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SharkNet Networks Applications in Smart Manufacturing Using IoT and Machine Learning

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Abstract: With the advancement of Industry 4.0, 3D printing has become a critical technology in smart manufacturing; however, challenges remain in the integrated management, quality control, and remote monitoring of multiple 3D printers. This study proposes an intelligent cloud monitoring system based on the SharkNet dynamic network, IoT, and artificial neural networks (ANNs). The system utilizes a SharkNet dynamic network to integrate low-cost sensors for environmental monitoring to enable low-latency data transmission and deploys ANN models on the cloud for print quality prediction and process parameter optimization. Next, we experimentally validated the system using the Taguchi design and ANN-based analysis, focusing on optimizing printing process parameters and improving surface quality. The main results show that the designed system has a communication delay of 40–50 ms and 99.8% transmission reliability under moderate load, and the system reduces the surface roughness prediction error to less than 17.2%. In addition, the ANN model outperforms conventional methods in capturing the nonlinear relationships of the variables, and the system can be based on the model to improve print quality and productivity by enabling real-time parameter adjustments. The system retains a high degree of scalability in terms of real-time monitoring and parallel or complex control of multiple devices, which demonstrates its potential for applications in smart manufacturing.

Keywords: multi-device 3D printing; SharkNet; artificial neural network; cloud monitoring system; surface roughness optimization

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1. Introduction

In Industry 4.0 era, smart manufacturing is profoundly reshaping the global manufacturing industry by integrating advanced technologies such as the Internet of Things (IoT), artificial intelligence (AI), and fieldbus into the production process [1,2]. These technologies enable the construction of smart factories, where machines, systems, and people can communicate and collaborate in real time, with increased automation, efficiency, and flexibility of the production process [3,4], allowing industries to optimize operations, reduce costs, and respond quickly to market demands.

The Internet of Things (IoT), by integrating sensing, actuation, information exchange, and data processing, has been widely used in the industrial sector, especially in the Industrial Internet of Things (IIoT), due to its intelligence, scalability, and adaptability of connected devices. Smart sensor arrays can effectively support equipment fault diagnosis, and in combination with machine learning (ML) technology, back-end systems can automatically adjust the processing parameters of the equipment, thereby improving manufacturing efficiency and simplifying maintenance [5,6].

1.1. Challenges and Needs of Smart Manufacturing Networks

Smart manufacturing networks, especially the IIoT, often rely on a layered control system [7,8]. In this system, the bottom layer consists of local controllers that are responsible for directly controlling the subsystems and communicating the results to higher levels for monitoring and coordination [8]. However, with the diversity of device types in smart manufacturing networks (e.g., mobile robots, robotic arms, 3D printers, etc.), different control interfaces and communication protocols make the traditional fieldbus technology face many challenges. In particular, in meeting the demands for high reliability, real-time communication, and scalability, existing fieldbus technologies struggle to cope with the complex demands of modern smart manufacturing systems, such as multi-node data acquisition, large-scale data transmission, image processing, and dynamic node access.

In order to meet these challenges, the intelligent manufacturing network not only needs efficient data acquisition and real-time processing capabilities, but also needs to have flexible dynamic reconfiguration capabilities to support a variety of network topologies, especially when the dynamic nodes (e.g., mobile robots, robotic arms, etc.) are accessed and disconnected, the network needs to be able to automatically reconfigure the network (including complex network topologies, etc.) in order to ensure the system's stability and efficiency. In addition, the intelligent manufacturing network must be highly multiplexed and fault-tolerant to ensure rapid recovery in case of equipment failures to avoid production disruptions; low latency is a key cornerstone of real-time control and task response, especially for high-precision and high-speed equipment; intelligent adaptive capabilities are also necessary, and the system should have the ability to automatically adjust the allocation of resources, optimize communication paths, dynamically adjust network policies, etc., to ensure the stability and efficiency of the system through the integration of AI and machine learning technologies. The system should have the ability to dynamically allocate resources, self-optimize communication paths, and dynamically adjust the complex network topology after integrating machine learning technologies, thus ensuring efficient system operation.

With the increase in interconnected devices in the network, smart manufacturing networks also need to have good interoperability to support seamless collaboration between different devices and protocols. To this end, the network should adopt standardized protocols and realize effective connectivity between devices through a protocol adaptation layer. Finally, the smart manufacturing network should be equipped with real-time monitoring, fault diagnosis and performance optimization to ensure efficient manufacturing processes and rapid diagnosis of problems.

1.2. Limitations of Existing Methods

To cope with the above requirements of intelligent manufacturing on fieldbus, this study takes the SharkNet dynamic network as the core network architecture and explores the application potential of SharkNet in the field of intelligent manufacturing by taking the manufacturing of high-volume 3D printers in intelligent manufacturing as an example [9,10]. Three-dimensional printers have a wide range of applications, but the current research mainly focuses on the monitoring system of a single printer and there are few studies on scalable intelligent integrated monitoring systems for multiple devices in large-scale production environments. Less research has been carried out on scalable intelligent integrated monitoring systems for multiple devices in mass production environments.

As a result, the challenges of parallel operation and real-time monitoring of multiple 3D printers [11,12] in mass production environments are more prominent.

Currently, there is a single method for monitoring the 3D printing process (e.g., physical sensors or video monitoring [13,14]), and these methods have significant limitations. Most studies focus on local monitoring and defect detection of a single 3D printer [15,16], and there is a lack of research on remote monitoring of multiple printers. This not only affects the flexibility and convenience of monitoring, but also adds additional human and material resources to the production process.

Traditional wired fieldbus systems (e.g., CAN bus and Modbus) have occupied an important position in industrial control due to their low latency and high stability [17]. However, these networks exhibit significant limitations in multi-device environments, such as complex wiring, poor scalability, and an inability to support dynamic network reconfiguration [18,19], making them inadequate for the flexibility and scalability demands of smart manufacturing. In contrast, wireless communication networks (e.g., Wi-Fi 6) offer advantages in terms of flexibility and scalability, making them suitable for dynamic device access. However, Wi-Fi often faces problems such as increased latency and unstable transmission in high-density, multi-device parallel operation scenarios (especially in environments with severe signal interference) [20,21], and the technology still lacks network auto-reconfiguration capabilities. In addition, bandwidth bottlenecks can seriously affect system performance and productivity when dealing with large-scale data transfers. Therefore, the application of batch 3D printing in smart manufacturing requires a balance between latency, reliability, and flexibility to ensure an efficient, accurate, and sustainable production process. This requires that the communication network system used should have a strong adaptive capability and the ability to dynamically adjust the communication network when multiple devices are working together to ensure stable data transmission and thus accurate synchronization and real-time control of the print jobs.

Existing methods (e.g., traditional regression methods, simple feedback systems, and basic machine learning techniques [22,23]) show significant limitations in exploring the complex relationships between variables and outcomes in the 3D printing process. Traditional regression and simple feedback systems have difficulty in capturing complex nonlinear relationships between multiple variables and outcomes; secondly, basic machine learning methods, although more advanced than traditional regression and simple feedback systems, still have limitations in responding to nonlinear dependencies in the 3D printing process in real time [24,25]. The above methods are unable to effectively model the nonlinear and multivariate relationships between process parameters and print quality in dynamic and high-dimensional manufacturing environments, and these limitations hinder the precise control and efficient management of batch 3D printing in smart manufacturing environments.

1.3. Contributions and Innovations of This Study

To address the above challenges this study proposes an intelligent cloud monitoring system based on IoT, SharkNet, and ANN, which can monitor multiple 3D printers in real time and dynamically optimize the relevant parameters. The main features of the system and the main contributions of this study are as follows:

1. Multi-sensor and video fusion: We integrate multiple sensors, such as temperature and humidity, with video surveillance to build a composite monitoring sensor network that provides users with a comprehensive view of the production process. This monitoring approach improves the accuracy and functionality of the system, and when the multi-sensor monitoring network is integrated with artificial intelligence

and other technologies, the network can comprehensively analyze heterogeneous data and make intelligent adjustments based on the relevant sensors.

2. SharkNet dynamic network: SharkNet has many advantages such as support for multiple topologies, redundant transmission, and multi-interface adaptation, and the most important feature of the network is the intelligent reconfiguration of the network. In addition, the network integrates technologies such as dynamic multipath scheduling and 5G [26,27], which makes the network more robust to break through data transmission bottlenecks in multi-device parallel operation. Therefore, the network has the advantages of both wired network's low latency and wireless network's flexibility, which makes it possible to improve the overall performance of the system while still ensuring the flexibility of the system, providing a strong real-time, highly reliable, highly dynamic, highly fault-tolerant, and easy-to-use communication network solution for the system.
3. Process parameter optimization by ANN: In this study, we adopt the ANN [28] model to overcome the limitations of traditional methods [29] in dealing with the complex nonlinear relationship between 3D printing process parameters and print quality [25]. The ANN is based on the real-time training and validation of a variety of sensor data (e.g., images, temperature, and humidity, etc.) collected by the system, and then dynamically optimizes the process parameters and performs quality control and defect detection. Compared with traditional methods, the ANN model significantly improves prediction accuracy and real-time response capability.

The rest of this paper is organized as follows: Section 2 provides an overview of research related to 3D printing quality monitoring and fieldbus; Section 3 details the design of the proposed intelligent cloud monitoring system; Section 4 discusses the experiments used to validate the system's performance; Section 5 analyzes and discusses the experimental results and the system's performance; and finally, Section 6 summarizes the results of the research and discusses the potential directions of future work.

2. Related Work

Although existing studies have made significant progress in 3D printing process monitoring, such as Kousiatza et al. using fiber Bragg grating sensors for strain and temperature monitoring [13], Yang et al. using acoustic emission technology for material fracture detection [14], and Kakade et al. solving the problem of material flow by means of a rotary encoder and a pressure sensor [30], these approaches all rely on a single monitoring method. In addition, visual monitoring techniques have received extensive attention from researchers, with Sánchez et al. using a Raspberry Pi for local video monitoring [31], Liu et al. developing an embedded remote monitoring system [32], and Nuchitprasitchai et al. utilizing a camera for comprehensive local monitoring [33]. However, it is difficult for a single monitoring method to meet the requirements of dynamic sensing, intelligent decision-making, and high-precision control imposed by smart manufacturing on the printing process.

To address these limitations, multi-source information fusion has become an important research direction to enhance the monitoring capability of 3D printing process. Integrating multi-sensor parameters with video data, this approach not only improves the system's dynamic perception and precise control of the printing process, but also provides powerful support for multi-parameter optimization of the printing process species and defect prediction of the printing results. The quantity and quality of multimodal data have a significant impact on the performance of machine learning-driven intelligent control algorithms. The integration of sensor networks and video surveillance technologies enables remote monitoring and real-time intelligent decision-making and provides a new research paradigm for 3D printing quality control with important theoretical and practical implications.

Intelligent manufacturing networks place high demands on communication protocols and fieldbus technologies such as low latency, high reliability, strong scalability, and high network destruction resistance. However, existing technologies (e.g., EtherCAT, PROFINET, Ethernet, and Modbus TCP/RTU) exhibit significant limitations in some areas. To clearly assess the advantages and disadvantages of these technologies and their applicability in smart manufacturing, we summarize and compare the key performance metrics of SharkNet with several mainstream fieldbus technologies in Table 1 [34].

Table 1. Comparison of SharkNet with other fieldbuses.

Feature	SharkNet	Ether CAT	PROFINET	Ethernet	Modbus TCP/RTU
Communication Latency	1.6 µs/hop (wired network) <60 ms (via 5G network and cloud server)	150 µs (256 digital I/O updates, 10 µs)	1–10 ms	10–100 ms	RTU: 10–100 ms TCP: 2–3 ms
Reliability	Extremely high	High	High	Medium	Medium
	Protocol adaptation, complex topology, decentralized network, intelligent network reconfiguration	Supports distributed clocks, error < 1 µs	Suitable for large-scale industrial automation	Depends on physical connection quality	Network fluctuations have greater impact
Scalability	High	Up to 65,535 nodes/networks	High	High	Medium
	Decentralized network, supports dynamic node access, various topologies, and wireless expansion		Supports various industrial topologies	Supports multi-device access, but complex wiring	Device expansion requires manual adjustment
Bandwidth	0.01~1 Gbps	100 Mbps–1 Gbps	100 Mbps–1 Gbps	10 Mbps–1 Gbps	RTU: 1.2–115.2 kbps TCP: 10/100 Mbps
	Future compatible			Depends on Ethernet standard	
Real-Time Capability	Extremely high	Extremely high	High	Low	Medium
	Synchronization error at ns level	Synchronization error < 1 µs	Real-time Ethernet supports low latency	Affected by network traffic	Depends on communication mode
Deployment Complexity	Low	High	High	Medium	Medium
	Wired network configuration automated, wireless reduces cabling needs	Requires complex network management	Requires high technical support	Depends on physical network maintenance	Manual adjustment and high cabling complexity
Dynamic Network Reconfiguration Capability	Intelligent dynamic network reconfiguration	None	None	None	None

Table 1 shows that SharkNet has significant advantages over other communication networks, such as fieldbus technologies like EtherCAT and PROFINET, in terms of communication latency, reliability, scalability, and intelligent network reconfiguration. In addition, SharkNet is deeply integrated with 5G using protocol adaptation techniques, which will further enhance the network's ability to support complex dynamic scenarios. These advantages make SharkNet well suited for smart manufacturing scenarios with multiple dynamic nodes and complex operations of multiple devices, thus providing powerful communication support for smart manufacturing. SharkNet offers solid possibilities for future smart factories to realize more efficient device collaborations, more precise real-time control, and more flexible device management.

Multivariate parameter fusion analysis and nonlinear models are inevitably a major trend in the field of smart manufacturing [23]. Therefore, traditional methods like the Support Vector Machine (SVM) and Random Forest (RF) are far from adequate in exploring the complex relationship between various types of process parameters and results in the field of intelligent manufacturing [23]. The SVM, although effective in some classification tasks, requires a large number of data preprocessing operations in order to deal with multi-parameters, and the method is poorly scalable [23,35]. Random Forests, although effective in dealing with noisy data, do not have capabilities such as real-time adjustment [23,35–37].

Unlike traditional methods, the ANN can accurately capture the complex relationship between process parameters (e.g., nozzle temperature, bed temperature, and print speed) and print quality (e.g., surface roughness) through its powerful nonlinear and multivariate data processing capabilities [35,38]. In addition, the ANN can efficiently process a large amount of data in the system and dynamically optimize the parameters based on these data by real-time training and inverse modeling, thus improving the print quality and productivity of the system. The ANN overcomes the shortcomings of traditional methods in this area through its ability to dynamically capture the complex relationships among parameters and provides a reliable technological solution for the optimization of smart manufacturing scenarios.

3. System Design and Method

3.1. Overall System Architecture

Figure 1 shows the overall architectural design of the SharkNet wireless and AI-based intelligent cloud monitoring system for multiple 3D printers. The main objective of the system design is to achieve low-latency, high-reliability, and user-friendly remote intelligent monitoring of multiple 3D printers, and secondly, the system can provide comprehensive and multifaceted data support for ANN model data analysis and process optimization, which will improve print quality and productivity. The architecture consists of the following main modules:

1. Environmental Parameter Monitoring Nodes: A low-cost sensor network continuously monitors key environmental parameters (e.g., temperature, humidity) in real-time (<200 ms) and transmits the collected data via SharkNet to the cloud for analysis after edge processing.
2. Video Monitoring and Remote Control Nodes: The Raspberry Pi controls an HD camera that continuously acquires real-time video streams of the printing process, and the module connects to the cloud via SharkNet to support remote monitoring and control.
3. SharkNet Dynamic Networks: SharkNet 5G provides a high-bandwidth, low-latency communication network environment to support efficient data transfer between multiple devices.
4. Cloud Platform: Processes all sensor data and video streams for real-time data analysis and process optimization through an artificial neural network (ANN) deployed in the cloud.

5. Remote Visualization Interface: A visual and user-friendly interactive visualization interface is deployed on the cloud platform, which allows users to remotely monitor the 3D printing process.

SharkNet's deep integration with the cloud platform makes the system not only a localized device communication network, but a comprehensive monitoring and management platform. The system can dynamically optimize and adjust multiple 3D printers based on real-time data analysis in the cloud, ensuring that the production process is always at its best.

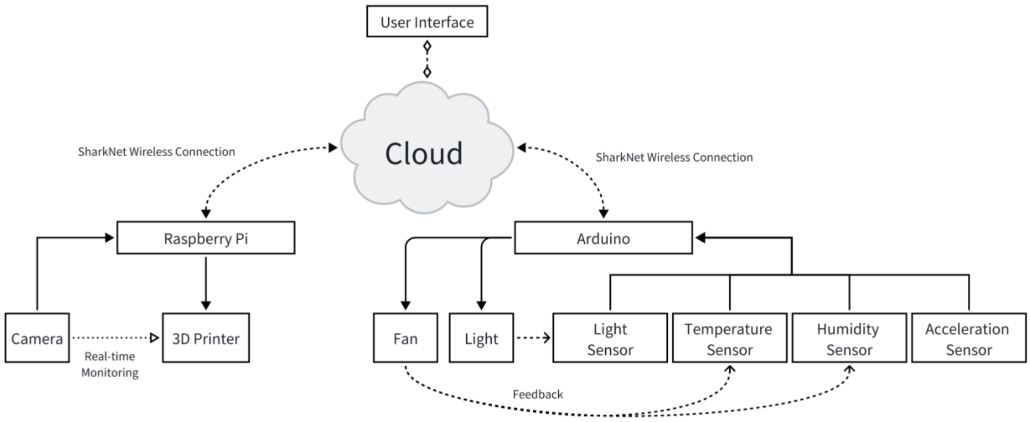


Figure 1. Overall design of intelligent cloud monitoring system.

Specifically, the cloud platform processes data from multiple 3D printers in real time and automatically identifies potential problems in the printing process (e.g., deterioration in print accuracy or abnormal temperature fluctuations), and it can send out alerts or perform automated adjustments to avoid production interruptions as soon as an abnormality is detected. Additionally, the cloud platform can utilize machine learning to use the historical data to identify early signs of equipment failures and schedule repairs in advance through predictive maintenance to ensure that equipment is repaired before failure occurs, thus avoiding production downtime. Through this intelligent cloud-based monitoring, manufacturing productivity will be significantly improved, while human intervention can be significantly reduced to promote the automation and intelligent production and greatly optimize the productivity and reliability of the entire production system.

3.2. Environmental Parameters Monitoring Node

Environmental parameters like temperature and humidity can affect significantly the adhesion of printing materials, curing speed, and the interlayer bonding quality in 3D printing. Full control of these parameters may be challenging, but real-time monitoring and adjustments can reduce printing defects and enhance print quality. Figure 2 shows the design of the environmental parameter monitoring node, a core system component that collects environmental data through various sensors. The system can also be connected to some other third-party sensors with strong scalability. The node consists of the following:

1. Sensors: The system incorporates temperature and humidity sensors, light sensors, and accelerometers. All of them are integrated in the companion Carrier board and managed via the Arduino MKR WIFI 1010. After edge-level preprocessing, data are transmitted to the cloud via the SharkNet wireless link.
2. Edge processing: To reduce cloud load and conserve network bandwidth, part of the data preprocessing is conducted locally, e.g., the system detects abrupt anomalies and generates rapid alerts via a buzzer, enabling immediate action to prevent potential defects in real time.

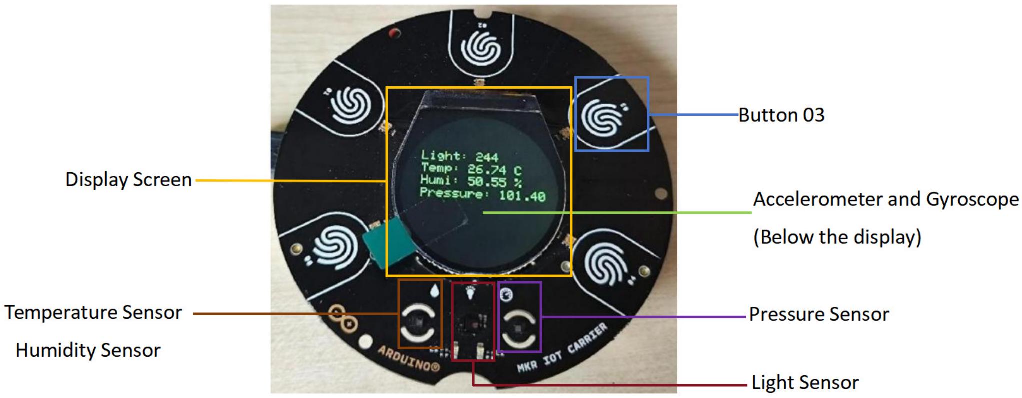


Figure 2. IoT node design.

3.3. Video Monitoring and Remote Control Nodes

Since sensor data alone may not provide an intuitive understanding of the 3D printing process, we utilized a video monitoring node with a Raspberry Pi 400 (Pi) and a USB (Universal Serial Bus) high-definition camera, which offers direct visual feedback of the printing process (Figure 3). The system consists of the following components:

1. Video data collection and transmission: The camera captures video of the printing process and transmits it to the cloud through SharkNet. The system can dynamically adjust video resolution according to latency feedback from the SharkNet wireless link, balancing network bandwidth with image quality requirements.
2. Local and remote control: The 3D printer is accessible for both local and remote control via its connection to the Pi. This enables users to manage the printer in real-time from the cloud, e.g., for pausing printing or adjusting parameters. A control system designed specifically for the 3D printer runs on the Pi, based on a secure, bidirectional communication link with the cloud. This setup not only transmits real-time video and sensor data, but also facilitates flexible, efficient remote control of the printer.
3. Process parameter monitoring: The 3D printer's built-in temperature sensors are used to monitor the printer's nozzle temperature and print bed temperature, two key process parameters; in addition, print speed and layer height are set during the 3D modeling process prior to the start of the print job.

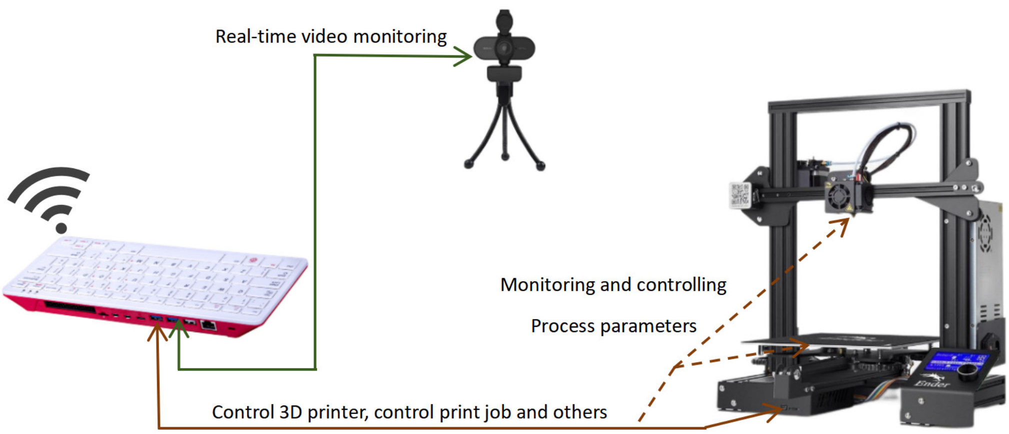


Figure 3. Three-dimensional printer video monitoring and control.

3.4. SharkNet Wireless Communication

When managing multiple printers in an integrated manner, where communication latency and stability are major challenges, SharkNet (including the SharkNet 5G wireless link) is ideally suited to meet the high demands of smart manufacturing by leveraging its significant technological advantages, flexibility, and ease of deployment. The details are as follows (the network architecture of SharkNet is shown in Figure 4):

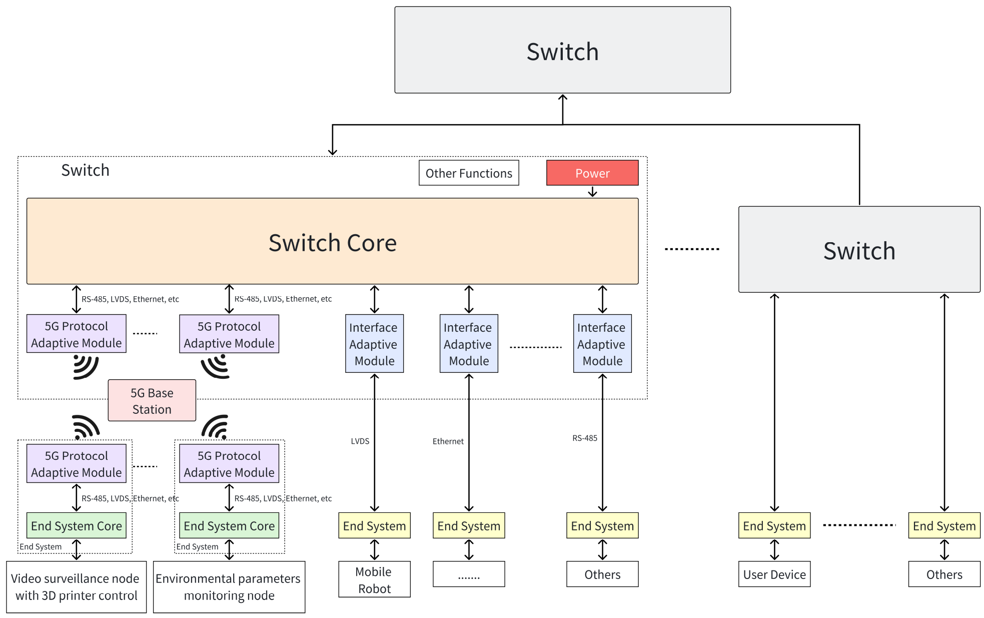


Figure 4. Network architecture for SharkNet dynamic networks (partial).

1. Highly reliable and low-latency communications: The SharkNet wired network enables nanosecond synchronization and high-speed reconfiguration in 30 microseconds to meet the real-time requirements of complex decision-making and parameter adjustment in the printing process. Unlike traditional Wi-Fi, SharkNet utilizes 5G's Quality of Service (QoS) mechanisms to prioritize critical packets to achieve instantaneous control signals. In addition, SharkNet eliminates the need for extensive cabling.
2. Scalable hybrid network topology and parallel communication: SharkNet's flexible hybrid network topology supports parallel communication between multiple printers. Its high bandwidth helps prevent congestion and ensure stable transmission. Whilst independent links minimize interference, dynamic load balancing allocates bandwidth intelligently according to the number of devices and communication requirements. SharkNet can then achieve a steady stream of data even under high load conditions, with a significant advantage compared with Wi-Fi's limited scalability and bandwidth contention.
3. Mobility support and enhanced resilience: Equipment in dynamic industrial environments may need to be moved for various reasons, e.g., maintenance or operational requirements. Traditional network communication technologies often fail to maintain stable connections in such situations, suffering possible disconnections or communication breakdowns. SharkNet's can provide stable access to the network with a high degree of flexibility and resilience even when the equipment is on the move and this is possible because of its use of 5G base station switching and intelligent network auto-reconfiguration. As a masterless network, SharkNet's multi-path network allows it to quickly adapt to equipment relocations and environmental changes, using automatic switching to the backup path for uninterrupted communication. Its high stability and flexibility are important in industrial applications, especially in smart manufacturing with frequent repositioning of equipment or mobile robots.
4. Protocol adaptation for efficiency and flexibility: The robust hardware and advanced protocol adaptation enable SharkNet to dynamically adjust data frame structures and communication parameters, with minimized latency and optimized bandwidth.

This adaptability is important for stable performance during network congestion or in device-dense environments. SharkNet's protocol adaptation module supports integration with various device interfaces including RS-485, LVDS (Low-Voltage Differential Signaling) and Ethernet. SharkNet can overcome the limitations of Wi-Fi and Ethernet with better latency, scalability, and mobility, suitable for real-time management of multiple 3D printers.

3.5. Cloud Server Platform

The design of the cloud server desk includes three main parts: data storage, data analysis and user interaction for efficient data management, and real-time optimization, as shown in Figure 5.

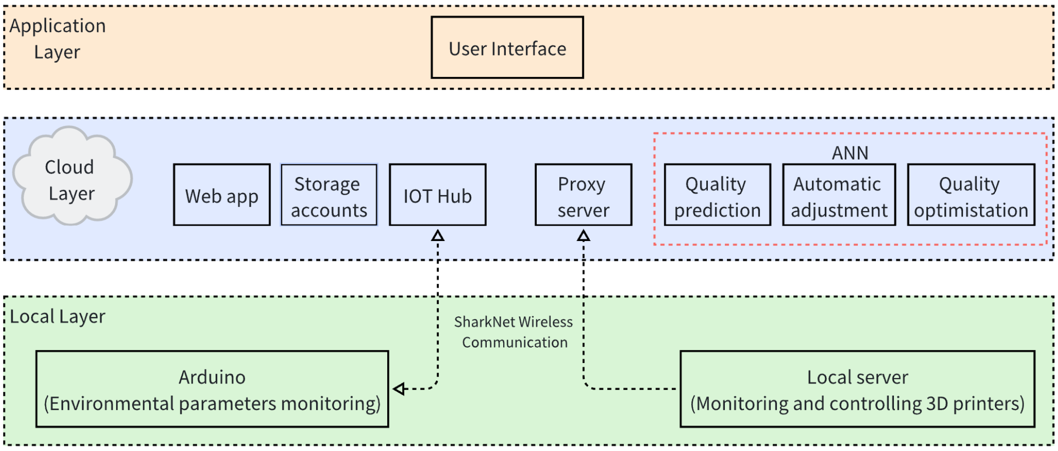


Figure 5. Cloud server architecture.

3.5.1. Data Storage

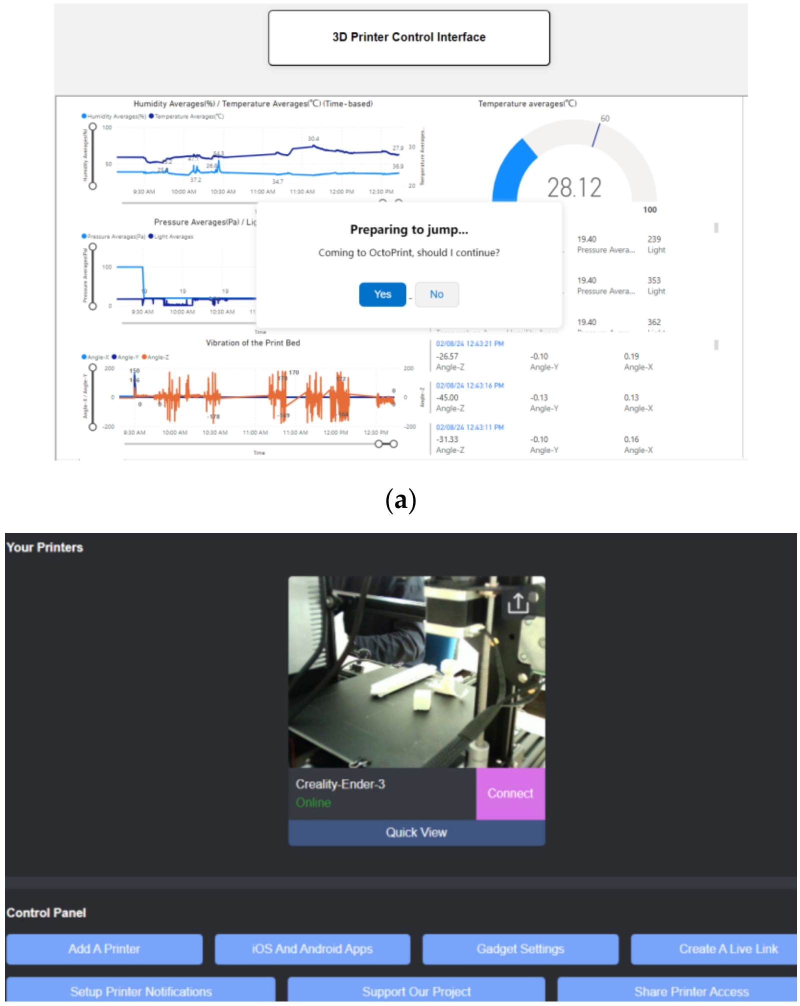
The system collects environmental and video data of the printing process in real time through sensor and video monitoring modules, with the data stored in the cloud database to support subsequent data analysis. The cloud database can efficiently handle simultaneous real-time data storage across multiple devices. These collected data can be used for fault diagnostics, quality control, and continual improvement.

3.5.2. Applications of Artificial Neural Networks

The cloud platform incorporates artificial neural networks (ANNs) to predict in real time how process parameters impact print quality (such as surface roughness and dimensional accuracy). Trained to model complex nonlinear relationships, the ANN can also be used for print parameter optimization. The ANN uses multi-inputs (including nozzle temperature, bed temperature, layer height, and printing speed) to predict print quality characteristics (e.g., surface roughness) in real time. The adjustments can be immediately sent to the printers through the SharkNet wireless link and presented to the user via a visual interface.

3.5.3. User Interface

The user interface is designed to support intuitive control and comprehensive functionality. Through the remote visualization interface, users can access ANN-based predictions and recommendations from any location, view real-time environmental parameters, as illustrated in Figure 6a, and monitor the printing status. Users can also directly control printer functions, such as pausing, resuming, and adjusting speed. In addition, the interface provides visualization of historical data, and the users can compare print parameters over multiple runs. Real-time synchronization with the cloud database helps the users operate with the latest data, enhancing both accuracy and responsiveness in decision-making.



(**a**)

(**b**)

Figure 6. (**a**) Environmental parameter monitoring interface and jump button. (**b**) 3D printer cloud control interface.

3.6. Security and Data Integrity

In industrial applications, data security and integrity are paramount. This system integrates a multi-layered data protection mechanism to secure information during transmission and operation. First, all sensor data and video streams are encrypted in real-time, using robust encryption protocols (like sensors' TLS security protocol, 5G's AES, etc.). The system also applies role-based access control, restricting user access based on the role. The operators are limited to real-time monitoring, but higher-level permissions are required for parameter adjustments. These security measures ensure operational compliance and data integrity, providing a secure foundation for intelligent monitoring.

4. Experiment Design and Method

The system we designed supports continuous monitoring, data storage, dynamic control, and status prediction. To assess the system's effectiveness and reliability, we conducted experiments to analyze the real-time responsiveness and stability of the SharkNet-based wireless communication system during concurrent multi-device operation. In addition, we employed the Taguchi experimental design and artificial neural networks (ANNs) to study the relationship between key process parameters and print quality (surface roughness), in order to predict and optimize print quality.

4.1. Experiment Preparation

The experiments were conducted in a laboratory environment designed to closely simulate realistic industrial conditions, aiming to evaluate system performance in an industry-grade multi-device setup. We used several Creality Ender-3 3D printers, using PLA (Polylactic Acid) as the printing material because of its good printability, low cost, and more stable mechanical properties, suitable for investigating the factors influencing the print quality (e.g., surface roughness), as a way of ensuring the consistency and reliability of the results. Each printer was equipped with various sensors to capture critical process parameters, such as nozzle temperature. The test samples were designed as PLA cubes with dimensions of 30 × 30 × 10 mm, with a fill density of 20% and a cubic fill structure. The simplicity of the geometry avoids additional errors due to shape complexity; moreover, the model provides enough flat area for surface roughness measurements. The test sample model and actual printed samples are shown in Figure 7.

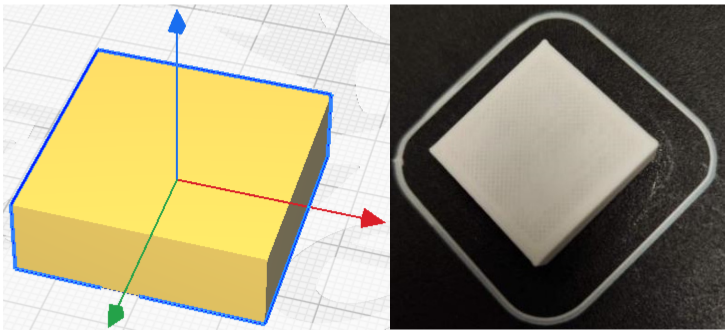


Figure 7. Test sample model and test sample entity.

In the experiment, a surface roughness tester was used to measure the roughness of the top and bottom surfaces of the test samples to assess surface quality. As shown in Figure 8, roughness was measured at five locations on each surface, with the average roughness values represented by Ra1, Ra2, Ra3, Ra4, and Ra5.

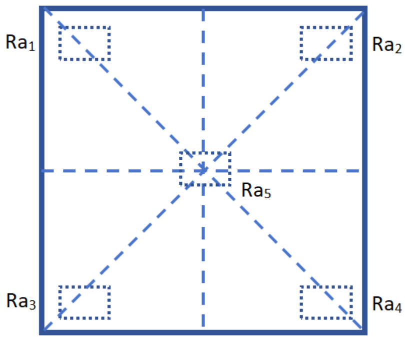


Figure 8. Test sample measurement position (Top view).

4.2. Experimental Design

4.2.1. Multi-Device Cooperative Work Experiment

In multi-device collaborative printing, the system must handle concurrent data transmissions and control signals to achieve reliable performance essential for managing communication latency and response speed across different printing loads and modes. Transmission reliability under high-load conditions is also recorded for the feasibility study of SharkNet wireless communication in large-scale industrial applications.

Our experimental design compares two transmission methods: Ethernet wired transmission and the SharkNet wireless solution. Four device groups were randomly selected from the network, with each group undergoing four sets of experiments to compare latency and transmission reliability. The average results from these experiments were used for final analysis. Real-time responsiveness was measured as the latency between the device endpoint and the cloud server and was calculated by the timestamp difference between device and cloud server test nodes. Transmission reliability was assessed by adjusting the control command transmission interval and calculating the ratio of information received by the cloud server to that sent by the device.

4.2.2. Printing Process Parameter Optimization Experiments

In order to ensure the accuracy and reliability of the system's monitoring and prediction, the ANN model was used in this study to model the relationship between process parameters and print quality, and the results were compared with those obtained using the traditional Taguchi method. In this case, the ANN model training is based on the various parameter data collected by the system sensors and the measured surface roughness data.

Due to the small size of the dataset, we chose to use a single hidden layer neural network. The model consists of 5 input neurons (nozzle temperature, print bed temperature, print speed, layer height, and ambient temperature), 49 hidden layer neurons, and 1 output neuron representing surface roughness. The number of neurons in the hidden layer was determined through multiple trials to avoid overfitting while maintaining prediction accuracy. Additionally, we used the backpropagation method to train the model, with a learning rate of 0.01, to achieve stable performance for the research objectives.

The Taguchi method was directly applied to the experimental design, focusing on five key factors: ambient temperature, nozzle temperature, bed temperature, printing speed, and layer height, each set at three levels except ambient temperature with two levels. The ambient temperature was designed with reference to UK outdoor and indoor temperatures, and the other factor values were referenced to the optimum range of process parameters for PLA materials. As shown in Tables 2 and 3, an L18 orthogonal array was used to study the relationship between the 3D printing parameter and print quality, and to further optimize the process and print quality.

The surface roughness of the samples was measured using a MarSurf PS 10 surface roughness tester. The probe moves across each sample's surface to obtain and display the Ra roughness value for recording and analysis. A flat square iron block was used as a support platform to ensure accurate positioning of the samples and measurement repeatability.

Table 2. Experimental factors and their levels.

Factor	Level			Code
	1	2	3	
Environmental Temperature	19 °C	29 °C	/	A
Nozzle Temperature	190 °C	208 °C	225 °C	B
Print bed Temperature	25 °C	48 °C	70 °C	C
Print Speed	30 mm/s	60 mm/s	90 mm/s	D
Layer Height	0.12 mm	0.24 mm	0.36 mm	E

Table 3. L18 experimental orthogonal array.

Trial	Control Factors				
	A (°C)	B (°C)	C (°C)	D (mm/s)	E (mm)
1	19	190	25	30	0.12
2	19	190	48	60	0.24
3	19	190	70	90	0.36
4	19	208	25	30	0.24
5	19	208	48	60	0.36
6	19	208	70	90	0.12
7	19	225	25	60	0.12
8	19	225	48	90	0.24
9	19	225	70	30	0.36
10	29	190	25	90	0.36
11	29	190	48	30	0.12
12	29	190	70	60	0.24
13	29	208	25	60	0.36
14	29	208	48	90	0.12
15	29	208	70	30	0.24
16	29	225	25	90	0.24
17	29	225	48	30	0.36
18	29	225	70	60	0.12

5. Results' Analysis and Discussion

5.1. System Performance Assessment

Figure 9 compares the transmission latency of the intelligent monitoring system using SharkNet wireless communication and traditional Ethernet in a multi-device collaborative setting. These results allow us to analyze real-time response performance for each method. As data packet volume rises, the latency for both methods gradually increases due to higher data flow and network congestion. Ethernet exhibits stable latency under various load conditions with an average of about 40–50 ms.

In contrast, SharkNet wireless communication shows latency close to Ethernet under low-load conditions, but experiences slightly longer latency as packet volume increases above the packet of 3000. This fluctuation occurs because the current SharkNet setup relies on commercial 5G and cloud server relays, and network variations impact real-time performance. Factors such as commercial 5G congestion, latency uncertainty, and cloud server forwarding delays can contribute to the longer system latency with potential challenges for large-scale industrial applications.

SharkNet wireless communication can provide scalable, flexible deployment without wiring, and is suitable for multi-device operations in industrial settings under low to moderate loads. To address latency fluctuation under high-load conditions, the SharkNet protocol adaptation can be used to mitigate cumulative delays through packet scheduling and priority management. Future upgrades will transmit SharkNet signals from commercial 5G and cloud servers to private base stations using a private core network to meet increasing demands for high-load applications.

Therefore, the SharkNet wireless link can offer high flexibility and robust real-time performance for intelligent monitoring of multiple printers using protocol adaptation technology. The system monitors real-time changes in ambient conditions via integrated sensors, with updates reflected in the prediction pipeline within 1 s. This capability ensures that environmental variability is promptly accounted for, and further enhances the system adaptability in dynamic manufacturing environments.

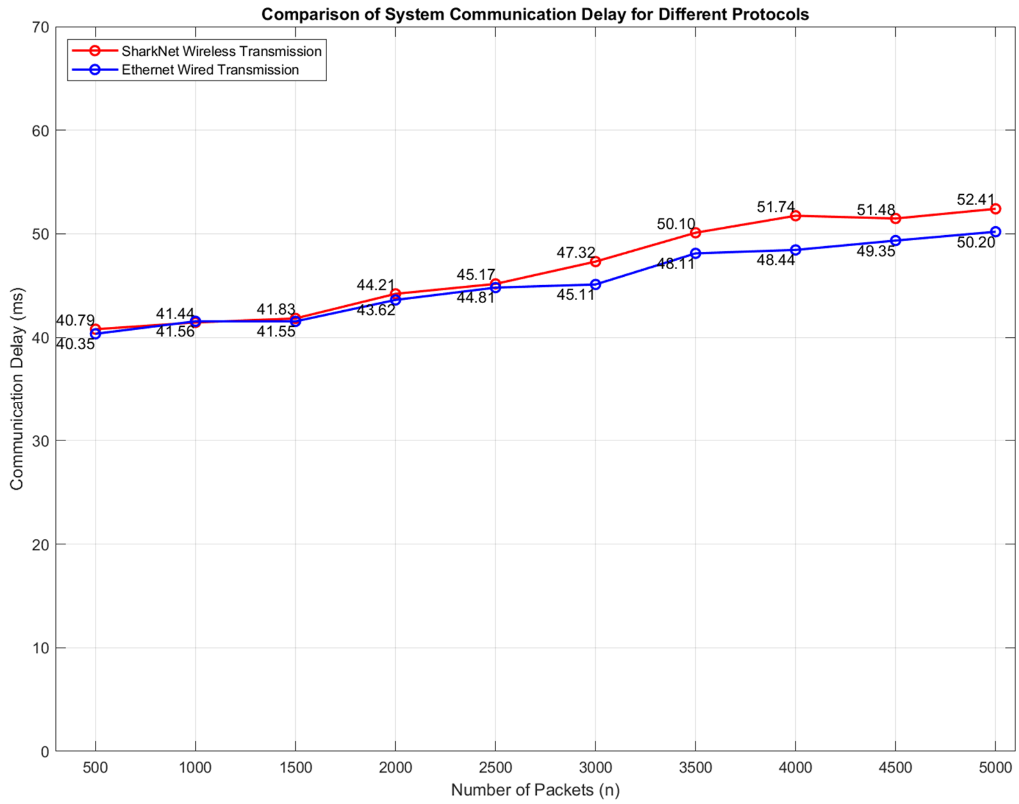


Figure 9. Comparison of system communication delay for different protocols.

Figure 10 shows the transmission reliability of the intelligent monitoring system using SharkNet wireless communication versus traditional Ethernet in a multi-device collaborative scenario, allowing us to assess suitability for real-time industrial control. As control cycle intervals lengthen, both transmission methods show significant reliability improvements, although there are differences in the rate of improvement and overall stability.

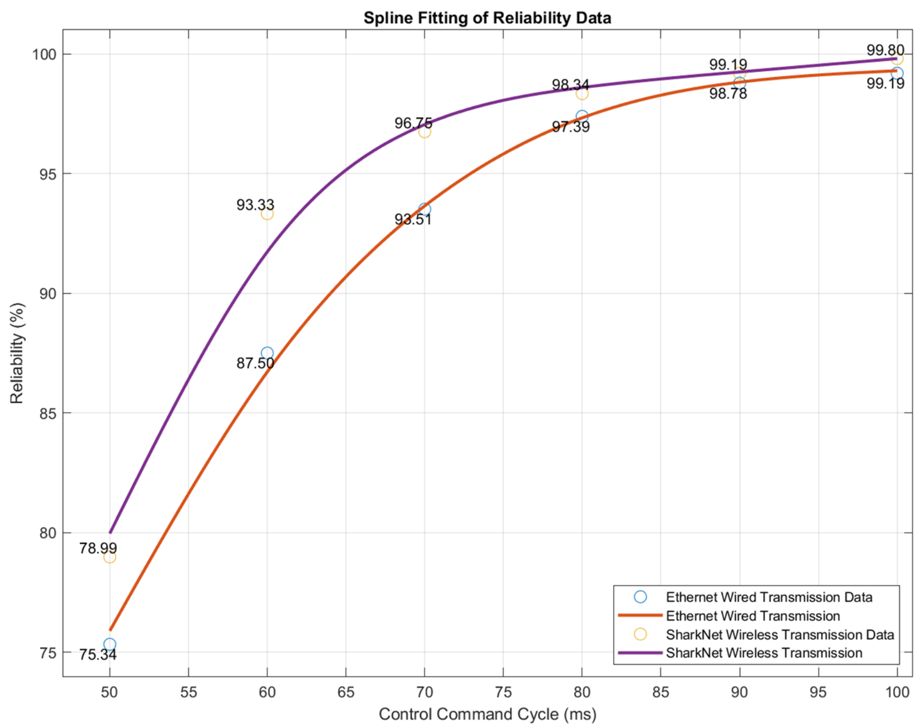


Figure 10. Comparison of system transmission reliability under different protocols.

For high-frequency control cycles (50 ms), Ethernet achieves a transmission reliability of 75.34%, while SharkNet surpasses it at 78.99%. This suggests that SharkNet offers reliable, flexible wireless transmission for high-frequency commands, which is advantageous in industrial environments with complex wiring or mobile equipment.

As control cycles increase, system reliability will be near saturation. At a 100 ms control cycle, SharkNet and Ethernet both achieve transmission reliability close to 99%, with SharkNet at 99.8% and Ethernet at 99.19%. Due to protocol optimization and 5G network support, SharkNet's wireless link attains reliability comparable to wired Ethernet, demonstrating high stability for multi-device coordination and real-time control. This high reliability, combined with SharkNet's wireless flexibility, highlights its potential for intelligent monitoring of 3D printer systems.

Curve fitting also indicates that in the 70–90 ms control cycle range, SharkNet's reliability improvement slightly exceeds Ethernet's, likely due to its protocol adaptation feature, which dynamically adjusts transmission parameters to network conditions. This adaptability is particularly valuable in industrial applications with frequent network fluctuations, where SharkNet's adaptability further boosts stability in challenging industrial environments.

Overall, SharkNet wireless communication demonstrates excellent reliability at medium to high control cycles, and consistently outperforms the wired Ethernet. Its wireless configuration provides enhanced scalability and deployment flexibility for multi-device monitoring systems.

5.2. Surface Roughness

5.2.1. Optimization of Printing Process Parameters by Conventional Methods

Figure 11 shows the main effects of the chosen 3D printing process factors and the optimal levels to minimize top surface roughness. The best results were observed at 19 °C ambient temperature, 225 °C nozzle temperature, 25 °C bed temperature, 90 mm/s printing speed, and 0.36 mm layer height. It can be seen that nozzle temperature has the most significant impacts on surface roughness, highlighting the importance of precise temperature control in achieving optimal print quality.

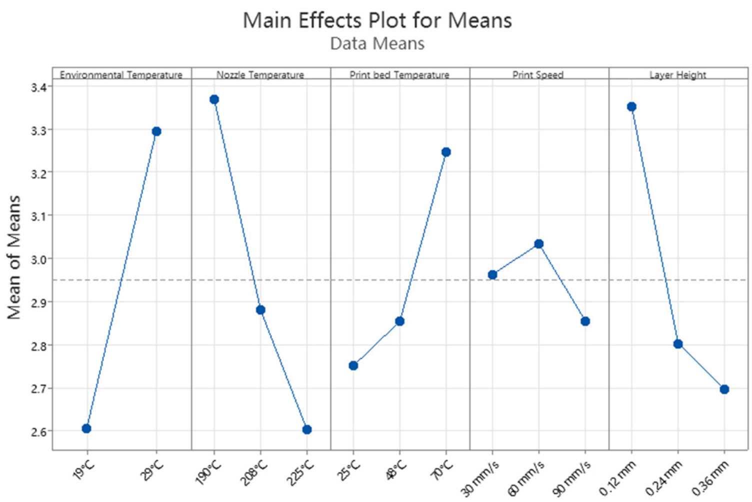


Figure 11. Main effects plot of means for top surface roughness.

Figure 12 shows the main effects of the process factors and the optimal levels to minimize bottom surface roughness. The optimal settings were 19 °C ambient temperature, 225 °C nozzle temperature, 25 °C bed temperature, 90 mm/s printing speed, and 0.36 mm layer height. The results again highlight the significant impact of nozzle temperature on surface roughness.

Figure 12. Main effects plot of means for bottom surface roughness.

5.2.2. Linear Regression

In this study, linear regression analysis was performed to predict the impact of process parameters on surface roughness. The regression equations are as follows:

$$TSR = 6.09 + 0.0689 \times ET - 0.02195 \times NT + 0.01096 \times PBT - 0.00180 \times PS - 2.728 \times LH \tag{1}$$

$$BSR = 7.56 + 0.0292 \times ET - 0.02155 \times NT + 0.00946 \times PBT - 0.00018 \times PS - 0.689 \times LH \tag{2}$$

In Equations (1) and (2), TSR represents top surface roughness, BSR represents bottom surface roughness, ET is environmental temperature, NT is nozzle temperature, PBT is print bed temperature, PS is print speed, and LH is layer height.

Table 4 provides the R-squared values, indicating each model's explained variance in surface roughness. The R^2 value for the top surface model was 81.19%, suggesting a strong correlation between parameters and surface roughness. The R^2 for the bottom surface model was 67.45%, indicating a significant relationship, though its predictive power is somewhat lower than that of the top surface model.

Table 4. Means response table for bottom surface roughness.

	S	R-sq	R-sq (adj)	R-sq (pred)
Top	0.339217	81.19%	73.35%	59.14%
Bottom	0.330562	67.45%	53.89%	25.93%

5.2.3. ANN Prediction of Printing Quality

As shown in Figure 13, the ANN model's predictions closely follow the measured surface roughness trend, closely capturing fluctuations across most sample points. This demonstrates the ANN model's predictive accuracy and stability under the complex non-linear influences of 3D printing process parameters. Such performance is essential for real-time optimization of the printing process parameters.

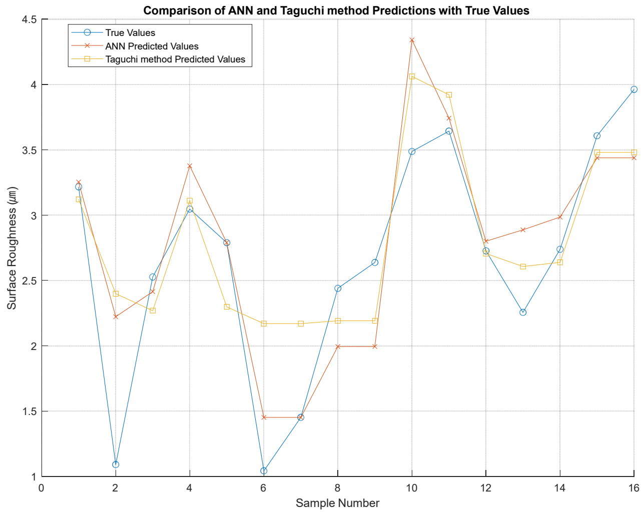


Figure 13. Comparison of surface roughness between ANN model predicted values, Taguchi method predicted values, and true values.

Although the Taguchi method has offered initial guidance in identifying significant factors, its linear statistical models fall short in capturing the complex nonlinear and multi-factor interactions present in 3D printing. In contrast, the ANN model can adaptively fit complex relationships between multiple factors and the print quality (surface roughness), offering superior prediction accuracy and robustness. It can be further used for process parameter optimization.

Figure 14 shows the fitting curve between the ANN model prediction output and the target surface roughness. Data points cluster around the fitted line, demonstrating the ANN model's accurate fit across different parameter combinations. This indicates the model's ability to handle complex interactions among process parameters.

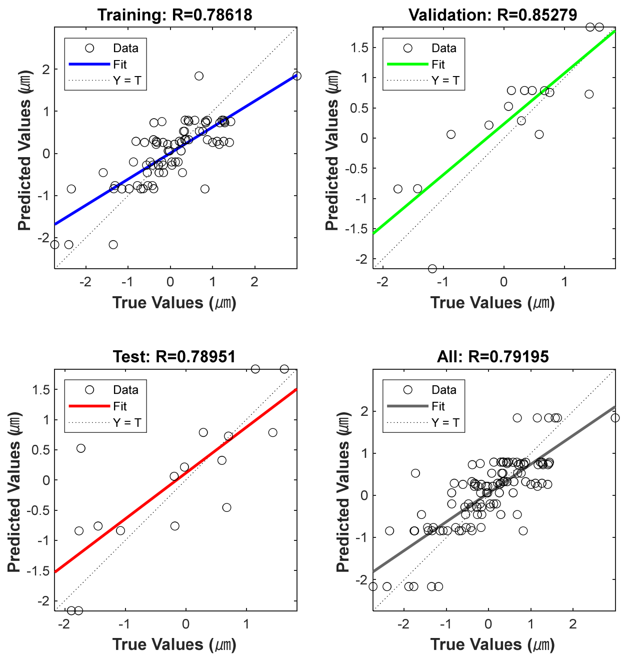


Figure 14. Regression fitting performance of the ANN model.

The Taguchi method's linear regression model struggles with accuracy when nonlinear relationships and interaction effects are significant. In contrast, the ANN model can effectively learn the complex parameter interactions, offering higher fitting accuracy than the Taguchi method. This capability is particularly valuable for real-time quality monitoring and optimization in 3D printing.

Figure 15 shows the error distribution of the ANN model predictions on the training, validation, and test datasets. Errors are centered around zero and follow an approximately symmetrical distribution.

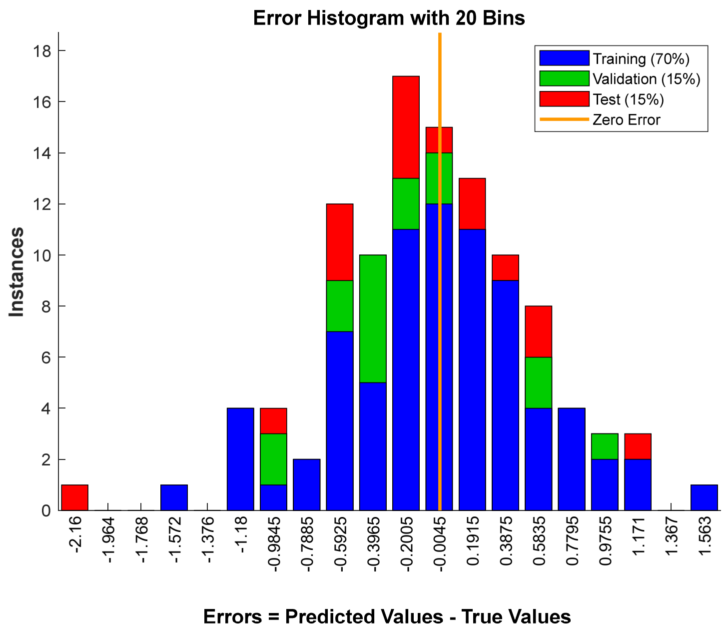


Figure 15. Error distribution of the ANN model with different datasets.

The Taguchi method with limited experimental data and average effects tends to struggles to achieve good predictive performance under different process conditions. The resulting prediction errors range from 0.194 to 0.326 μm. In contrast, the ANN model demonstrates strong generalization ability, as evidenced by its consistently low error distribution.

5.2.4. ANN Optimization of Printing Process Parameters

To further optimize the 3D printing process parameters, this study uses an ANN model to explore the application of inverse modeling, taking nozzle temperature as an example. This is because, as observed in previous experiments, nozzle temperature has a significant impact on surface roughness. This parameter directly affects material melting, layer bonding strength, and ultimately the surface roughness of the printed product. Variations in this parameter during the printing process can lead to unstable quality and increased material waste. Therefore, controlling the nozzle temperature is important for maintaining high-quality printing and reducing defects.

In this study, the input and output of the ANN model were reversed. Surface roughness was used as the input, while nozzle temperature was selected as the output. With other process parameters such as print speed, environmental temperature, and bed temperature kept constant, this approach allowed the model to predict the optimal nozzle temperature required to achieve the target surface roughness. Figure 16 compares the predicted and actual nozzle temperatures, showing a high degree of consistency with minimal prediction error.

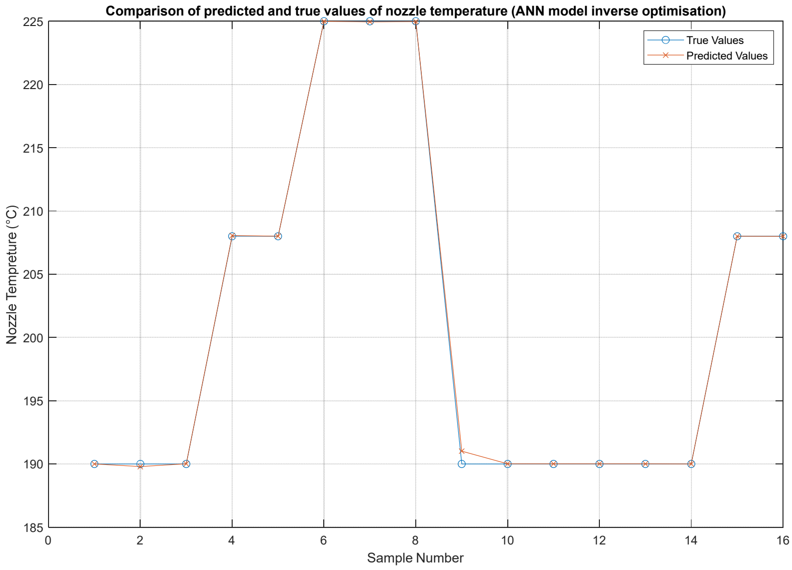


Figure 16. Comparison of predicted and true values of nozzle temperature using the inverse ANN model.

This inverse modeling approach highlights the ability of the ANN model to go beyond traditional forward prediction, providing a practical tool for real-time process optimization. By accurately determining key parameters such as nozzle temperature, the system helps improve consistency in print quality and minimize trial-and-error adjustments.

6. Conclusions

In this paper, we successfully developed an intelligent cloud monitoring system based on IoT, SharkNet, and ANN technologies for the smart manufacturing field (multiple 3D printing scenarios as an example). The results show that the system has significant achievements in real-time, reliability, scalability, and process optimization. The main contributions are summarized as follows:

1. System performance: Our experimental results show that the 5G wireless link of the SharkNet network has a latency of 40–50 ms under moderate load (comparable to the performance of Ethernet, which is widely used today). Secondly, the transmission reliability is 99.8%. Therefore, the SharkNet network provides a trustable solution for fieldbus applications in smart manufacturing and Industry 4.0.
2. Prediction accuracy: We found that based on SharkNet, the ANN model performs better in 3D printing quality monitoring and prediction, with an average prediction error of surface roughness less than 17.2% and a reduction of 88.5% compared to the traditional method. By learning the complex relationship between print parameters and print results, the model can assist the system to achieve precise dynamic optimization of parameters and further complex intelligent decision-making.
3. Operational efficiency: The results show that the system is able to adjust process parameters in a timely manner, which significantly reduces downtime and thus improves productivity in manufacturing, among other things. This is due to the fact that multiple sources of data provide solid data support for subsequent real-time analysis, and the high performance of the SharkNet network allows the system to react more quickly to abnormal processes.

To further cope with the inevitable high load scenarios in the future, future work will upgrade the commercial core network currently in use to a dedicated core network to further reduce SharkNet latency jitter and further improve its other performance metrics, including reliability. In addition, we will also try to integrate other machine learning models to predict network congestion in SharkNet and further enable dynamic optimization of the performance of the network itself, so that the network can further support more device-dense and complex smart manufacturing scenarios.

In the long run, this will lay the foundations for a new production model that is data-driven and intelligently autonomous. A high-performance SharkNet communication network, together with artificial intelligence and digital twin technology, will drive factories towards intelligent autonomy. In addition, this will lead to a more efficient use of resources, a reduction in costly waste, and a further promotion of sustainable production methods, all of which are in line with the ambitious goals of Industry 4.0.

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Abbreviations

Abbreviation	**Full Form**
3D	Three-Dimensional
ANN	Artificial Neural Network
IoT	Internet of Things
PLA	Polylactic Acid
QoS	Quality of Service
URLLC	Ultra-Reliable Low-Latency Communication
FDM	Fused Deposition Modeling
LVDS	Low-Voltage Differential Signaling
USB	Universal Serial Bus
WIFI	Wireless Fidelity

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