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Scalable Real-time Energy Monitoring, Analysis, and Optimization in Five-axis Machine Tools: An Industrial Internet of Energy-based Approach

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The industrial sector remains one of the largest energy consumers, with a heavy reliance on fossil fuels that contribute significantly to global greenhouse gas emissions. Additionally, most studies focus on one machine component rather than a whole system that considers multiple influencing factors, such as spindle speed, feed rate, and washdown pump operations. This gap highlights the need for an advanced, data-driven system capable of continuous energy monitoring, analysis, and optimization. In this paper, authors propose a dual-Raspberry Pi architecture for an industrial internet of energy-based monitoring system for real-time energy analysis and optimization in five-axis machine tools to address these challenges. The system employs Modbus RS485 communication to facilitate efficient data acquisition and visualization. Energy consumption patterns are further analyzed using the Affinity Law to optimize washdown pump operations. Experimental findings demonstrate that decreasing the washdown speed from 3500 to 2900 rpm results in a 43.2% reduction in energy consumption, saving approximately 2.216 kWh per day and reducing CO_2 emissions by 1.097 kg. Additionally, reducing the feed rate from 100 to 50% significantly enhances spindle energy efficiency, achieving the greatest savings of up to 62.5% without compromising machining performance. The proposed real-time monitoring and optimization system effectively reduces energy costs, minimizes carbon emissions, and promotes sustainable manufacturing practices.

1. Introduction

Fossil fuels remain the primary source of electricity generation worldwide. Consequently, industries reliant on fossil fuels should consider strategies to reduce energy consumption. Machine tools play a crucial role in the industrial sector; however, they are also significant

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contributors to energy consumption and greenhouse gas emissions. As per the U.S. Energy Information Administration (EIA), the industrial sector accounted for more than 50% of global energy consumption in 2018.[1] Energy-intensive manufacturing, including industries such as food production, pulp and paper, basic chemicals, refining, iron and steel, nonferrous metals, and nonmetallic minerals, comprised 52% of total energy consumption, whereas non-energy-intensive manufacturing, including metal-based durables, other chemicals, and miscellaneous manufacturing, accounted for 35%.[2]

Over the past 30 years, globalization, population growth, and industrial expansion have led to a near doubling of global energy demand.[3] The EIA projects that global energy demand will increase by approximately 50% between 2018 and 2050.[4] Among industrial activities, manufacturing processes are particularly energy-intensive, consuming approximately 85–90% of the sector's total energy.[5] Additionally, these processes contribute to 19% of global greenhouse gas emissions.[6] In the United States, machining alone accounts for 83% of the total energy consumed by the manufacturing sector.[5] However, the energy efficiency of machine tools is estimated to be only between 14.8 and 30%.[7] These statistics highlight the urgent need for strategies to enhance energy efficiency and mitigate the environmental impact of manufacturing operations.

In modern manufacturing where high precision and efficiency are required, computer numerical control (CNC) machine tools play a vital role. The spindle and C-axis, essential for complex geometries, consume energy on the basis of speed, load, material, and operation time. Understanding their energy use is key to enhancing efficiency. Notably, starting spindle acceleration or increasing speed without cutting requires much more energy than steady operation owing to the high torque needed to overcome inertia and mechanical losses.[8] Experimental studies have been conducted to quantify the power requirements of spindle acceleration. Avram and Xirouchakis[9] investigated the energy demand associated with spindle acceleration, highlighting the additional power required to compensate for mechanical losses and accelerate the spindle's moment of inertia. However, a primary limitation of empirical studies is their high cost, time-intensive nature, and machine-specific results. Zhong *et al.*[10] examined various empirical models related to spindle rotation, acceleration, feed rate, and material removal energy consumption, proposing a ranking framework for evaluating these models. Huang *et al.*[11] also developed a method to determine start-up energy consumption in machine tools using a database-driven approach. By identifying start-up processes through power rate changes and modeling energy-spindle speed relations, the method improves accuracy in energy forecasting and quota planning for manufacturing. These studies highlight the importance of accurate modeling in optimizing energy efficiency in machining processes.

Efficient energy management has become a critical priority in modern manufacturing industries, particularly in CNC machining processes characterized by high energy consumption. Predicting energy consumption in CNC machining is a fundamental challenge that must be addressed to develop effective and achievable energy efficiency optimization strategies.[12] Accurate energy consumption predictions are essential for identifying key influencing factors, enabling industries to optimize machining parameters and minimize energy waste without compromising product quality. Addressing this challenge not only leads to cost savings but also supports global sustainability objectives by reducing the carbon footprint of manufacturing operations. In this context, energy monitoring has emerged as a crucial component of sustainable manufacturing and operational efficiency.

The primary objective of energy management is to develop strategies that minimize energy consumption, reduce costs, and mitigate environmental impact while ensuring optimal conditions for individuals operating within a given space.(13) Chooruang and Meekul(14) developed an IoT-based energy monitoring system designed to be both cost-effective and efficient. The system integrated key components, including the PZEM-004T energy meter, current transformer sensors, and the ESP8266 Wemos Mini microcontroller, with a Raspberry Pi 3 Model B serving as a local server for data storage in a time-series database. This approach demonstrated the effectiveness of IoT-based solutions in monitoring voltage, current, active power, and cumulative energy consumption, highlighting their potential for enhancing real-time energy management and optimization.

The technological advancements that drive industrial evolution encompass a range of innovations, including IoT, artificial intelligence (AI), augmented reality (AR), sensors, and network analyzers. Each of these technologies plays a distinct role in modern industrial progress. IoT enables seamless data exchange between interconnected devices, while sensors and network analyzers facilitate the real-time monitoring of conditions and performance.(15) Covrig *et al.*(16) proposed a system that utilizes the Node-RED interface to establish connections among its components. Data collection and transmission are achieved through communication protocols such as 57 Comm, Open Platform Communication (OPC),(17) and Modbus.(18) Technological innovations in this domain include IoT-enabled device connectivity, machine-to-machine communication, distributed computing, emerging edge technologies, and cloud-based solutions such as container technology, microservices, and event-driven architecture. Additionally, advancements in timing and big data analytics, machine learning, and AI contribute to optimizing industrial processes and decision-making. As companies increasingly adopt technologies associated with the fourth industrial revolution, they aim to enhance automation and flexibility, making manufacturing operations more agile, adaptable, and responsive to evolving market demands. These advancements not only provide a competitive advantage but also enable businesses to optimize production efficiency and improve customer satisfaction.(19) Further research into industrial communication has demonstrated the effectiveness of integrating advanced frameworks into manufacturing systems. Tabaa *et al.*(20) proposed industrial communication using the Node-RED framework in combination with the Modbus and message queuing telemetry transport (MQTT) protocols. Similarly, Sun *et al.*(21) enhanced system robustness for diverse industrial IoT applications by integrating an edge gateway with Node-RED, improving data processing and connectivity within industrial environments.

Advanced communication technologies are essential for real-time industrial automation and energy management. However, current energy monitoring systems face key challenges, including the lack of accessible, real-time energy consumption data, which limits operators' ability to make informed decisions. Additionally, many systems offer only limited insights, hindering a comprehensive analysis of energy usage across various machine components. Addressing these limitations is crucial for promoting more energy-efficient, cost-effective, and sustainable manufacturing practices. To enhance energy monitoring, we integrated a Raspberry Pi as a central processing unit within the sensor network, offering the flexibility and capability of a personal computer. However, the use of Modbus RTU via RJ45 ports for data communication created port limitations for the industrial internet of energy (IIoE) system. To resolve this, an RTC was implemented as a network time server, and an additional Raspberry Pi, referred to as the 'Raspberry slave,' was introduced to act as a dedicated server. The primary Raspberry Pi handles data acquisition, whereas the slave Raspberry Pi manages the IIoE server through Node-RED and Modbus. Communication between the two is facilitated via Wi-Fi, whereas the IIoE system connects through a router. This architecture improves system reliability and processing efficiency, and reduces the risk of overheating. It is especially useful in complex CNC environments using up to 21 sensors across seven machine components with three-phase setups. Furthermore, we applied the Affinity Law to optimize the washdown pump efficiency, contributing to effective energy analysis and overall system performance.

2. Methodology

We adopted a systematic and data-driven approach to develop an IIoE system aimed at optimizing energy consumption in five-axis CNC machining. The methodology was designed to ensure real-time data acquisition, efficient processing, and user-friendly visualization for enhanced decision-making. The system was developed with a five-layer architecture, namely, machine equipment and hardware setup, control system, communication protocol, software protocol, and production management layers, which work in tandem to monitor and analyze energy usage across different machine components. The hardware infrastructure includes two Raspberry Pi 5, noninvasive clamp sensors, and Modbus RS485 communication, ensuring accurate and high-speed data collection. The software framework integrates Node-RED for data handling, Laravel for backend processing, and a web-based dashboard for real-time monitoring. Controlled experiments were conducted under varying machining conditions to validate the system's effectiveness, with energy consumption patterns analyzed using the Affinity Law. The following sections detail the hardware configuration, software implementation, data acquisition, and analytical techniques employed to enhance the energy efficiency of the CNC machining process.

2.1 System architecture

The proposed real-time monitoring system adopts a multilayered architecture to enable efficient data acquisition, communication, and processing within industrial environments. At the base level, the hardware layer includes essential machine components such as the five-axis roller cam, spindle system, washdown pump, and current sensors. These components support core machining functions, namely, multi-axis motion, rotational cutting, cooling, and energy monitoring, respectively. Above this is the control system layer, which incorporates a Raspberry Pi to handle data acquisition and interface with the hardware. This layer serves as the bridge between physical equipment and the digital network, ensuring reliable sensor data processing and communication.

The communication protocol layer supports standardized data transmission using the widely adopted Modbus protocol. It supports two main interfaces: Transmission Control Protocol (TCP)/Internet Protocol (IP) via an OPC server for remote access and system integration, and RS485 for robust, noise-resistant serial communication. At the software level, the system supports both standalone platforms and Node-RED. While the standalone solution offers localized control, Node-RED enhances flexibility with its flow-based, graphical programming interface making it easier to integrate with existing automation infrastructures. At the top layer, the energy management system (EMS) oversees production and energy monitoring. It analyzes performance metrics such as power usage, carbon footprint, and operational efficiency, and connects to a web server for real-time remote access. This integrated IIoE framework improves productivity, energy optimization, and decision-making, providing a scalable and sustainable solution for modern manufacturing. Figure 1 shows a generalized architecture that presents a comprehensive and scalable framework for the IIoE system.

2.1.1 User interface development

Figure 2 shows the network topology of the proposed system. Clamp sensors are deployed to measure electrical parameters and communicate via the RS485 protocol. The RS485 transceiver gathers this data and transmits it through an RJ45 connection to the Raspberry Pi, which acts as the system's core processing unit. The processed data is then sent via another RJ45 Ethernet connection to a router, enabling seamless data flow across the local network. This architecture allows the PC to function as the monitoring station, offering a user-friendly interface for real-

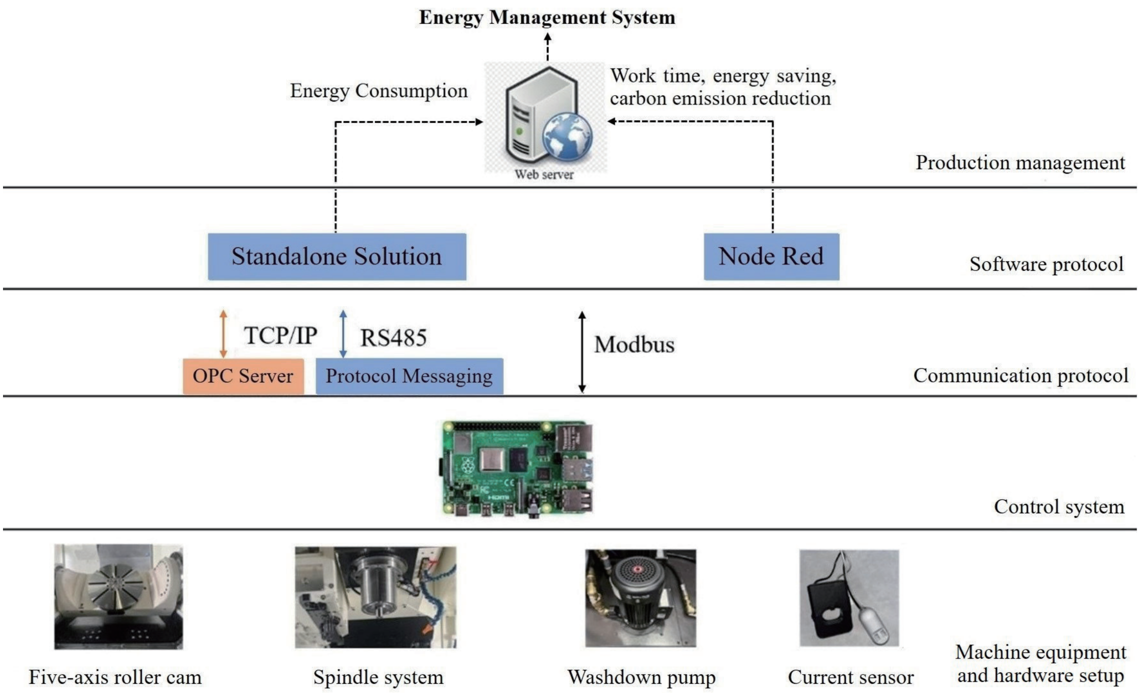


Fig. 1. (Color online) Generalized architecture of proposed real-time monitoring system.

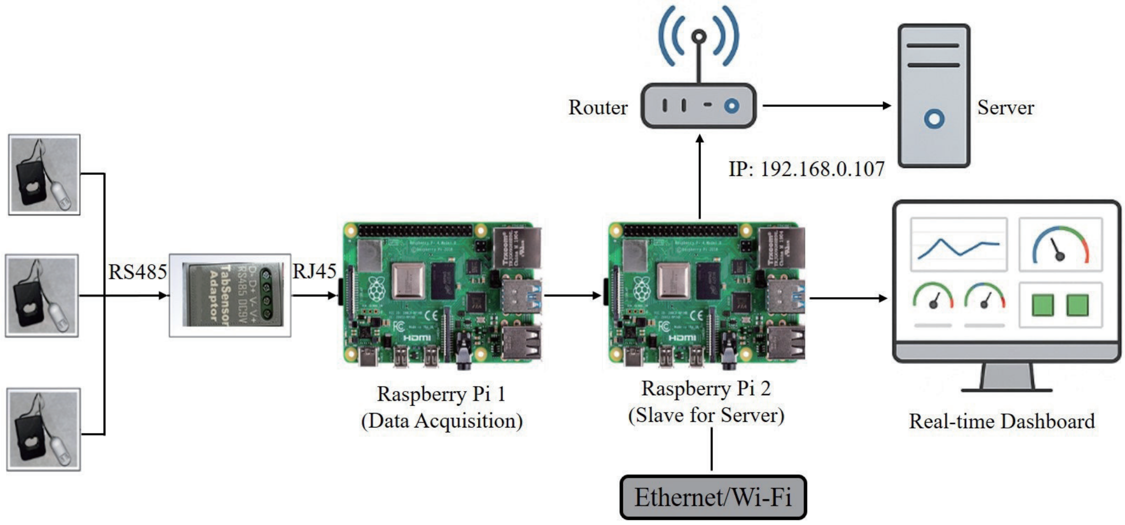


Fig. 2. (Color online) Schematic illustration of proposed system network topology.

time analysis and efficient energy management. The system uses a localhost environment for development and monitoring purposes. "Localhost" refers to a local web page hosted on the same machine, accessed through the loopback IP address (127.0.0.1). This configuration allows developers to test and debug web applications without deploying them to external servers. Servers such as Apache, Nginx, or development tools such as XAMPP, WAMP, and MAMP manage HTTP requests and serve content to browsers through localhost.

2.1.2 Real-time energy monitoring

The energy monitoring system comprises multiple integrated components that facilitate real-time energy consumption, data transfer, processing, and visualization, as shown in Fig. 3. The workflow initiates with data acquisition through the Modbus protocol, which retrieves and transmits data from measurement devices to the network. This data is then directed to a router with the IP address 192.168.7.1, which serves as the central traffic management unit, ensuring the efficient routing of information. Subsequently, the router forwards the acquired data to Node-RED for real-time processing and integration. The Modbus data is processed, analyzed, and relayed to relevant interfaces within Node-RED. The processed data is then accessed via a PC, which functions as the system's server, user, monitoring interface, and primary processing unit. This setup enables users to monitor, analyze, and control energy consumption effectively. Laravel is employed as the backend framework to ensure structured data management, facilitating communication between the front-end interface and the database while implementing essential logic and APIs. Finally, localhost IP 127.0.0.1 acts as the gateway for data visualization, presenting processed information as energy consumption graphs and sensor status through a web-based interface integrated with Laravel. This comprehensive system architecture ensures the efficient, real-time monitoring and analysis of energy consumption, providing users with an interactive and reliable platform for energy management.

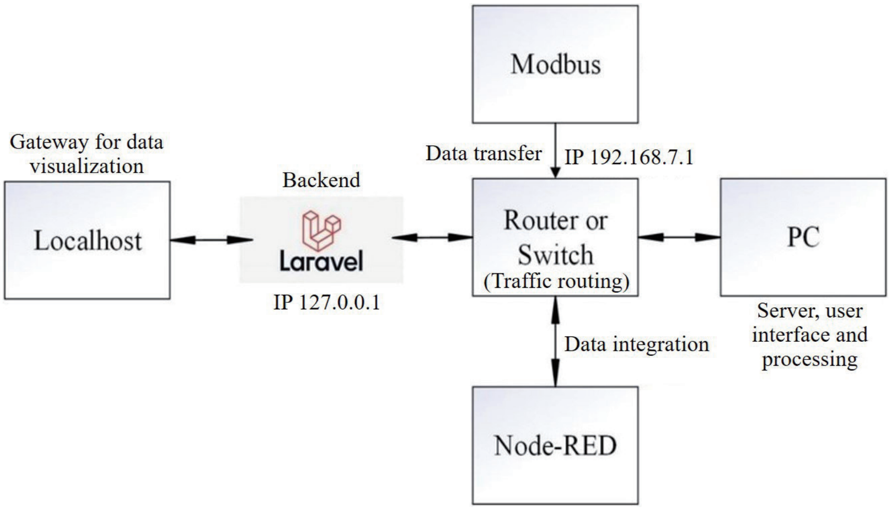


Fig. 3. (Color online) Schematic architecture of proposed real-time monitoring system.

To ensure real-time capability, the system was quantitatively evaluated for temporal performance. The sensor data acquisition rate was maintained at 1 Hz per sensor to provide continuous energy monitoring. Communication latency between the primary and slave Raspberry Pi units via Wi-Fi averaged 30–50 ms. The Node-RED-based dashboard was configured with a data refresh interval of 2 s to ensure the timely visualization of updated energy metrics. Additionally, user interactions with the dashboard such as filter selection or navigation showed a typical response time of less than 1 s to enable responsive and monitoring control.

2.2 Experimental setup

Figure 4 shows the process involved in the measurement equipment's setup, operation, and analysis. The procedure begins with the installation and initialization of the equipment. If operational issues arise, troubleshooting measures are undertaken to resolve them. Once the device functions properly, it enters a standby mode, ready for measurement tasks. The measurement phase includes critical parameters, including the A-axis, C-axis, Cartesian axis, spindle speed, and washdown pump performance, assessed at a full feed rate of 100%. A dry run is conducted, followed by a wet run at a reduced feed rate of 50%. The data gathered from these tests undergoes rigorous analysis using established methodologies such as the Affinity Law and the Taguchi Method. These analytical approaches facilitate extracting meaningful insights from the experimental results, ensuring the optimal performance and reliability of the measuring equipment.

2.2.1 Measuring equipment setup

Before starting the experiment, the measuring equipment must be installed inside the electrical control panel of the machine. Once the installation is complete, turn on the computer

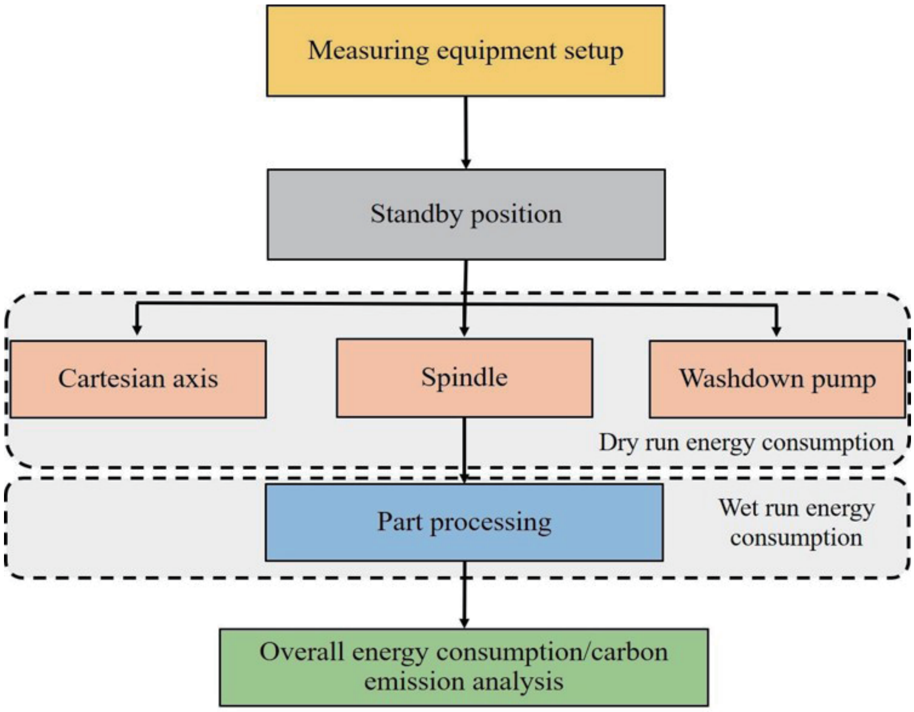


Fig. 4. (Color online) Schematic illustration of energy measurement and optimization strategy.

and connect it to the internet. Then, check all connections of the measuring equipment to ensure they are correct. After confirming, turn on the machine power and use the monitoring interface to check whether the sensor values are within a reasonable range to avoid installation errors.

Figure 5(a) shows the axis configuration and movements of a 5-axis CNC machine, widely used for advanced manufacturing precision machining. The machine operates with three linear axes, X, Y, and Z, and two rotational axes, A and C, that provide flexibility in orienting the workpiece relative to the cutting tool spindle. The linear axes enable movements along the horizontal, vertical, and depth directions. In contrast, the rotational axes allow the tilting and rotating of the workpiece, ensuring that complex geometries can be machined accurately. This multiaxis capability reduces the need to reposition the workpiece, improving efficiency and precision in machining operations. Figures 5(b) and 5(c) show the power measurement sensors installed at the spindle, cartesian axis, and washdown pump for the real-time individual component's power consumption measurements. These sensors are connected to the developed monitoring device so that energy consumption patterns can be monitored remotely through a computer, as shown in Fig. 5(d).

2.2.2 Test conditions

To evaluate the effectiveness of the proposed methodology in this study, experimental verification was carried out on a five-axis machine tool manufactured by Yeong Chin Machinery Industries Co., Ltd. (YCM), as shown in Fig. 5. Figure 5(a) shows a five-axis rotary table-cutting machine with a direct drive (DD). The optimal rotation speed for the spindle of the five-axis

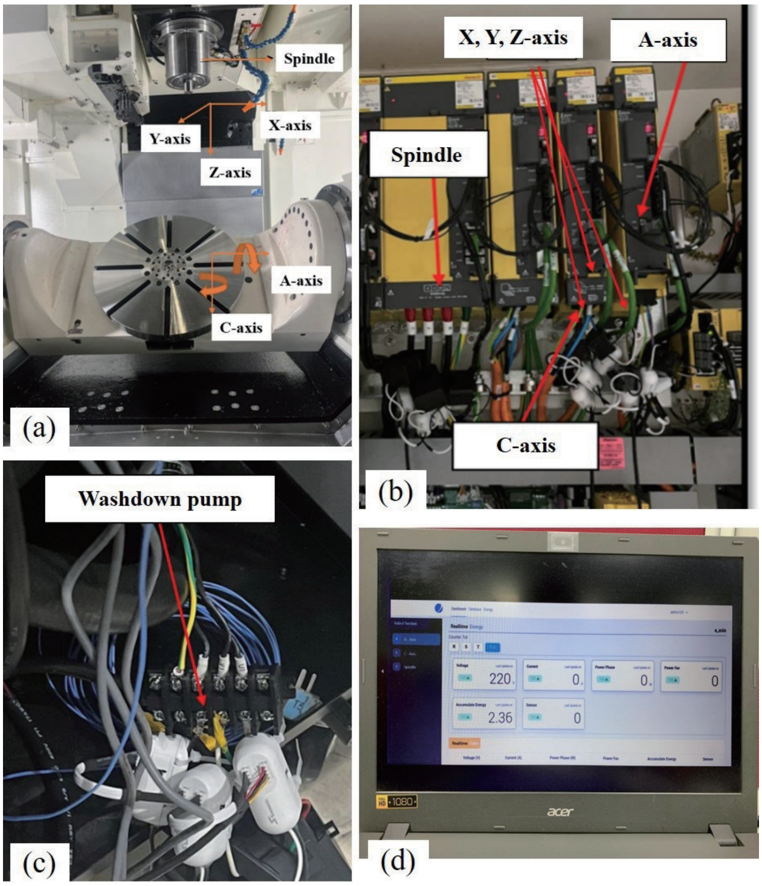


Fig. 5. (Color online) Setup for power measurement instruments: (a) main machining section, (b) sensors installed on the *X*-, *Y*-, *Z*-, *A*-, and *C*-axes, and spindle, (c) sensors installed on the washdown pump, and (d) remote monitoring computer.

machine tool is 12000 rpm. The rotary table DD comprises two components: axes *A* and *C*. The rotary table's rotation speeds on axes *A* and *C* are 100 and 120 rpm, respectively. In this study, a dry run is conducted, followed by a wet run for the real-world machining analysis, to analyze the efficiency and effectiveness of the developed system.

2.3 Energy consumption

Energy consumption refers to the amount of energy a system, machine, or process uses over a specific period. In the context of manufacturing, energy consumption is a crucial metric because it directly impacts both the operational cost and the environmental footprint of production activities. Therefore, energy efficiency emerges as a key approach to managing energy consumption. The international energy agency regards energy efficiency as the goal to reduce the energy demand of products and services or to obtain the same quality and end-use energy with less energy input.[22] The power consumed by a machine during manufacturing can be calculated using the following equation:

$$P = F_C \times V_C, \tag{1}$$

where P is the power in watts (W), F_C is the cutting force in newtons (N), and V_C is the cutting speed in meters per second (m/s).

The energy consumed by the machine during machining is calculated as

$$E = P \times t, \tag{2}$$

where E is the energy consumed in Joules (J), P is the power in watts (W), and t is the operation time in seconds (s).

The average energy consumption can be obtained from the following formula:

$$E_{AV} = \frac{\sum_{i=1}^{n} E_i}{n}, \tag{3}$$

where E_i is the energy consumption at each speed (for each condition) and n is the total number of measurements.

Carbon emission can be calculated as

$$C = E \times \mathrm{FCO_2e}, \tag{4}$$

where FCO_2e is the carbon emission factor associated with energy consumption, which is 0.494 $kgCO_2e$ per kilowatt-hour (kWh).[23]

Energy saving can be calculated as

$$E_s = E_{old} - E_{new}, \tag{5}$$

where E_{old} is the previous energy consumption and E_{new} is the new energy consumption.

Carbon emission reduction can be calculated as

$$C_r = E_s \times \mathrm{FCO_2e}. \tag{6}$$

The average carbon emission can be calculated as

$$C_{AV} = \left(\frac{\sum_{i=1}^{n} E_i}{n} \right) \times \mathrm{FCO_2e}. \tag{7}$$

The payback period of the developed IIoE system can be calculated as

$$\textit{Payback period} = \frac{\textit{Total system cost}\,(\mathrm{USD})}{\textit{Daily energy saving}\,(\mathrm{kWh}) \times \textit{Electricity cost}\,(\mathrm{USD/kWh}) \times \textit{Annual no. of working days}}. \tag{8}$$

2.4 Optimization strategy

The Affinity Law is a fundamental principle in fluid dynamics and engineering, describing the mathematical relationships between the speed, flow rate, pressure, and power of centrifugal machines such as pumps, fans, and compressors.[24] This law is essential in optimizing the performance and energy efficiency of such machines, as it enables engineers to predict the effects of changes in rotational speed or impeller size on system performance. By using the Affinity Law, industries can achieve significant operational cost savings and reduce energy consumption, aligning with sustainable practices and economic efficiency. The Affinity Law can be defined as

$$\frac{P_1}{P_2} = \left(\frac{N_1}{N_2}\right)^3, \tag{9}$$

where P_1 is the energy consumption at the original speed, P_2 is the energy consumption at the lower speed, N_1 is the low speed of the pump, and N_2 is the original speed of the pump.

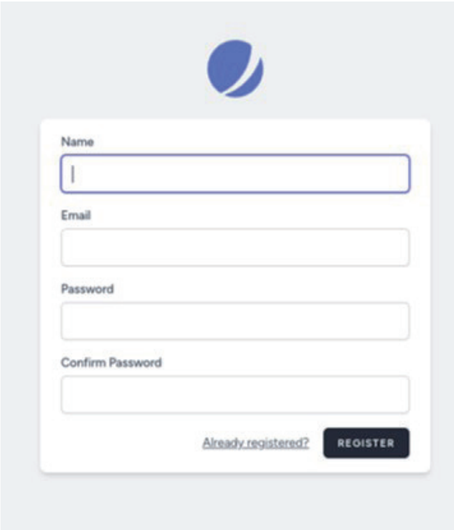
A mathematical simulation was conducted to analyze the energy consumption of the washdown pump in the five-axis machine to study the relationship between pump speed, flow rate, and power consumption. The simulation focused on a motor pump operating within a speed range of 2900 to 3500 rpm. Specifically, the analysis simulated the energy consumption at three different speeds, namely, 3500, 3200, and 2900 rpm, to observe the impact of reducing rotational speed on performance parameters such as flow rate, pressure, and power usage.

3. Results and Discussion

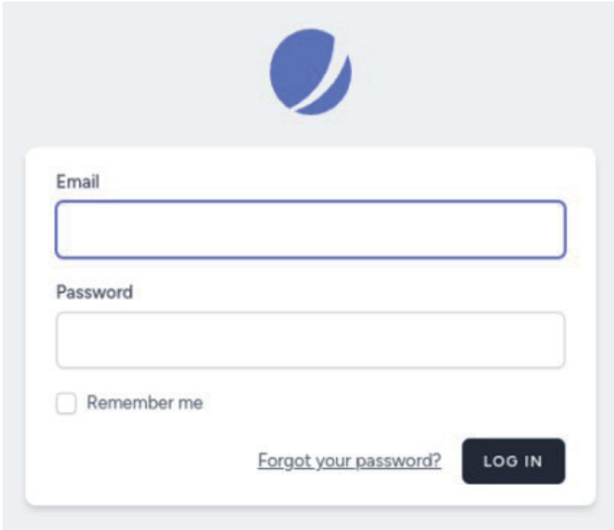
Experiments were conducted, and different datasets were recorded using the developed IIoE system to analyze the energy consumption of various components of the five-axis machine, including the spindle, *X*-, *Y*-, *Z*-, *A*-, and *C*-axes, and the washdown pump. Measurements were recorded under two different operational conditions, feed rates of 50 and 100%, to analyze the impact of various feed rates on energy consumption. Each component's energy consumption was monitored in real time using connected sensors, and data were logged at regular intervals to ensure accuracy and consistency. The data for this experiment were recorded over 1 h per trial. This approach provides a comprehensive dataset to evaluate the performance and energy demands of the machine under different operating conditions.

3.1 User interface

The IIoE system has a user-friendly web application for efficient data management and analysis. Figure 6(a) shows the registration interface of the web application. The screen showcases a registration form that prompts users to input their name, email, password, and confirmation of the password. A "Register" button below the form allows users to submit their registration details. As with the login interface, the application runs locally on a development



(a)

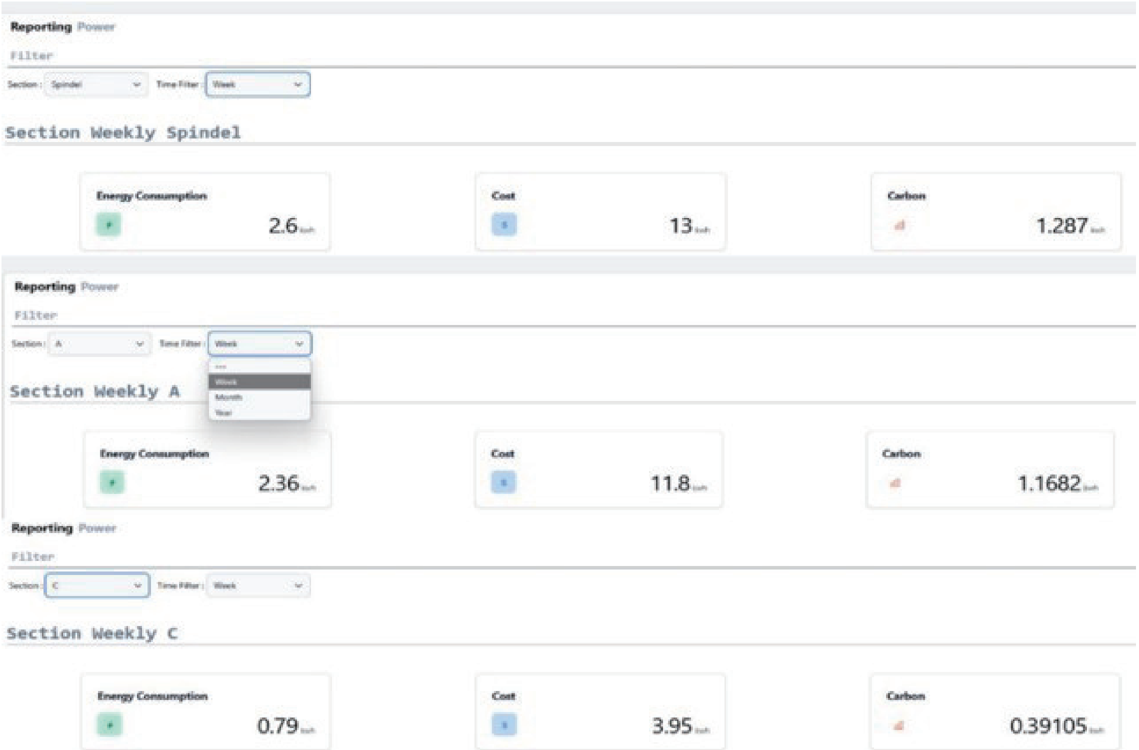


(b)

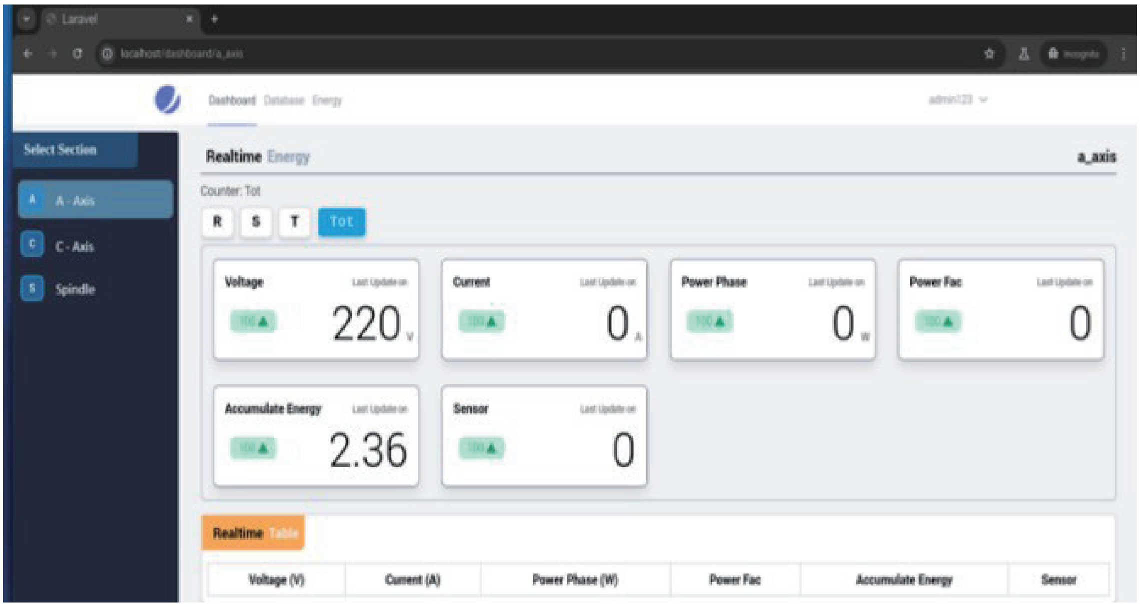
Fig. 6. (Color online) User login interface: (a) user registration and (b) user login.

server, with the URL at port 8000. Additionally, Fig. 6(b) shows the login interface of the web application. This design ensures a streamlined user experience while maintaining efficient functionality for monitoring and analyzing energy consumption data. Users must log in through the provided interface to access the system's features.

The implementation of the energy consumption monitoring system is based on the integration of Modbus, Node-RED, and MQTT, combining both hardware and software components to facilitate real-time energy data acquisition, processing, and visualization. The first step involves configuring Modbus within Node-RED to establish a connection between the Modbus-based power meter and the Node-RED platform. This connection is achieved through TCP/IP (192.168.7.1), ensuring accurate real-time data acquisition from the power meter. Once the data is acquired, it is transmitted using the MQTT protocol. The data received from the MQTT broker is then visualized through a monitoring dashboard developed in Node-RED. The dashboard has interactive features, as shown in Fig. 7(a), allowing users to apply time filters (daily, weekly, monthly) and view key performance indicators, including energy consumption, associated costs, and carbon emissions. Figure 7(b) shows the real-time energy monitoring dashboard of the web application. The interface consists of multiple panels, each displaying critical energy metrics, such as voltage, current, power phase, power factor, accumulated energy, and sensor status. These metrics are organized in a grid layout for enhanced readability, with each panel clearly labeled and presenting values with appropriate units. A navigation bar on the left lets users switch between sections such as "Home", "Admin", and "Real-time Energy", while a table at the bottom of the page presents the metrics in a tabular format for continuous monitoring. The clean, structured design of the interface ensures ease of use, making it highly suitable for energy monitoring applications. This comprehensive hardware and software integration enables the efficient monitoring and analysis of energy consumption data, facilitating informed decision-making for energy optimization.



(a)



(b)

Fig. 7. (Color online) Energy monitoring dashboard: (a) time filters including key performance indicators and (b) real-time energy monitoring dashboard.

To ensure practical usability, the dashboard was designed to be clean and intuitive with a focus on user-friendly navigation and real-time data visibility. Informal usability testing was conducted with researchers and machine operators, who reported that the interface required minimal training and was easy to operate. Key features such as time-based filtering, energy indicators, and tabular views were found to be effective for energy tracking. Performance analysis showed that data updates and user interface responses met real-time requirements with average user interface latency under 1 s and dashboard refresh intervals set at 2 s. The system also supports multiuser access through Laravel's built-in authentication and session management features. This allows different users to securely log in, with the option to assign role-based permissions for enhanced control and system management. To address system reliability, error detection and recovery functions were embedded into the Node-RED flow logic. In cases of sensor disconnection or communication failure, the system automatically flags an alert on the dashboard and logs the incident. The affected sensor data is marked "offline" to ensure that users are informed of real-time faults and can take timely corrective actions. These features contribute to the robustness and operational dependability of the proposed IIoE monitoring system.

3.2 Energy consumption analysis

Figure 8 shows the energy consumption at the spindle system and C-axis at two different feed rates, i.e., 50 and 100%. It shows that at lower spindle speeds, both feed rates experience a sharp increase in energy consumption, but the 50% feed rate consistently consumes less energy. As the speed increases beyond 2000 rpm, the energy consumption for both feed rates fluctuates but remains lower for the 50% feed rate across most speed ranges. The 100% feed rate has high energy consumption, especially around 4000 rpm, whereas the 50% feed rate remains more

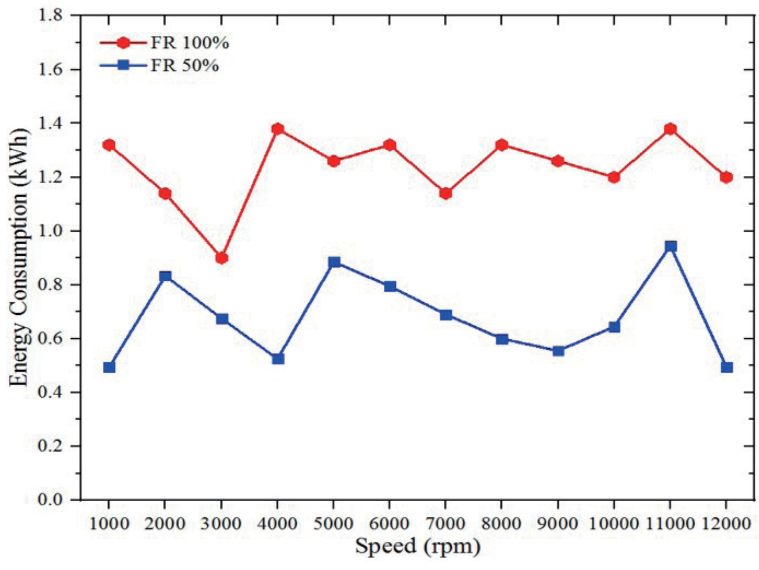


Fig. 8. (Color online) Energy consumption at different feed rates of the spindle.

Table 1
Energy consumption analysis results of the spindle at a feed rate of 50% over the feed rate of 100%.

Spindle speed (rpm)	Reduction (%)
1000	62.50
2000	36.57
3000	25.00
4000	61.95
5000	29.76
6000	39.77
7000	39.47
8000	54.54
9000	55.95
10000	51.13
11000	31.52
12000	58.75

stable and efficient throughout. Additionally, Table 1 shows that the 50% feed rate is more efficient, offering approximately 45% less energy consumption than the 100% feed rate, making it the better choice for energy efficiency across different speeds. These findings highlight the importance of selecting appropriate feed rates on the basis of specific machining conditions to optimize energy consumption.

3.3 Energy savings and carbon emission reduction

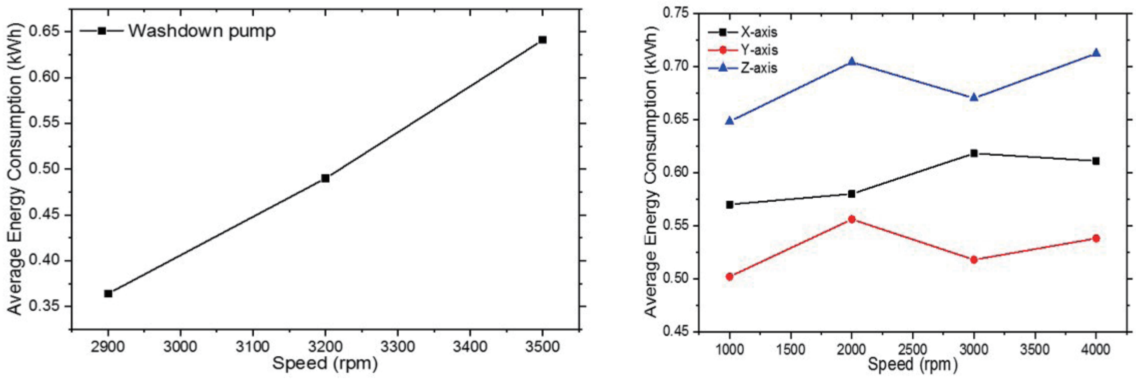
We utilized the washdown pump model TPHK 2T4-4, which operates at different motor speeds of 2900 and 3500 rpm. The Affinity Law was applied to estimate the reduced energy consumption at 2900 rpm. Experimental findings demonstrate that reducing the washdown pump speed from 3500 to 2900 rpm reduces energy consumption from 0.641 to 0.364 kWh per operation cycle.

Table 2 and Fig. 9(a) show the relationship between speed and energy consumption for a washdown pump based on the Affinity Law. The graph shows that energy consumption decreased significantly as the motor speed was reduced. For instance, at a motor speed of 2900 rpm, the energy consumption is 0.364 kWh, representing a reduction of up to 43.2% compared with the maximum speed of 3500 rpm. This indicates that lowering the motor speed can effectively improve the energy efficiency in pump systems.

Figure 9(b) shows the energy consumption patterns across various motor speeds for the *X*-, *Y*-, and *Z*-axes. For the *X*-axis, energy consumption remains relatively stable, fluctuating between 0.57 and 0.61 kWh across all tested speeds. This stability indicates that motor speed minimizes energy usage, highlighting an efficient system design that ensures consistent energy consumption regardless of operational speed. The uniformity across different scenarios further emphasizes the effectiveness of optimized energy control strategies, which contribute to reliable performance and efficiency at various motor speeds. Energy consumption exhibits slight variations between scenarios for the *Y*-axis, with values ranging from approximately 0.5 to 0.55 kWh. Notably, at 2000 and 3000 rpm, some scenarios show a marginal increase in consumption

Table 2
Energy consumption of washdown pump during part processing.

No.	Speed (rpm)	Power consumption (kWh)	Reduction (%)
1	3500	641×10^{-3}	0.00
2	3200	490×10^{-3}	23.5
3	2900	364×10^{-3}	43.2



(a) (b)

Fig. 9. (Color online) Average energy consumption at various repeated experiments of (a) washdown pump and (b) Cartesian axis.

compared with the values observed at 1000 and 4000 rpm, suggesting a potential fluctuation in efficiency at intermediate speeds. Despite these minor variations, the overall pattern demonstrates relatively steady energy consumption, reflecting the system's capacity to maintain efficient energy usage with only minor adjustments across the motor speed range. In the case of the *Z*-axis, energy consumption shows a consistent increase, ranging from approximately 0.64 to 0.71 kWh across all motor speeds. The differences between scenarios are minimal, indicating that the system successfully maintains a uniform energy consumption pattern regardless of speed changes. This consistent behavior highlights the efficiency of the system in managing energy usage, even as motor speed increases, which is particularly important for applications requiring stable energy performance under various operational conditions.

The energy consumption was analyzed to produce 160 products per day over one month (30 days) to analyze the energy demand of different components in real machining. It revealed significant variations across machine components, reinforcing the trends observed in the energy usage patterns at different speeds. The spindle remains the most energy-intensive component, consuming 2.032 kWh daily. Similarly, the washdown pump, which was previously noted for its increasing energy consumption with speed, also demonstrates a high daily usage of 1.632 kWh. These findings emphasize the considerable impact of these components on overall energy consumption. The *X*-axis consumes 1.12 kWh daily for the machine axes, whereas the *Y*-axis consumes 0.8 kWh daily. The *Z*-axis, which previously had an increasing energy trend with speed, uses 1.44 kWh daily consumption. Additionally, the *A*- and *C*-axes, with significantly lower daily energy consumptions of 0.16 and 0.096 kWh, respectively, confirmed their minimal total energy consumption.

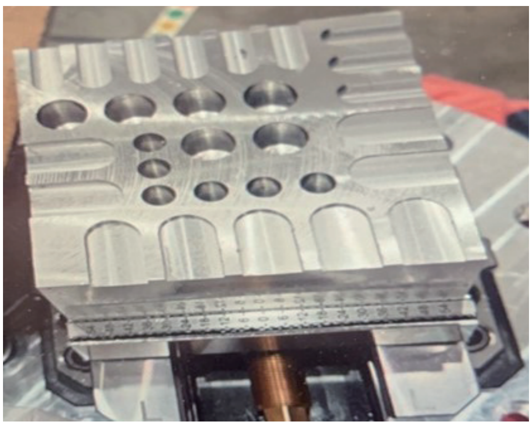
From an environmental perspective, the spindle is the largest contributor to carbon emissions, generating 30.11 $kgCO_2e$ monthly. This is consistent with its role as the highest energy-consuming component. Similarly, previously identified as a major energy user at higher speeds, the washdown pump produces 24.18 $kgCO_2e$ monthly, highlighting its environmental impact. Among the machine axes, the Z-axis contributes 21.34 $kgCO_2e$, followed by the *X*-axis (16.59 $kgCO_2e$) and the *Y*-axis (11.85 $kgCO_2e$), reflecting their energy consumption patterns over time. The *A*- and *C*-axes, with 2.37 and 1.42 $kgCO_2e$, respectively, remain minor contributors. These findings highlight the importance of focusing on the spindle, washdown pump, and *Z*-axis when seeking energy efficiency improvements.

Figure 10(a) shows the finished product and Fig. 10(b) shows the energy consumption distribution across all components. The spindle accounts for 27.91% of the total energy consumption, followed by the washdown pump at 22.42% and the *Z*-axis at 19.78%, reinforcing their roles as major contributors to energy costs and carbon emissions. Table 3 shows the energy consumption of the different machine components during the machining of finished products.

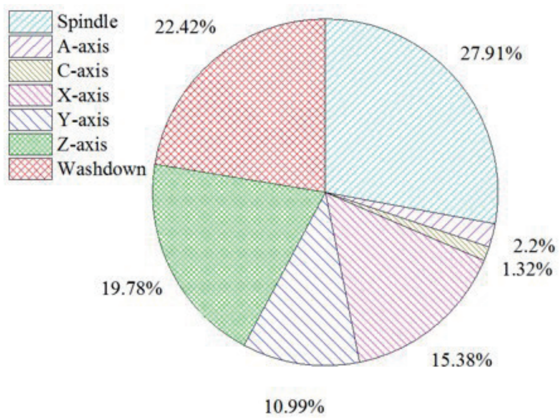
3.4 Economic feasibility and data security

To evaluate the practical viability of the proposed IIoE monitoring system, an economic feasibility assessment was conducted. The hardware setup for a single five-axis CNC machine includes two Raspberry Pi units, noninvasive clamp current sensors, an RS485 transceiver, power supplies, microSD cards, a Wi-Fi router, a housing cabinet, Ethernet cables, cable ties, and supporting wiring. The total capital cost was estimated to be USD 375 and is detailed in Table 4.

Energy savings were calculated on the basis of the reduced power usage of the spindle and washdown pump during optimized operation. Considering that the washdown pump operates only about 5% of the total machining cycle time across 160 parts per day, the normalized energy saving is 2.216 kWh. The spindle's normalized daily energy saving is 0.915 kWh based on its



(a)



(b)

Fig. 10. (Color online) Wet run machining condition: (a) finished product and (b) energy consumption percentage of all components.

Table 3
Energy consumption of finished product during wet run.

Components	Energy consumption (kWh)		
	1 product	20 products	160 products
Spindle	12.7×10^{-3}	254×10^{-3}	2032×10^{-3}
A-axis	1×10^{-3}	20×10^{-3}	160×10^{-3}
C-axis	0.6×10^{-3}	12×10^{-3}	96×10^{-3}
X-axis	7×10^{-3}	14×10^{-3}	1120×10^{-3}
Y-axis	5×10^{-3}	100×10^{-3}	800×10^{-3}
Z-axis	9×10^{-3}	180×10^{-3}	1440×10^{-3}
Washdown pump	10.2×10^{-3}	204×10^{-3}	1632×10^{-3}
Total	$\mathbf{45.5 \times 10^{-3}}$	$\mathbf{784 \times 10^{-3}}$	$\mathbf{7280 \times 10^{-3}}$

Table 4
Estimated capital cost breakdown for IIoE-based energy monitoring.

Components	Quantity	Unit price (USD)	Total (USD)
Raspberry Pi	2	85	170
Noninvasive clamp current sensors	7 (3-phase × spindle, axes, pump)	10	70
RS485 transceiver	2	15	30
Adapters	2	15	30
MicroSD cards	2	10	20
Wi-Fi router	1	10	10
Housing cabinet	1	25	25
Ethernet cables, wire, connectors, and cable ties	—	—	20
	Total capital cost		**375**

daily energy use of 2.032 kWh and an average reduction of approximately 45% at a 50% feed rate. Together, these results demonstrated a total daily energy saving of approximately 3.131 kWh, corresponding to an estimated cost saving of USD 0.691/day. This calculation is based on the average commercial electricity tariff in Taiwan, considered to be USD 0.221/kWh.[25] Considering 320 annual working days and using Eq. 8, the payback period for the proposed system is calculated to be approximately 1.7 years.

In addition to economic feasibility, data security is essential when implementing real-time industrial monitoring systems. To ensure the secure handling of sensitive operational data during acquisition and transmission, several protective measures have been integrated into the system. The user interface, developed using the Laravel framework, includes secure login and role-based access control. The system operates on a secure local area network, reducing exposure to external cyber threats. While unencrypted communication is used within this trusted network during testing, the system architecture supports the implementation of Transport Layer Security (TLS)/Secure Sockets Layer (SSL) encryption and Virtual Private Network (VPN) tunneling for secure remote access. Additional security features include password-protected Raspberry Pi units, restricted Secure Shell (SSH) access, and regular system updates. These measures collectively enhance the system's security, reliability, and industrial readiness.

4. Conclusions

In this study, we developed and validated an IIoE-based real-time energy monitoring and optimization system for five-axis CNC machining. Modbus RS485 communication enabled efficient data acquisition and analysis to monitor energy consumption accurately. Notably, integration with industrial protocols such as Modbus TCP/IP, MQTT, and OPC UA enables compatibility with factory automation platforms, including manufacturing execution systems, Supervisory Control and Data Acquisition (SCADA), and cloud-based services. Experimental results demonstrated that reducing the washdown pump speed from 3500 to 2900 rpm led to a 43.2% reduction in energy usage, while optimizing feed rates resulted in up to a 62.5% improvement in spindle energy efficiency. These findings validate the potential for significant energy savings and CO_2 emission reduction without affecting machining precision. Beyond its technical effectiveness, the system is designed for industrial scalability. Its modular Raspberry Pi architecture can be used across machines, and Node-RED enables flexible deployment with REST APIs for enterprise integration. Network security features such as user authentication, encryption, and local data storage with cloud backup options ensure long-term reliability. This work shows a practical foundation for large-scale digital transformation in energy-efficient and sustainable manufacturing environments.

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