A Production Interface to Enable Legacy Factories for Industry 4.0

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Abstract. Due to the recent pandemic, our factory operations have experienced significant setbacks, prompting the need for factory automation to maintain productivity. However, most of our factories rely heavily on human input and oversight and cannot operate remotely. Automating our factories has revealed technological gaps that fall short of our expectations, needs, and vision. Therefore, the purpose of this paper is to bridge this gap by introducing practical methodologies and applied technology that can enhance legacy factories and their equipment. Our proposed solution is the ORiON Production Interface (OPI) unit, which can function as a smart networked edge device for virtually any machine, allowing the factory to operate efficiently. We have incorporated various computer vision algorithms into the OPI unit, enabling it to autonomously detect errors, make decentralized decisions, and control quality. Despite the concept of Industry 4.0 (I4.0) being known, many machines in use today are closed source and unable to communicate or join a network. Our research offers a viable solution to implement Industry 4.0 in existing factories, and experimental results have demonstrated various applications such as process monitoring, part positioning, and broken tool detection. Our intelligent networked system is novel and enables factories to be more innovative and responsive, ultimately leading to enhanced productivity. All manufacturing companies interested in adopting Industry 4.0 technology can benefit from it, and the OPI, being an IoT device, is also an appealing option for developers and hobbyists alike.

1. Introduction

Industry 4.0 (I4.0) refers to the ongoing shift in manufacturing towards digital transformation [1, 2], leveraging technologies such as the Internet of Things (IoT), additive manufacturing (AM), cognitive computing, identification, analytics, and more [3]. Key features of I4.0 include enabling seamless communication between machines and people, providing information from all system points, supporting technical assistance to humans, and facilitating decentralized decision-making. I4.0 has the

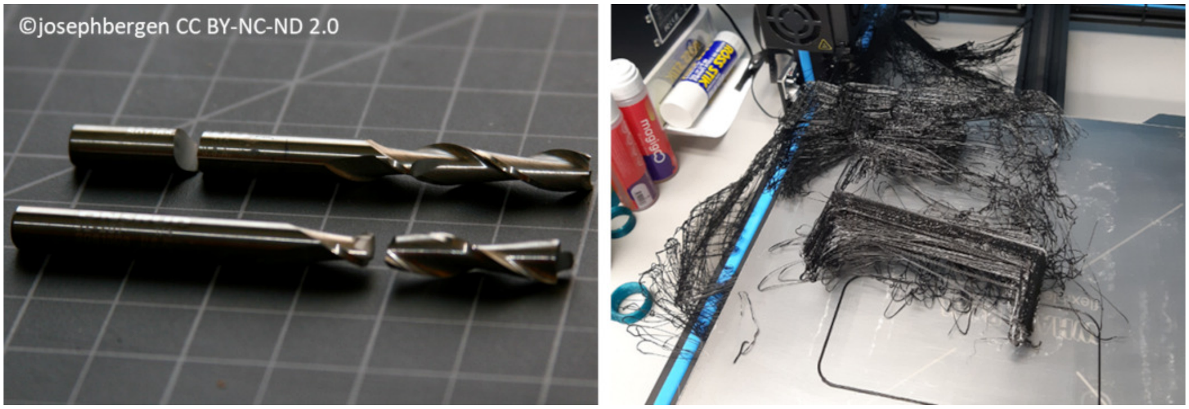

Figure 1. Examples of manufacturing failures: broken tools and work holding failures.

potential to create an autonomous production environment that can run a factory without human intervention and even offer predictive maintenance. The COVID-19 pandemic has further underscored the need for factory automation, particularly for the manufacture of personal protective equipment (PPE), given the restrictions on physical distancing and the high demand for PPE. However, the majority of factories currently rely heavily on human input and oversight, and cannot function autonomously or remotely. As a result, technology has fallen short of expectations and vision [4, 5].

For our factories to operate with greater autonomy and remote capabilities, we must equip the manufacturing system to perceive, comprehend, predict, and interact with both machines and products. The system must be capable of monitoring physical processes and collaborating with humans to adjust these processes and achieve desired outputs. Figure 1 provides two examples of manufacturing failures: broken tools in cutting machines and work holding issues in three-dimensional (3D) printing. When a tool breaks, it fails to cut properly, causing damage to the part, wasting materials, and even harming the cutting machine. Similarly, if a 3D print does not adhere to the build bed, it results in printing "spaghetti" and accumulating material at the nozzle, which can lead to nozzle damage. Thus, detecting failures and inspecting work-in-progress (WIP) are crucial for achieving higher accuracy and quality in part production. Regrettably, the majority of presently operating machines are closed source and lack the capability to connect or integrate with a network for this intended purpose, while replacing them is a costly alternative.

Taking inspiration from the concept of retrofitting, which involves adding new equipment to an old machine to improve its performance, this paper aims to bridge the technology gap and address the need for automating existing factories by creating a workable solution for remote process control. The solution must be uncomplicated, cost-effective, and compact to encourage more factory owners to adopt it. The research question that this paper seeks to answer is what such a solution should look like. Upon observation, we have noticed that CNC machines commonly use a serial port configuration to link up with a monitor. The serial port transfers information sequentially, one bit at a time. However, a dedicated monitor at the machine is unnecessary for factory automation. Therefore, we propose repurposing the serial port and creating an interface that acts as a mediator, allowing the network to communicate with the CNC machines via the serial port.

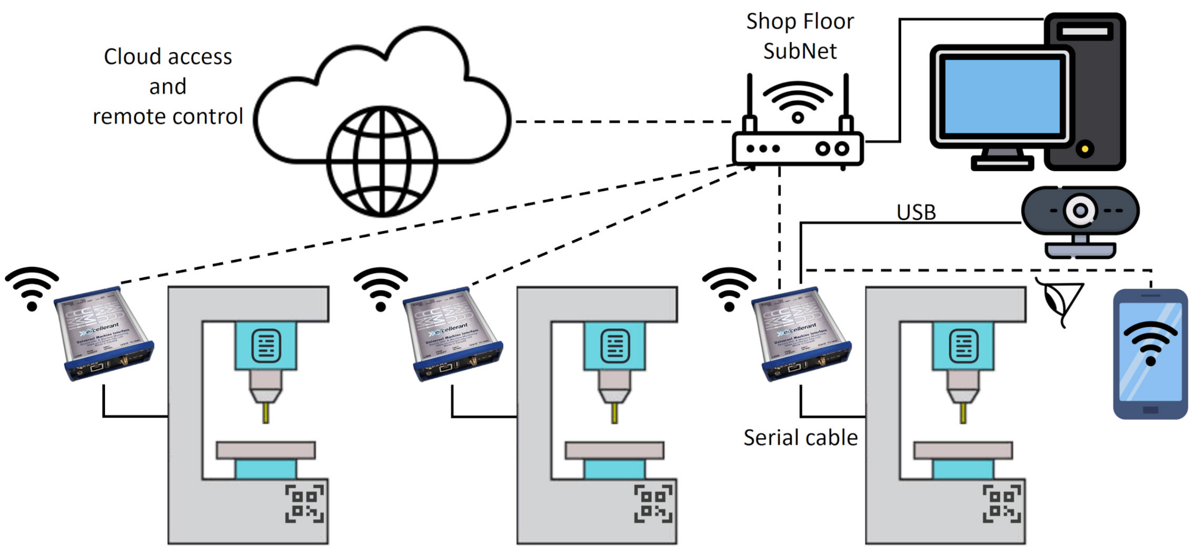

Figure 2. The architecture of the proposed system.

Specifically, we introduce the ORiON Production Interface (OPI), an IoT solution designed for computer numerical control (CNC) machines, enabling wired/wireless access for direct numerical control (DNC) and machine monitoring. The architecture of the proposed system is illustrated in Fig. 2. Moreover, we investigate the integration of computer vision (CV) tools into the solution, connecting cameras to the OPI to "look" at the machines and WIP, and communicate with the machine control unit (MCU) directly. The solution can monitor the machines' status, detect tool conditions, identify failures, and locate part position and orientation. To achieve a smart system that can handle different situations and operations, we utilize fiducials to self-identify the WIP and its process needs. QR codes can distinguish tools, and barcodes can identify tool numbers and establish datums. CV algorithms are implemented in the OPI unit to process collected data, which the unit sends to the MCU for direct control and to the master system through the Intranet for other system information. Overall, this paper's contributions include:

(i) An uncomplicated yet effective remedy that can establish a remote process control system by connecting legacy machines and enabling direct communication with the control unit.

(ii) Creating an identification system using fiducials to enable interactions between machines, parts, and the vision system.

(iii) Incorporating computer vision technologies into the decision-making process, which is non-invasive and rapid enough to provide feedback in a timely manner.

The result allows our factories to become smarter and facilitate remote operations, paving the way for exploring cutting-edge technologies that can improve factory productivity while providing customization options [6].

The paper is structured as follows: Section 2 provides an overview of the relevant literature, while Section 3 outlines the methodology used. Section 4 examines the applications, and Section 5 offers a discussion of the findings. Finally, the paper concludes with Section 6.

2. Literature review

The integration of IoT and computer vision systems is crucial for the development of the proposed system in this paper. These systems play a pivotal role in enabling remote, real-time monitoring and control, enhancing automation, and facilitating seamless connectivity and data sharing. Therefore, this section provides an overview of the relevant literature and key works in the domains of IoT and vision systems for manufacturing systems.

Internet of Things (IoT) IoT technologies can be applied to various aspects of production, including supply chain [7], scheduling [8], inventory management [9], assembly [10], and quality control [11]. One significant application is real-time monitoring and control of production processes [12]. By connecting sensors and devices to the internet, manufacturers can track the status of machines, production lines, and products in real-time. This real-time data can be used to optimize production schedules, improve product quality, and reduce waste. Another application of IoT technologies in manufacturing systems is predictive maintenance [13]. By using machine learning algorithms to analyze data from sensors, manufacturers can identify potential equipment failures before they occur. This allows for proactive maintenance and reduces downtime, saving time and money. IoT technologies can also be used for logistics management [14], enabling enterprises to achieve on-time order fulfilment. This can improve logistics productivity and increase delivery efficiency. However, the widespread adoption of IoT technologies in manufacturing systems also presents several challenges. One significant challenge is the integration of IoT devices with existing manufacturing systems. Many manufacturers have legacy equipment and software systems that may not be compatible or have limited computational resources to work with IoT technologies [15]. Another challenge is cybersecurity. IoT devices are vulnerable to cyber attacks, and manufacturers must ensure that their systems are secure to protect sensitive data and intellectual property [16]. Recent research has focused on addressing these challenges by developing new IoT technologies and improving existing ones. For example, cloud computing can be used to integrate IoT devices with existing manufacturing systems [17]. Artificial intelligence and machine learning algorithms are also being used to analyze data from IoT devices and improve manufacturing processes [18]. For example, deep learning algorithms can be used for predictive maintenance and quality control. In addition to technological advancements, recent research has also focused on the organizational and managerial aspects of IoT adoption in manufacturing systems [19]. Manufacturers must develop new processes and workflows to take advantage of IoT technologies effectively.

Vision systems The utilization of computer vision (CV) technologies in manufacturing systems is widespread and serves various purposes, such as enhancing quality control, automating manufacturing tasks, and enabling closed-loop control systems, among others [20, 21]. For instance, CV algorithms can be used to detect defects in products and components, such as surface cracks [22], weld defects [23], and misalignments [24]. Monitoring and analyzing sensor data from the production line can enhance quality control and defect prevention [25]. Automation of inspection tasks, such as measuring dimensions, identifying parts, and verifying assemblies, has been achieved using CV technologies [26]. CV technologies can also observe human actions during manufacturing processes, facilitating HMI [27]. For example, motion capture using

	Applications	**Challenges**
IoT	Real-time monitoring and control, optimization of production schedules [12]	Integration challenges with existing manufacturing systems, compatibility issues with legacy equipment and software [15]
	Predictive maintenance, reducing downtime and saving costs [13]	Limited computational resources [15], cybersecurity risks [16]
	Logistics management, improving productivity and delivery efficiency [14]	
CV	Quality control, defect detection in products and components [22, 23, 24]	Complex deployment, infrastructure requirements [20]
	Automation of manufacturing tasks, improving efficiency and accuracy [26]	Calibration and accuracy validation requirements, limitations in handling complex variations or low-contrast features
	Human activity observation, facilitating human-machine interaction, ergonomics assessment [27, 28]	Camera positioning and angle requirements for accurate observation
	Integration with emerging technologies, enhancing functionality [29, 30, 31]	Additional hardware and software integration requirements, limitations in real-time synchronization and data transfer
	Machine learning integration, improving accuracy and quality [32, 33]	Requirements for sufficient training data and computational resources

Table 1. A comparison of the systems in the literature.

depth cameras can be employed to digitalize human activity for collaborative robots [34] and ergonomics assessment [28]. Similarly, Faccio et al. [35] developed a human factor analyzer for work measurement during manufacturing and assembly. CV technologies can also be integrated with virtual reality (VR) [29], augmented reality (AR) [30], and digital twin [31] applications to further enhance their functionality. The incorporation of machine learning can further improve the accuracy and quality of CV applications in manufacturing [32, 33]. However, the deployment of CV systems in manufacturing environments can be complex and require significant infrastructure.

In conclusion, Table 1 provides a summary of the applications and challenges of IoT and CV technologies based on the literature review. Driven by the challenges identified, this paper aims to develop a user-friendly interface that leverages readily accessible equipment and tools. The objective is to facilitate the seamless implementation of IoT and CV, providing a straightforward and comprehensive approach for real-time monitoring and management across various scenarios.

3. Methodology

3.1. Machines and setup

The primary focus of this study is on computer numerical control (CNC) machines, which include a drilling router (Zenbot CNC, Visalia, USA) and a desktop 3D printer (Comgrow, Shenzhen, China), as illustrated in Fig. 3. The CNC router is capable of

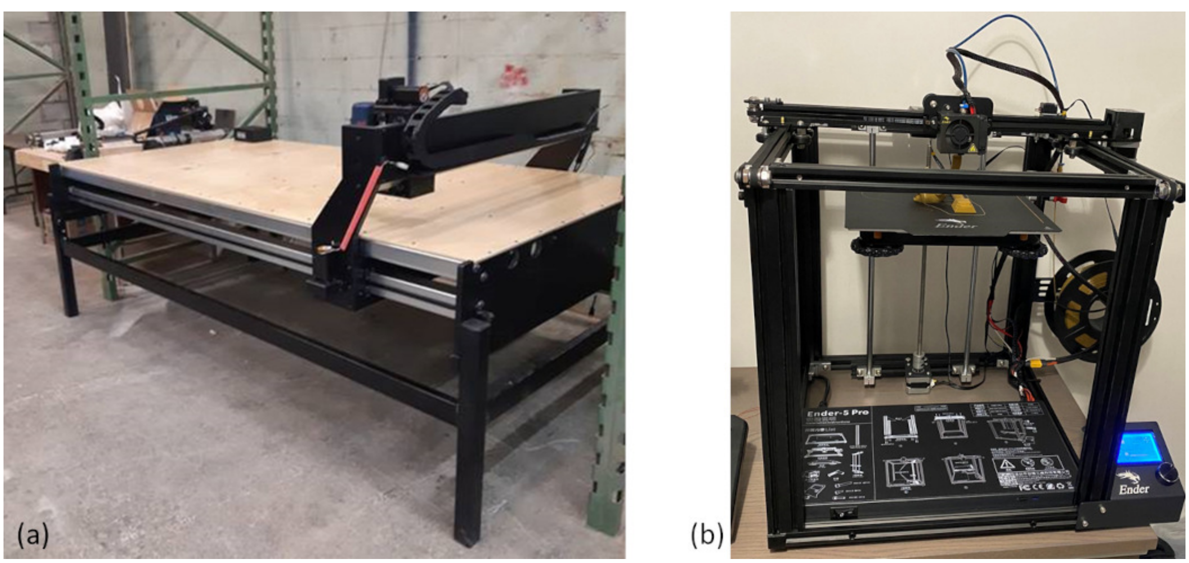

Figure 3. CNC machines: (a) Drilling router. (b) 3D printer.

cutting sheets of material up to 4” × 8”. It can perform accurate inlays, 3D carvings, and engraving, and we will use it to cut plastic sheets. Additionally, we will utilize the 3D printer to produce proof-of-concept fiducials by printing PLA (Polylactic Acid) materials. To create an IoT solution for these machines, the ORiON Production

Interface (OPI) has been designed and developed, which is a compact box (measuring 5”×4”×1.5”) intended to be integrated into the CNC machines (refer to Fig. 4). The OPI also has a dual RS-232 DB9 serial port for establishing a direct numerical

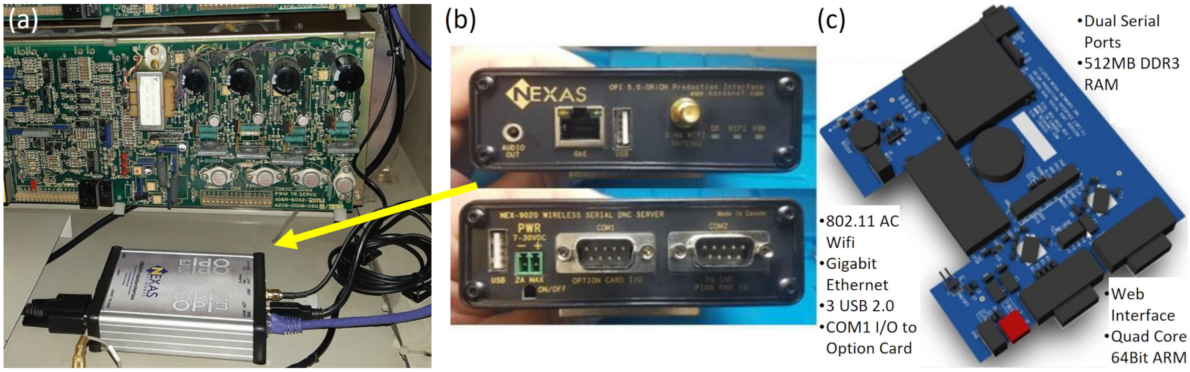

Figure 4. (a) Nexas ORiON Production Interface (OPI) installed in CNC machines. (b) Front and back view of the OPI. (c) Circuit board of the OPI.

control (DNC) link with the CNC machines through serial cables. Installing the OPI is straightforward due to its magnetic mount, detachable screw down power connector, and flexible 24V DC power options – power can even be picked up from the DB9 pin 9 on Fanuc cables that link to the CNC machine. We just need to first find the Fanuc DB25F serial connector in the CNC machine and unscrew it to pull it back. Then, we plug in a DB25M-DB9F null modem cable with power to the Fanuc DB25F connector and to the OPI. The OPI can connect to the internet through either Ethernet cable or Wi-Fi. It also has a couple of universal serial bus (USB) ports, which can be used for connecting a camera in this study. Therefore, acting as a file storage and embedded DNC engine, the OPI serves as a simple and cost-effective adapter that enables USB and serial DNC links to the CNC machines, rendering them compatible and online. The schematic diagram of the OPI is depicted in Fig. 5, showcasing the port configuration and connectors interfacing. Moreover, the OPI can be accessed through any browser

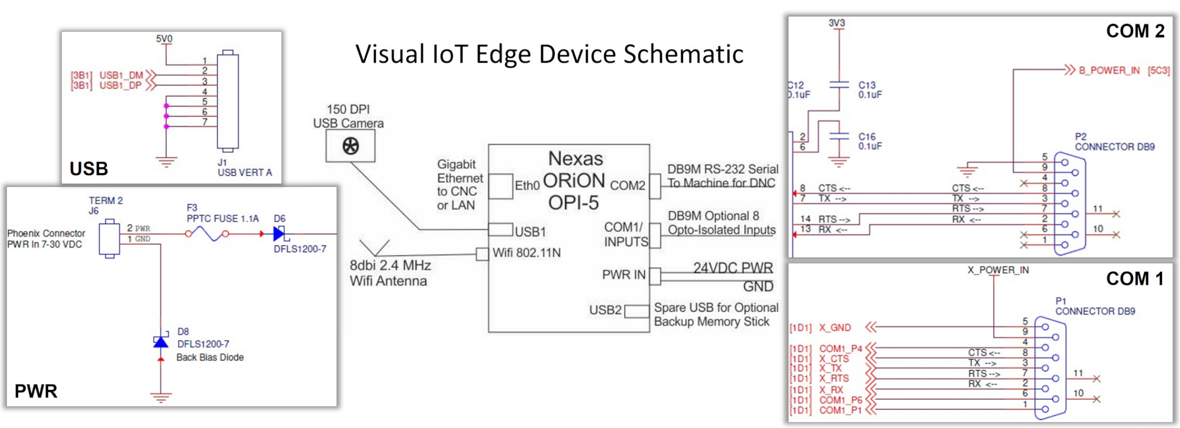

Figure 5. The schematic diagram of the OPI and the detail of the connectors.

using a laptop, tablet, smartphone, or iOS device (as depicted in Fig. 6). The web-based interface enables configuration of various settings for CNC machines, including setting up the serial port, configuring transmit and receive options, defining directories to be utilized, and specifying remote commands. Additionally, a control interface is available for manual sending of commands and reading responses.

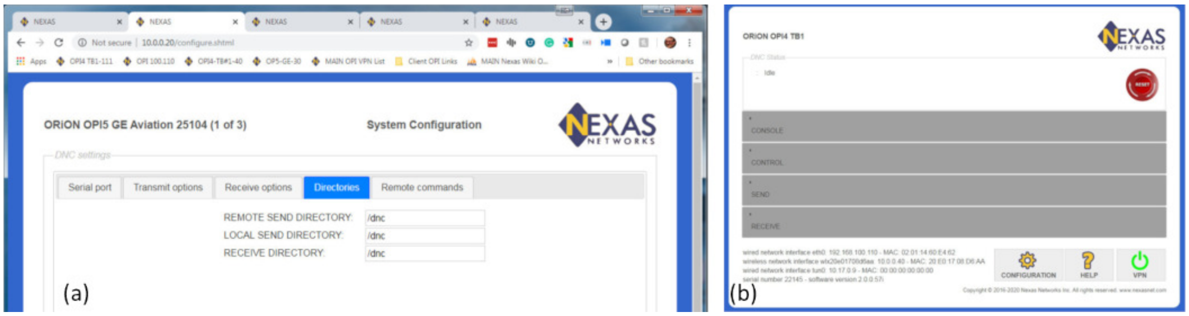

Figure 6. (a) Web interface and (b) control interface of the OPI.

3.2. Fiducials

This study employs two types of machine-readable codes to enable efficient identification. The first type is one-dimensional (1D) barcodes, which use a series of parallel lines to encode data. These barcodes are applied to cylindrical surfaces, such as drill bits, to ensure they can be read even when the surface is rotating. The second type is quick response (QR) codes, which are two-dimensional (2D) barcodes that can store much more information. QR codes are used to enable parts to self-identify themselves, allowing the system to respond accordingly. The finder pattern in a QR code can provide information about the location and orientation of what it is tagging on, and the physical length of the QR code can be used to calculate scale from image size to physical size. The OPI has these codes stored in memory as part of its programs and can produce them on demand, for example, by engraving them in the material or 3D printing them. These data-rich fiducials provide a new tool for operators to quickly identify, position, and size objects during the manufacturing process, which is a significant improvement at minimal cost. This approach enables machines to actively communicate with the system about their physical status, which has a lot of potential for improving the manufacturing process.

3.3. Computer vision and control

In order to provide the system with visual capabilities for monitoring the machines and work-in-process (WIP), a 1080P HD USB digital camera (Jinye Tiancheng Tec., China) was connected to the OPI. This camera, which costs less than USD\$5, is driver-free and has a resolution of 1600×1200 and 30 fps. Using this low-cost, off-the-shelf technology demonstrates that even low-end vision systems can provide significant benefits at a high benefit-cost ratio. For efficient real-time communication, the system must process data swiftly and transmit only essential data to minimize network latency or limited bandwidth delays. Additionally, the system's response time must be minimized. Therefore, it is crucial to design algorithms that can efficiently process data and extract only the necessary information. The computer vision algorithms for the system were implemented at the OPI to scan and decode barcodes and QR codes in less than a second. The decoded data is then processed by the program to determine which subroutine to call. For instance, when the keywords "base" and "part" are present, the "pose" mode is activated to locate and orient the part. When the keyword "tool" is detected, the "tool" mode is activated to verify that the tool is in good condition. The OPI then sends logical controls from each subroutine to the machines and reports the status to the main system via the Intranet. This real-time monitoring and control capability enables process verification and potential customization functions. The framework is highly modular, allowing for easy addition of other functions and operations.

3.4. Implementation

The OPI is a circuit board that consists of a Quad-Core 32 Bit ARM AllWinner H5 Cortex-A53 Processor, along with a Mali-450 GPU and 512 MB of DDR3 RAM with a CPU Clock Speed of 1.5Ghz. It can transmit and receive data at a rate of approximately 896.5 Mbits/sec. Moreover, the OPI runs on Ubuntu Linux 16.04 LTS Core and supports various protocols such as PING, Windows Mapped Drives with SAMBA Server, HTTP server (for web pages), NTP (for time synchronization), SSH Server (for Maintenance), and several others. Additionally, it has a 16 GB internal SD flash drive, a Gigabit Ethernet port, an 802.11 B/G/N Wi-Fi connection, a dual RS-232 DB9 serial port, and a couple of USB ports. Typically, the OPI requires about 14 Watts at 24VDC, drawing roughly 600 mA in normal operation. These specifications make it an ideal candidate for various applications, including computer vision. The system's computer vision algorithms were implemented on the OPI using the C++ programming language. To read barcodes and QR codes, the open-source ZBar library (GNU LGPL 2.1) was utilized. With these powerful tools, the OPI can detect and interpret barcodes and QR codes with ease and speed. Overall, the OPI is a reliable and robust IoT device with impressive specifications and a diverse range of protocols that make it an ideal choice for various applications. Its speed, power, and versatility make it an attractive option for developers and hobbyists alike.

4. Applications

Incorporating "eyesight" and intelligent systems logic into manufacturing systems, this paper has introduced a visual engine capable of addressing a wide range of manufacturing challenges. The following section highlights some of these issues.

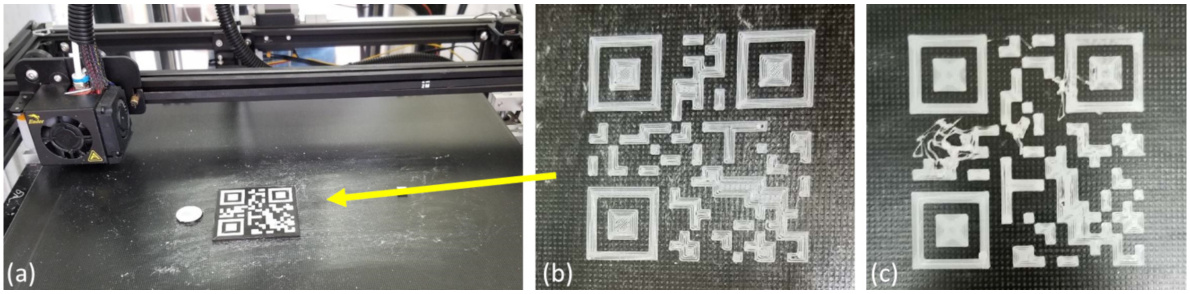

Figure 7. Using fiducials in 3D printing to inspect adhesion.

4.1. Autonomous communication

By storing the fiducials in the OPI, the manufacturing process gains the ability to communicate with the vision system autonomously by creating "structures with messages". One possible application is detecting anomalies during production, such as the importance of proper adherence of the first layer to the build plate in the fused filament fabrication (FFF) 3D printing. To ensure good adhesion, a QR code is printed as the adhesive layer, which is a fiducial that enables the vision system to monitor the process (as depicted in Fig. 7a). The vision engine is capable of reading the 2"×2" QR code from a distance of over one meter (as shown in Fig. 7b). If the vision system fails to recognize the QR code, it suggests that the layer is not adhering properly (as shown in Fig. 7c), and the system will pause and issue an alert. By generating a feedback mechanism that the vision system can assess in real-time, it enables the engineering of quality into the production process. Moreover, this approach simplifies the assessment of production milestones, the auditing of production, and the operation of unattended processes to improve throughput.

4.2. Part location and orientation

To avoid scrapping a run or wasting time due to stock shifting or misalignment, it's crucial to know the location and orientation of the part. This is achieved by using two QR codes, namely "part" and "base", which activate the "pose" mode when the vision engine detects both of them (as illustrated in Fig. 8). The "part" QR code is attached to the part and moves with it, while the "base" QR code is fixed on the worktable. Since each QR code is square, the ordered corners can provide information about the position and orientation of the code. By comparing both QR codes, we can determine the pose of the part. Additionally, the "base" QR code includes the length of the physical code (i.e., "base 30" in Fig. 8 for the code with a 30 mm side length), which aids in computing the physical distance from the image distance between the codes. Figure 8 demonstrates two scenarios where the x-axis points to the right, the y-axis points downwards, and the rotation is in a clockwise direction. The system can identify the part's location and orientation, such as the first case, where the part is positioned at $(-64.3, -72.7)$ mm from the base at an angle of $-2.6°$ relative to the base, or the second case, where the

Figure 8. Use of two QR codes for locating parts of different positions and orientations.

part is located at $(-59.5, -69.4)$ mm at an angle of $-28.9°$ from the base. Using this information, the system can adjust the tool's position concerning the part's location and orientation, resulting in potential applications such as adaptive machining, which can correct errors, increase throughput, and reduce waste. Additionally, this approach can reduce the need for fixtures and extend the cut beyond the machine's bed size, as illustrated in Fig. 9. This proof-of-concept application shows promising implications for various industries.

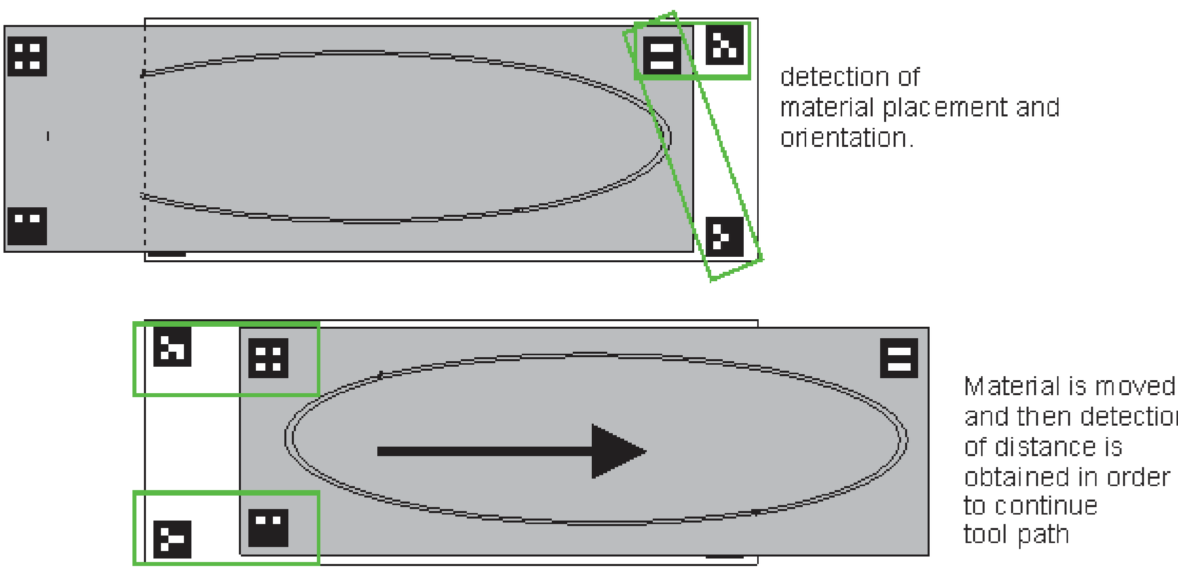

Figure 9. Illustration of extending a cut beyond bed size with the help of fiducials.

4.3. Tool detection and inspection

In machining processes, a significant amount of time is spent by operators to ensure that the correct tool is being used and to determine whether the tool is broken during the machining process. To address this, we use a QR code with the keyword "tool" to activate the "tool" mode. The QR code also includes its side length, which helps in scaling from image size to physical size, as shown in Fig. 10. We wrap a UPC-E barcode

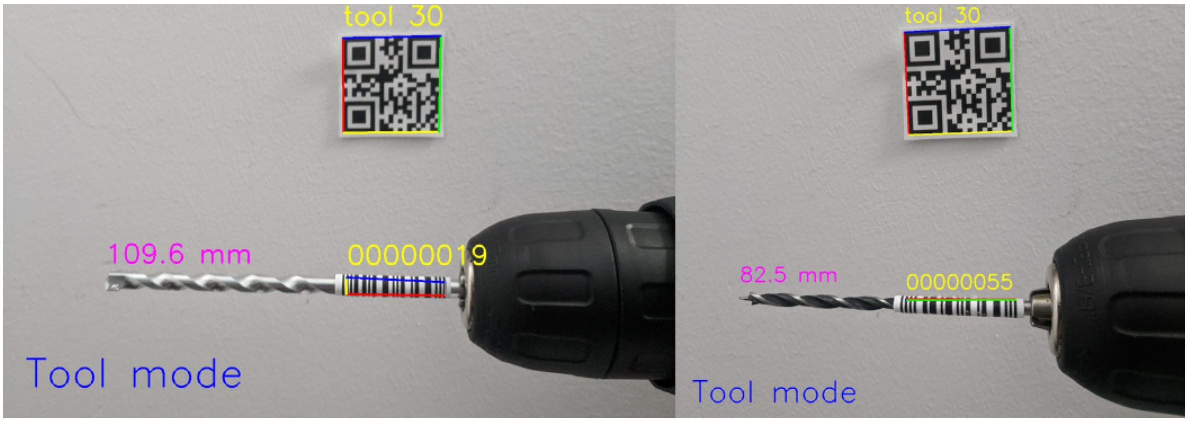

Figure 10. Using a QR code and a barcode for tool detection.

around the tool, which stores the tool number. Typically, there is space to place one barcode just above the cutting bit of most tools. By segmenting the regions of the tool and the drill chuck in the image, the system can compute the tool length by measuring from the end of the tool to the drill chuck, where the thickness changes sharply. The vision engine can detect multiple tools, as shown in Fig. 10, where it has detected two tools with barcodes 00000019 and 00000055, respectively. Since the last digit is a check digit for accuracy, they represent tools #1 and #5, respectively, with lengths of 109.5 mm and 82.5 mm, respectively, which were calculated using the QR code's side length of 30 mm. This approach reduces the time spent by operators on tool selection and verification, improving productivity and reducing errors.

5. Discussion

The current era of I4.0 is witnessing a proliferation of new technologies being developed for modern factories. However, the focus of this paper is on bringing legacy factories up to speed with the latest advancements. In order to achieve this, our approach involves the development of a production interface that can communicate with both machines and the cloud, thus realizing IoT in traditional factories. Our solution is the ORiON Production Interface (OPI), which has been designed to be user-friendly by employing standard equipment and tools. It has modest computational power, which is sufficient to run computer vision and image processing algorithms. Additionally, to ensure that the data transfer between the OPI and the cloud is seamless, the interface has both Ethernet and Wi-Fi connection capabilities. The network infrastructure has been optimized to minimize any delays in the transfer of data across the network, allowing for direct mapping and synchronization of drives. To make the approach comprehensive for various scenarios, we have adopted a format that uses a keyword plus a value, which is then encoded using fiducials. This format is simple enough to shorten the system's response time but generic enough to be used across different scenarios. The selection of input data is also crucial to enable efficient operation and achieve the goals of implementing I4.0 in existing factories. The basis for selecting input data revolves around identifying key variables and parameters that are essential for the OPI unit's smart networked edge device functionality. The selected input data include:

(i) Machine Compatibility Data: Information about closed-source machines and their communication capabilities. Understanding machine compatibility allows the OPI unit to establish connectivity with these machines and facilitate data exchange, bridging the gap between legacy factories and I4.0 concepts.

(ii) Sensor Data: Real-time data from sensors integrated into the CNC machines, capturing available information such as machine status and error messages. This data allows the OPI unit to monitor the production process in real-time and make decentralized decisions.

(iii) Computer Vision Data: Input from computer vision algorithms that detect errors, defects, and misalignments in products and components. This data is crucial for the OPI unit to autonomously control quality and optimize production processes.

(iv) Part Positioning Data: Information about the positions of parts and components during production. This data enables the OPI unit to optimize part positioning and ensure accurate localization.

(v) Broken Tool Detection Data: Data related to tool condition and wear, enabling the OPI unit to detect broken tools and trigger proactive maintenance actions.

The results of selecting these input data enable the OPI unit to function as a smart networked edge device, facilitating seamless communication with various machines in the factory.

Our solution is just the beginning of what is possible, and it makes I4.0 a reality without requiring equipment replacement. It is worthwhile to mention that both the hardware and software for our solution are open source. This means that high-end solutions can be achieved using low-end tools, providing cost-effective benefits to companies. Our approach provides a viable solution for bringing legacy factories into the I4.0 era, without requiring costly equipment replacements. By utilizing the OPI, companies can take advantage of the latest technologies and achieve higher levels of efficiency and productivity. The fact that our solution is open source and has been developed through a collaboration between academia and industry is a testament to its effectiveness and potential for future developments. Furthermore, as an academic-industry collaboration, we have been able to bring the technology readiness level (TRL) of the work from 3 (a proof-of-concept) to 7, where it is now fully functioning in an operational environment. In fact, our solution has already been deployed in the production of PPE, proving its effectiveness in real-world settings, as presented in the following.

5.1. Production of Personal Protective Equipment (PPE)

Due to the COVID-19 pandemic, there has been a surge in demand for personal protective equipment (PPE). As an example, we aimed to produce an endotracheal intubation hood (refer to Fig. 11). This transparent plastic cover is designed to protect

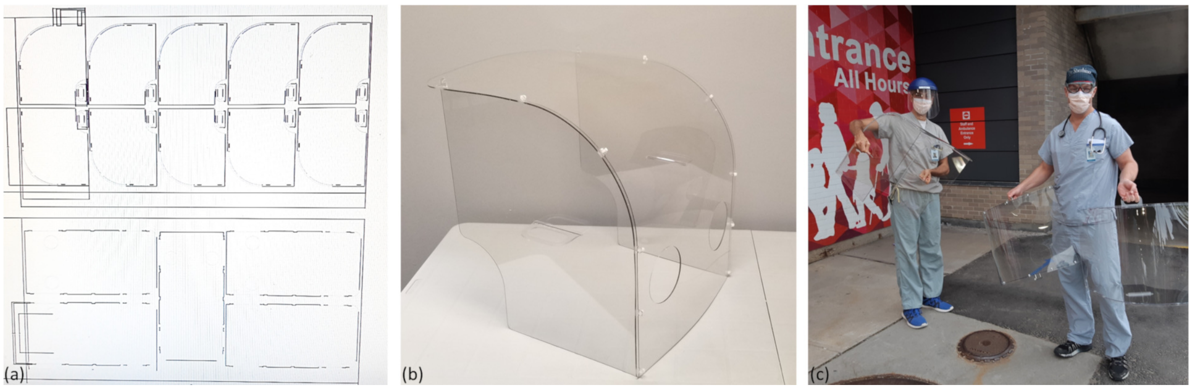

Figure 11. The NexMED ClearVIEW™ endotracheal intubation hood: (a) CAD drawing, (b) assembled product, and (c) actual size with users.

clinicians from exposure to the virus during airway procedures. Our local hospitals approved the design as an effective tool, and we needed to produce over 10,000 hoods efficiently to distribute to at least 1,400 hospitals. The raw material used for the hoods is the 4" $\times$ 8" $\times$ 1/8" Lexan sheets (P&A Plastics Inc., Hamilton, ON). One of the key steps in fabricating the hoods involves using a CNC router to machine the shapes and create holes in the sheets. However, errors such as improper tool offset and misalignment can occur during this step, resulting in wasted manufacturing time and damaged equipment (refer to Fig. 12). Thus, the present system is crucial to mass-produce high-quality

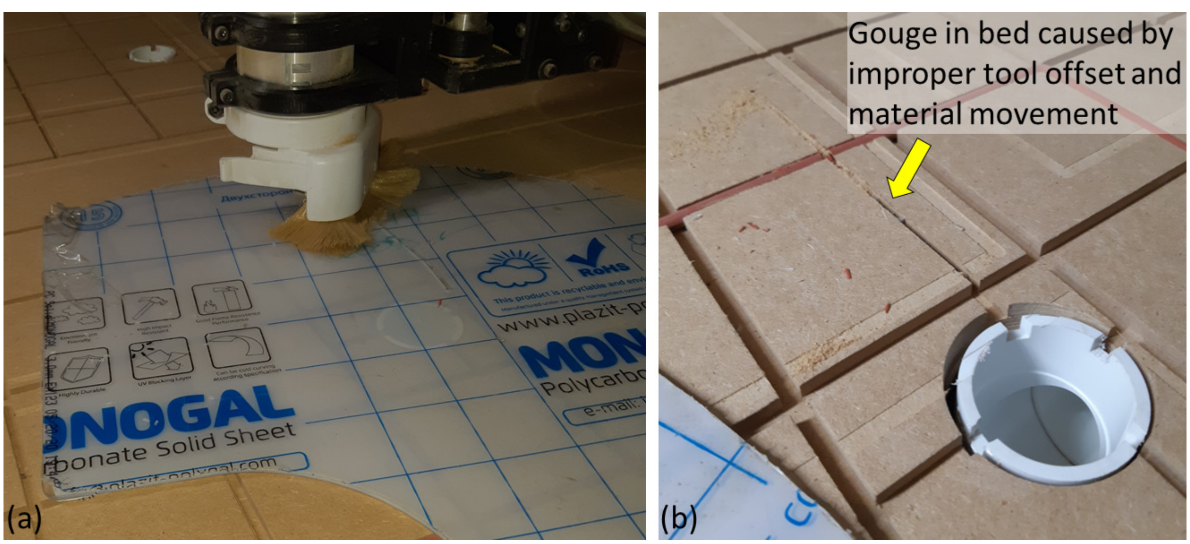

Figure 12. (a) CNC milling the plastic sheet. (b) Damaged bed because of errors.

hoods efficiently. The CNC router was outfitted with the current system (as shown in Fig. 13), allowing the camera to monitor both the milling tool and the part during operations. The system successfully identified cases where a tool was broken or a part

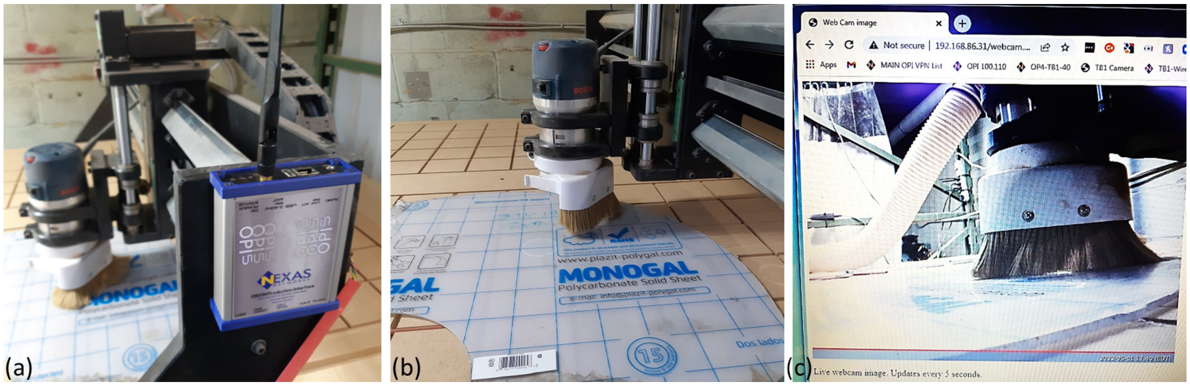

Figure 13. (a) OPI-5 installed on the CNC router. (b) Camera view. (c) A screenshot of another view from the web interface.

was displaced. Currently, the system promptly halts the operation upon detecting any errors, preventing additional loss or harm. One of the future works is to incorporate a restoration mechanism. Figure 14 depicts images of the halted positions for these two scenarios.

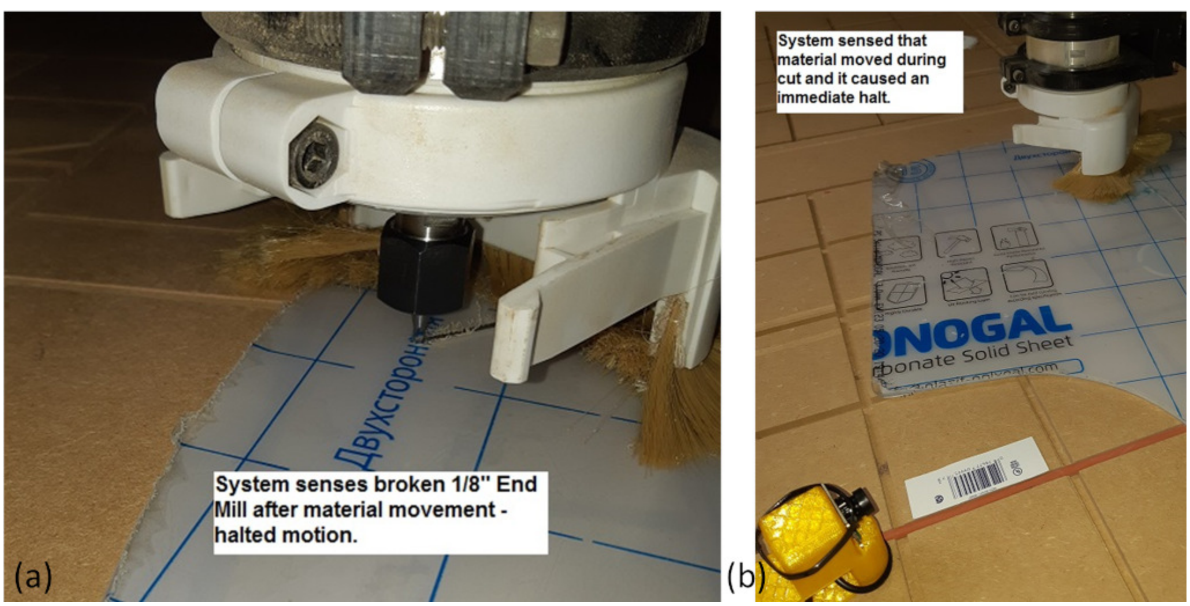

Figure 14. (a) Broken tool detected. (b) Part movement detected.

6. Conclusion

This paper presents a practical and efficient solution for equipping existing factories with communication and vision capabilities. The proposed system establishes a remote process control system that directly communicates with the control unit of legacy machines, which is an uncomplicated yet effective way to retrofit old factories. In addition, a generic identification system using fiducials is developed to enable interactions between machines, parts, and the vision system. The system's functionality is demonstrated through the use of fiducials such as QR codes and barcodes, which allow for monitoring processes, locating parts, detecting tools, and identifying errors. The entire system is simple and effective in achieving real-time communication. This study holds novelty and significance in multiple aspects. In terms of theoretical implications, it contributes to bridging the gap between legacy factories and I4.0 concepts. By integrating closed-source machines into a networked ecosystem and enabling connectivity and data exchange, it provides valuable insights. The incorporation of CV algorithms for real-time monitoring and decision-making further enhances the theoretical understanding of their applications in manufacturing systems. Consequently, this study establishes a solid theoretical foundation for future research and advancements in the realm of smart factories and IoT-based automation. From a practical perspective, the proposed system has far-reaching implications. It offers a practical and viable solution for manufacturing companies seeking to adopt I4.0 technologies, enabling them to modernize their operations without extensive infrastructural changes. The versatility of the OPI unit as a smart networked edge device makes it applicable to various machines, enhancing their functionality and promoting efficient operations. Furthermore, the experimental results obtained from the study showcase the practical applications of the system, thus highlighting its potential to significantly impact factory performance and product quality. These implications collectively underscore the study's potential to drive innovation, improve productivity, and facilitate the adoption of I4.0 technologies in existing factories.

Despite the promising results, the system has some limitations. Firstly, the environment must be clean for the vision system to operate correctly. Any dirt or debris can obstruct the fiducials and features, necessitating periodic cleaning to ensure system fidelity. Additionally, there should be sufficient contrast for the information to be read, and a complex background should be avoided. While the system can detect issues, it currently can only halt the process and request human intervention. In the future, the focus will be on error restoration, which will necessitate the use of robotic arms. Overall, this solution is a significant step forward in retrofitting older factories with the latest communication and vision capabilities, allowing for improved process control and error detection.

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Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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