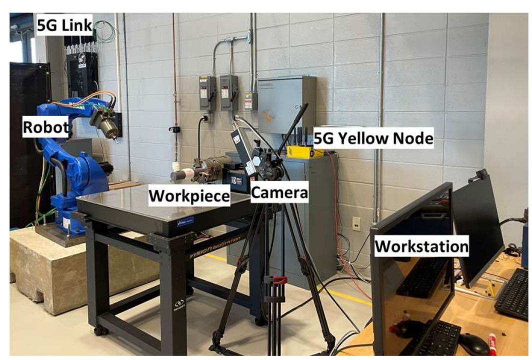

Fig. 5. 5G robot milling testbed.

3.2. 5G CNC milling testbed

The architecture of the 5G Milling Testbed is described in Fig. 6. Similar to the 5G Robotic Testbed, the vibration sensor attached to the workpiece is connected to the Data Acquisition (DAQ) unit. The DAQ is connected to the 5G yellow node to integrate with the 5G platform. The measured data is transmitted via the 5G link to the 5G edge for post-processing and then downloaded for visualization.

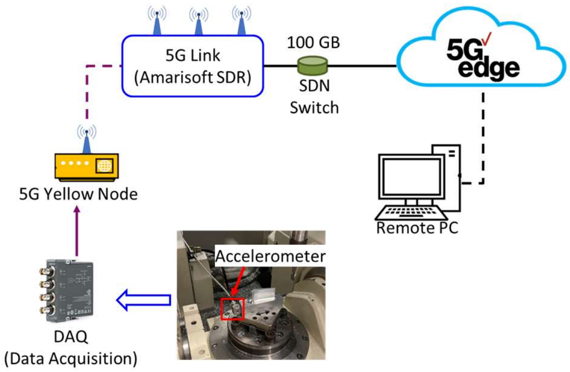

Fig. 6. 5G CNC milling testbed architecture.

Fig. 7. shows the 5G milling testbed which is based on a Microlution 5100 5-axis milling machine with a 5-enabled accelerometer. The milling tool is a 6.35 mm two-flute flat-end mill. A Kistler 8763B100 tri-axial accelerometer is attached to the workpiece to monitor process vibration. The NI-9234 data acquisition unit collects the vibration data from the sensor. The DAQ uses the TCP/IP interface to connect with a 5G yellow node to transmit measured data wirelessly. A Python script has been deployed on the 5G edge to access the DAQ via the NI Python application interface (API).

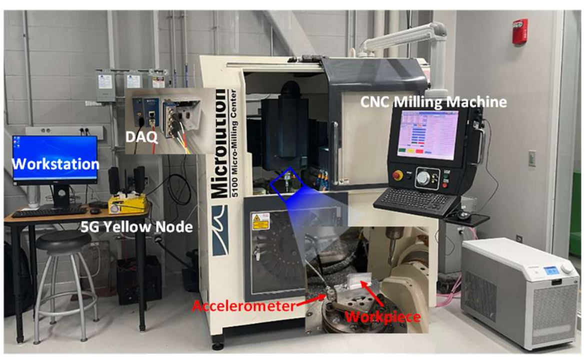

Fig. 7. 5G CNC milling testbed.

4. Results and Discussion

4.1 5G-enabled imaging and visualization

In the robotic milling testbed, the workpiece with a defect simulant is measured by a 5G-enabled laser scanner shown in Fig. 8. The measured data cloud is up streamed to the 5G edge server in which edge computing, i.e., data analytics, is performed. A cylindrical workpiece is mounted on a rotary table, while the Gocator laser scanner is positioned adjacent to the workpiece for surface scanning. The initial scanning output from the laser scanner consists of a line profile that measures the distance (Z-axis) between the current laser-illuminated location (X-axis) on the workpiece and the scanner. During the scanning process, the rotary table rotates counterclockwise, allowing the scanner to capture the entire surface of the workpiece. It should be mentioned that the rotation and workpiece axes might not be perfectly aligned, which could result in a certain fluctuation in the acquired data of surface topography.

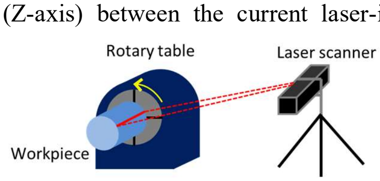

Fig. 8. Camera scanning process.

The measured raw data is noted as M_{raw}, where M_{raw} is given by Eq. (1):

$$M_{raw} = [x(t_i), z(t_i)]_i \quad (1)$$

where $x(t_i)$ stands for the X-axis distance and $z(t_i)$ stands for the distance between the workpiece surface and the scanner. The timestamp for each scanned line profile is t_i, where i = 1,2,3… Fig. 9 shows a plot of the raw measured data. Note the measured raw data is a set of timed line profiles. A post-process converted the timed raw measurement data into a 3D topography. Eqs. (2-4) express the operation of converting the raw measurement. The distance between the workpiece rotation center and the laser scanner is measured and noted as d_{ref}. And $\omega \cdot \sum_1^n t_i$ stands for the angles that the workpiece has rotated since the measurement started, where ω stands for the rotating angler speed, and n stands for the current time stamp. Fig. 10 shows the post-processed workpiece measurement.

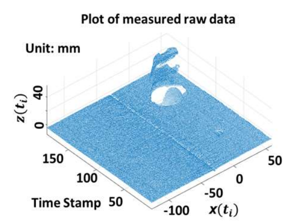

Fig. 9. Plot of measured raw data cloud.

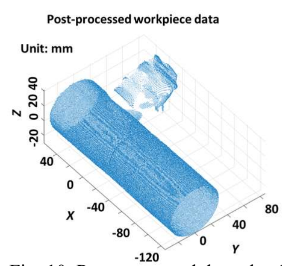

Fig. 10. Post-processed data cloud.

$$M_{post} = [X_{topo}, Y_{topo}, Z_{topo}], where\ X_{topo} = [x(t_i)] \quad (2)$$

$$Y_{topo} = [(d_{ref} + z(t_i)) \cdot \cos(\omega \cdot \textstyle\sum_1^n t_i)] \quad (3)$$

$$Z_{topo} = [(d_{ref} + z(t_i)) \cdot \sin(\omega \cdot \textstyle\sum_1^n t_i)] \quad (4)$$

To identify the location of the defect simulant, a CAD model of the referred workpiece is converted into a point cloud (C_{ref}) to compare with the measurement data cloud. Note that the CAD model is the workpiece design file and has a higher resolution than the measured data. The C_{ref} and M_{post} coordinates can be aligned using the iterative closest point (ICP) algorithm. To identify the defect coordinates, each point in M_{post} is iterated for searching the closet point in C_{ref}. If the distance between those points is less than the camera resolution, the points in M_{post} are marked as normal. Otherwise, it is marked as a defect. Fig. 11 shows the defect points of the workpiece selected by this process.

Generating a surface from the point cloud is a well-studied topic in computer graphics. Many algorithms are already developed for these purposes. In this study, we used the Ball Pivoting Algorithm (BPA) to connect the individual points to the surface [41]. The algorithm operates by iteratively "pivoting" a ball of a specified radius around each edge in the

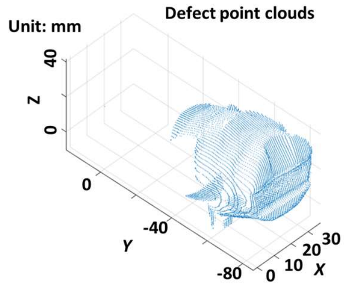

Fig. 11. Defect point cloud of the workpiece.

cloud. When the ball touches a new point, a triangle is formed with the edge's vertices, generating the surface mesh. The process continues until all edges are processed, with the ball radius and initial seed triangle significantly influencing the final output. It's notable for its adaptability to handle large data sets and the flexibility provided by the tuneable ball radius. The typical ball radius is set close to the average distance of the points cloud. In this study, several ball radii are tested. Fig.12 shows the generated surface topography of the defect region using different radii, in which R=8×*avg_dist* gives the best results among others.

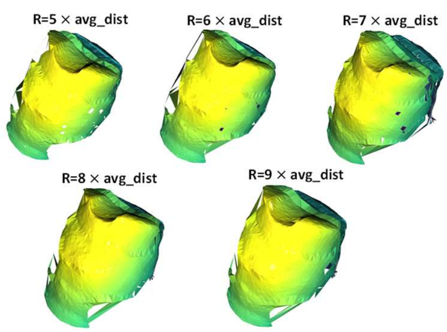

Fig. 12. Generated surfaces of defect simulant with different radius.

4.2 5G-enabled CNC milling vibration monitoring and visualization

In the CNC milling testbed, the process vibration is measured by a 5G-enabled accelerometer and is up streamed to the 5G edge for data analysis, and then, the vibration data is sent back to a local computer for data visualization. The milling experiments were carried out to validate the functionality of the milling testbed. Fig. 13 shows the experiment setup with the milling tool path. The accelerometer was affixed to the base of the workpiece to capture the vibration signals throughout the milling operation. The milling tool path started before the tool engaged with the workpiece material to create a 70 mm x 3.175

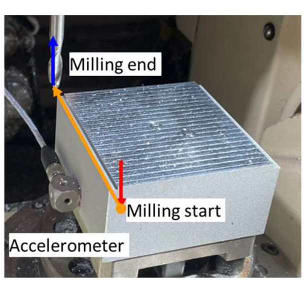

Fig. 13. Milling tool path.

mm slot, concluding with another air-cutting phase. The data acquisition starts recording the vibration signals shortly before the initiation of the milling process.

During the data acquisition, the DAQ system establishes a connection with a 5G yellow node, facilitating the transmission of collected data to the 5G edge for temporary storage and pre-processing. The data was acquired from the tri-axial accelerometer at 51.2 KHz for each channel. Given the rapid data generation, amassing over 2 million data points within a mere 20 seconds of milling, storing the massive vibration data in a single file proved impractical. Therefore, the data was streamed to the 5G edge and divided into smaller ".py" format files, each comprising 51.2 K samples from each channel. This arrangement facilitated real-time computation/analysis of the vibration data on the 5G edge, providing a clear and immediate visual representation of the milling process's vibrations. An example of such real-time vibration monitoring during a stable milling process is illustrated in Fig. 14. A more comprehensive study can be performed for both stable and unstable (e.g., chattering) milling processes in the future.

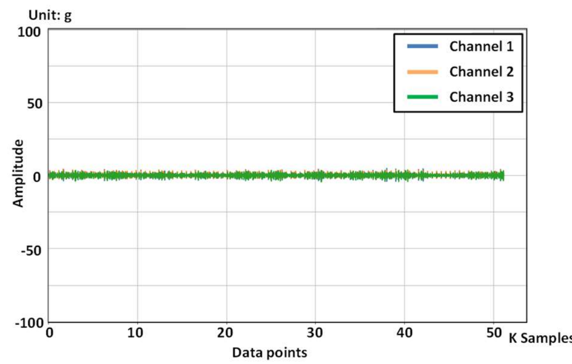

Fig. 14. Workpiece vibration during a stable milling process

The DAQ system stops recording the vibration signals shortly after the milling process concludes. Subsequently, the segmented recording files are merged into a comprehensive file containing all the vibration data. This consolidated data file was then transmitted from the 5G edge to a remote local PC for real-time visualization, as shown in Fig. 15.

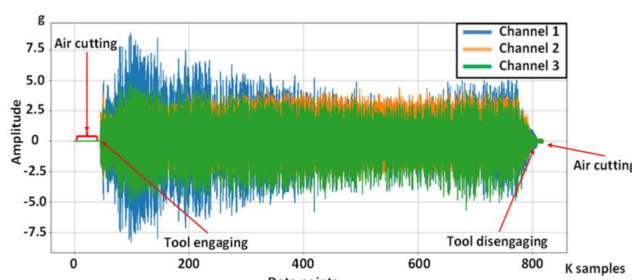

Fig. 15. Visualization on the remote local PC after edge computing.

Table 3 shows the communication ping test of the 5G network used in both testbeds. The network's performance was evaluated across two bandwidths, 20 MHz and 40 MHz, both utilizing 64-byte packet size and 1000-byte packet size. In each scenario, 10,000 packets were sent in the test, achieving an average 0.0027% packet loss rate. The Round-Trip Time

(RTT) measures the communication latency from the sender to the receiver and back. The network's Downlink (DL) Throughput was recorded at 64 Mbps for the 20 MHz bandwidth and 72 Mbps for the 40 MHz bandwidth. Meanwhile, the Uplink (UL) Throughput significantly increased from 10.5 Mbps at 20 MHz to 43 Mbps at 40 MHz, underscoring the enhanced performance offered by the wider bandwidth.

Table 3. 5G testbed communication test

Bandwidth	RTT (64B)	RTT (1000B)	DL Throughput	UL Throughput
20 MHz	21.1 ms	31.5 ms	64 Mbps	10.5 Mbps
40 MHz	23.9 ms	30.8 ms	72 Mbps	43 Mbps

It is worth mentioning that reliable 5G communication is dependent on high-frequency band signals which could impose several challenges, including electromagnetic interference, physical obstructions, and signal attenuation, which need to be addressed in future research. Furthermore, a comparison between a 5G monitoring system and conventional monitoring methods (either wired or wireless) demonstrates the performance benefits of 5G in terms of latency and reliability. This type of comparison will be helpful even though it has been well-documented that 5G provides tremendous advantages over conventional communications. Such comparisons, while not the focus of this work, are aligned with the longer-term research objectives and are crucial for providing a comprehensive understanding of 5G's advantages and areas for improvement.

5. Summary

This study provides an innovative 5G-enabled architecture, implementation, and feasibility for real-time process monitoring, edge computing, and local visualization in milling processes. Two distinct milling testbeds have been designed and implemented to showcase the unique capabilities of this 5G-enabled process monitoring system.

In the 5G robotic milling testbed, the comprehensive geometric data cloud of the workpiece with a defect simulant was acquired through a 5G-enabled laser scanner, enabling a meticulous comparison with the respective CAD model at the edge to precisely identify and visually represent defect geometry. In the 5G CNC milling testbed, workpiece vibration signals were monitored in real-time using a 5G-enabled accelerometer, streamed to the 5G edge for data analytics, and transmitted back to a remote local PC for visualization and analysis of the milling process.

The adoption of 5G technology, characterized by its ultra-low latency and high-speed data transmission, sped up defect identification in remanufacturing and monitoring a milling process condition. The feasibility study underscores the effectiveness of the 5G process monitoring system in milling operations, highlighting its significant potential as an enabling tool for future research and development initiatives in advanced manufacturing sectors.

Acknowledgment

The authors would like to thank the financial support from the DOE/CESMII (grant # DE-EE0007613), the NSF (grant # CMMI-2040358), and the Siemens Corporation, Technology (grant # 830392)

References

[1] P. Koshy, R. Dewes, and D. Aspinwall, High speed end milling of hardened AISI D2 tool steel (~ 58 HRC). Journal of Materials Processing Technology, 2002. 127(2): p. 266-273.
[2] S. Smith and J. Tlusty, An overview of modeling and simulation of the milling process. Journal of Manufacturing Science and Engineering, 1991. 113(2): p. 169-175.
[3] M. Zhao and B. Balachandran, Dynamics and stability of milling process. International journal of solids and structures, 2001. 38(10-13): p. 2233-2248.
[4] T.L. Schmitz and K.S. Smith, Milling dynamics. Machining Dynamics: Frequency Response to Improved Productivity, 2019: p. 129-212.
[5] T. Mohanraj, S. Shankar, R. Rajasekar, N. Sakthivel, and A. Pramanik, Tool condition monitoring techniques in milling process—A review. Journal of Materials Research Technology, 2020. 9(1): p. 1032-1042.
[6] C. Ratnam, K.A. Vikram, B. Ben, and B. Murthy, Process monitoring and effects of process parameters on responses in turn-milling operations based on SN ratio and ANOVA. Journal of Measurement, 2016. 94: p. 221-232.
[7] I. Daniyan, F. Fameso, F. Ale, K. Bello, and I. Tlhabadira, Modelling, simulation and experimental validation of the milling operation of titanium alloy (Ti6Al4V). The International Journal of Advanced Manufacturing Technology, 2020. 109: p. 1853-1866.
[8] D. Novovic, R. Dewes, D. Aspinwall, W. Voice, and P. Bowen, The effect of machined topography and integrity on fatigue life. International Journal of Machine Tools Manufacture, 2004. 44(2-3): p. 125-134.
[9] J.Z. Zhang and J.C. Chen, Tool condition monitoring in an end-milling operation based on the vibration signal collected through a microcontroller-based data acquisition system. The International Journal of Advanced Manufacturing Technology, 2008. 39: p. 118-128.
[10] M.F. Gomez and T.L. Schmitz, Displacement-based dynamometer for milling force measurement. Procedia Manufacturing, 2019. 34: p. 867-875.
[11] T.L.L. Oliveira, R. Zitoune, A.C. Ancelotti Jr, and S.S. da Cunha Jr, Smart machining: Monitoring of CFRP milling using AE and IR. Composite Structures, 2020. 249: p. 112611.
[12] A. Honeycutt and T.L. Schmitz, Milling stability interrogation by subharmonic sampling. Journal of Manufacturing Science and Engineering, 2017. 139(4): p. 041009.
[13] T.L. Schmitz, Chatter recognition by a statistical evaluation of the synchronously sampled audio signal. Journal of Sound and Vibration, 2003. 262(3): p. 721-730.
[14] T. Schmitz, A. Cornelius, J. Karandikar, C. Tyler, and S. Smith, Receptance coupling substructure analysis and chatter frequency-informed machine learning for milling stability. CIRP Annals, 2022. 71(1): p. 321-324.
[15] D.Y. Pimenov, A. Bustillo, and T. Mikolajczyk, Artificial intelligence for automatic prediction of required surface roughness by monitoring wear on face mill teeth. Journal of Intelligent Manufacturing, 2018. 29(5): p. 1045-1061.
[16] L. Cao, T. Huang, X.-M. Zhang, and H. Ding, Generative adversarial network for prediction of workpiece surface topography in machining stage. IEEE/ASME Transactions on Mechatronics, 2020. 26(1): p. 480-490.
[17] N.J. van Dijk, N. van de Wouw, E.J. Doppenberg, H.A. Oosterling, and H. Nijmeijer, Robust active chatter control in the high-speed milling process. IEEE Transactions on Control Systems Technology, 2011. 20(4): p. 901-917.
[18] J. Munoa, X. Beudaert, Z. Dombovari, Y. Altintas, E. Budak, C. Brecher, and G. Stepan, Chatter suppression techniques in metal cutting. CIRP annals, 2016. 65(2): p. 785-808.

[19] S. Wan, X. Li, W. Su, J. Yuan, and J. Hong, Active chatter suppression for milling process with sliding mode control and electromagnetic actuator. Journal of Mechanical Systems Signal Processing, 2020. 136: p. 106528.
[20] E. Garcia Plaza, P. Nunez Lopez, and E. Beamud Gonzalez, Multi-sensor data fusion for real-time surface quality control in automated machining systems. Journal of Sensors, 2018. 18(12): p. 4381.
[21] X. Zhang, X. Lu, S. Wang, W. Wang, and W. Li, A multi-sensor based online tool condition monitoring system for milling process. Procedia CIRP, 2018. 72: p. 1136-1141.
[22] J. Mennig, L. Hajek, and P. Münder, 5G in Production. 2019.
[23] M. Noor-A-Rahim, J. John, F. Firyaguna, H.H.R. Sherazi, S. Kushch, A. Vijayan, E. O'Connell, D. Pesch, B. O'Flynn, and W. O'Brien, Wireless communications for smart manufacturing and industrial IoT: Existing technologies, 5G and beyond. Journal of Sensors, 2022. 23(1): p. 73.
[24] D. Mourtzis, J. Angelopoulos, and N. Panopoulos, Smart manufacturing and tactile internet based on 5G in industry 4.0: Challenges, applications and new trends. Journal of Electronics, 2021. 10(24): p. 3175.
[25] S.K. Rao and R. Prasad, Impact of 5G technologies on industry 4.0. Wireless personal communications, 2018. 100: p. 145-159.
[26] Z.M. Temesvári, D. Maros, and P. Kádár, Review of Mobile Communication and the 5G in Manufacturing. Procedia Manufacturing, 2019. 32: p. 600-612.
[27] S. Jun, Y. Kang, J. Kim, and C. Kim, Ultra - low - latency services in 5G systems: A perspective from 3GPP standards. ETRI Journal, 2020. 42(5): p. 721-733.
[28] J. Ansari, C. Andersson, P. de Bruin, J. Farkas, L. Grosjean, J. Sachs, J. Torsner, B. Varga, D. Harutyunyan, and N. König, Performance of 5G trials for industrial automation. Electronics, 2022. 11(3): p. 412.
[29] B. Chen, J. Wan, L. Shu, P. Li, M. Mukherjee, and B. Yin, Smart factory of industry 4.0: Key technologies, application case, and challenges. Ieee Access, 2017. 6: p. 6505-6519.
[30] Y. Siriwardhana, P. Porambage, M. Liyanage, and M. Ylianttila, A survey on mobile augmented reality with 5G mobile edge computing: architectures, applications, and technical aspects. IEEE Communications Surveys & Tutorials, 2021. 23(2): p. 1160-1192.
[31] R. Kufakunesu, G.P. Hancke, and A.M. Abu-Mahfouz, A survey on adaptive data rate optimization in lorawan: Recent solutions and major challenges. Journal of Sensors, 2020. 20(18): p. 5044.
[32] P. Mohanram, A. Passarella, E. Zattoni, R. Padovani, N. König, and R.H. Schmitt, 5G-Based Multi-Sensor Platform for Monitoring of Workpieces and Machines: Prototype Hardware Design and Firmware. Electronics, 2022. 11(10): p. 1619.
[33] P. Kehl, J. Ansari, M.H. Jafari, P. Becker, J. Sachs, N. König, A. Göppert, and R.H. Schmitt, Prototype of 5G integrated with TSN for edge-controlled mobile robotics. Electronics, 2022. 11(11): p. 1666.
[34] E.C. IndustryLab, A case study on real-time control in manufacturing. Ericsson Reports, April 2018.
[35] M. Gundall, J. Schneider, H.D. Schotten, M. Aleksy, D. Schulz, N. Franchi, N. Schwarzenberg, C. Markwart, R. Halfmann, and P. Rost. 5G as enabler for Industrie 4.0 use cases: challenges and concepts. in 2018 IEEE 23rd international conference on emerging technologies and factory automation (ETFA). 2018. IEEE.
[36] H.W.X. Labs, Cloud Robotics: Trends, Technologies, Communications. GTI 5G and Cloud Robotics White Paper, 2017.
[37] D. Raychaudhuri, I. Seskar, G. Zussman, T. Korakis, D. Kilper, T. Chen, J. Kolodziejski, M. Sherman, Z. Kostic, and X. Gu. Challenge: COSMOS: A city-scale programmable testbed for experimentation with advanced wireless. in Proceedings of the 26th Annual International Conference on Mobile Computing and Networking. 2020.
[38] F.K. Jondral, Software-defined radio—basics and evolution to cognitive radio. EURASIP Journal on Wireless Communications and Networking, 2005. 2005(3): p. 1-9.
[39] N. Nikaein, M.K. Marina, S. Manickam, A. Dawson, R. Knopp, and C. Bonnet, OpenAirInterface: A flexible platform for 5G research. ACM SIGCOMM Computer Communication Review, 2014. 44(5): p. 33-38.
[40] F. Gringoli, P. Patras, C. Donato, P. Serrano, and Y. Grunenberger, Performance assessment of open software platforms for 5G prototyping. IEEE Wireless Communications, 2018. 25(5): p. 10-15.
[41] F. Bernardini, J. Mittleman, H. Rushmeier, C. Silva, and G. Taubin, The ball-pivoting algorithm for surface reconstruction. IEEE transactions on visualization, 1999. 5(4): p. 349-359.