

Digital Twin Framework for Real-Time Simulation and Monitoring of Three-Axis CNC Machines in Industry 4.0

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Abstract

Digital twin technology is rapidly transforming industrial operations by enabling real-time synchronization between physical systems and their virtual counterparts. Within the framework of Industry 4.0, this integration leverages advances in AI, IoT, and simulation to enhance system monitoring, analysis, and control. This paper presents the design and implementation of a cost-effective digital twin for a three-axis CNC milling machine using open-source software and embedded hardware. The system enables real-time visualization of spindle speed, axis movement, and vibration data, offering remote access via cloud tunnels.

A 3D model created in Fusion 360 is synchronized with real-time data through a URDF-based simulation in ROS, driven by inputs from AS5600 encoders and ESP32 microcontrollers. Calibration and testing procedures validate the system's accuracy and responsiveness under practical machining conditions. This digital twin provides a replicable, affordable framework suitable for academic, research, and small-scale industrial applications.

By integrating low-cost sensing, data acquisition, and real-time simulation, this work demonstrates a practical approach to implementing digital twins beyond large-scale industrial settings. It contributes to the broader adoption of Industry 4.0 technologies by offering a scalable and educationally relevant prototype that bridges the gap between theory and hands-on industrial practice.

Keywords: Digital Twin, Three-Axis Machine, Industry 4.0, IoT, Edge Computing, Machine Learning, Real-Time Simulation, Predictive Maintenance

1 Introduction

The evolution of manufacturing systems has significantly transformed how raw materials are converted into finished goods, emphasizing efficiency, quality, and sustainability. A typical manufacturing system comprises multiple stages: planning, design, procurement, production, quality control, distribution, and maintenance. Each stage contributes to streamlining operations, minimizing waste, and enhancing product quality. Continuous improvement processes further optimize these stages to reduce costs and improve efficiency, ensuring the system remains competitive in the dynamic industrial landscape. Advancements in Application Managed Services (AMS) have paralleled these developments, revolutionizing IT applications in manufacturing. AMS has evolved from providing basic maintenance to offering tailored solutions and value-added services, supporting digital transformation initiatives. By adopting innovative pricing models and leveraging advanced technologies, AMS providers now serve as strategic partners, helping organizations achieve operational excellence and modernization. The integration of digital transformation tools, such as AI, ML, and web development, has further expanded the potential of AMS in optimizing manufacturing processes and enhancing decision-making. A breakthrough innovation in this domain is digital twin technology, a virtual representation of physical objects or systems, enabling real-time analysis and simulation. By utilizing AI and ML, digital twins offer insights into performance, predictive maintenance, and process optimization across industries such as manufacturing, healthcare, and transportation. This technology bridges the gap between physical and virtual systems, empowering industries to improve efficiency, reduce downtime, and enhance product quality. The integration of machine learning enhances digital twins by enabling anomaly detection, predictive repair, and advanced analytics, making it a transformative tool for industries seeking data-driven solutions.

Incorporating adaptive control mechanisms further complements these advancements. Adaptive controllers dynamically adjust parameters to respond to changes in the process, optimizing control conditions and improving machining precision. This approach integrates seamlessly with CNC systems, where parameters like cutting speed and feed rate are intelligently optimized. The digital twin's ability to monitor spindle speeds and linear displacement provides invaluable data for performance monitoring, quality control, predictive maintenance, and process optimization, making it a cornerstone of modern manufacturing. The objectives of this study are to leverage these advanced technologies to enhance machine performance monitoring, improve resource allocation, and optimize production processes. By integrating AI-driven digital twins and adaptive control systems, this research aims to establish a robust framework for precision manufacturing, aligning with the broader goals of Industry 4.0.

2 Literature Review

Digital Twin (DT) technology has emerged as a pivotal tool for advancing manufacturing processes by integrating virtual simulations with real-time data to optimize design, production, and maintenance operations. A growing body of research underscores its transformative potential across diverse applications in machining, quality control, predictive maintenance, and sustainable manufacturing.

Digital Twin for Process Optimization and Manufacturing Automation

Vishnu proposed a DT framework for CNC machining processes, focusing on the prediction and optimization of surface roughness during the process planning and machining stages using historical and real-time data [1]. Anbalagan extended this concept by integrating CAD automation and multi-axis milling in DT development for impeller and blade manufacturing. The study emphasized concurrent verification of design and manufacturing processes to achieve Industry 4.0 objectives [2]. Similarly, Dharmawardhana developed a STEP-NC compliant CNC controller to ensure continuous CAD/CAM/CNC integration, enabling real-time toolpath generation and condition monitoring through a low-cost, open

architecture solution [3]. Combining these studies highlights DT's role in enhancing process precision, adaptability, and real-time responsiveness.

Digital Twin for Predictive Maintenance and Fault Diagnosis

Qiao introduced a hybrid DT model with Deep Stacked GRU for predicting tool wear using vibration data in milling operations, showcasing its effectiveness in condition monitoring [4]. Wang proposed a DT reference model for fault diagnosis in rotating machinery, incorporating parameter sensitivity analysis to address nonlinear dynamics and uncertainty in machinery degradation [5]. These studies collectively demonstrate the potential of DTs in predictive maintenance, enabling accurate fault detection and reducing industrial downtime.

Quality Control and Optimization in Manufacturing

Liu proposed a DT-driven approach for traceability and dynamic control of processing quality, integrating Bayesian networks, IoT systems, and real-time data collection to enhance quality control [6]. Li focused on the digital twin shop-floor (DTS), which integrates physical and virtual processes for real-time decision-making and resource optimization in manufacturing [7]. These contributions highlight DT's ability to improve quality assurance and operational efficiency.

Application of Digital Twin in Product Lifecycle and Smart Manufacturing

Soori reviewed DT applications in smart manufacturing, emphasizing lifecycle management, predictive maintenance, and workflow optimization to reduce defects and improve production efficiency [8]. Fernando proposed a DT data architecture for Product-Service Systems (PSS), enabling real-time monitoring, data fidelity, and integration of design and manufacturing processes [9]. Ma advanced this concept by integrating DT with big data technologies to achieve sustainable smart manufacturing in energy-intensive industries, reducing costs and improving energy efficiency through lifecycle analysis [10]. These studies demonstrate the versatility of DTs in optimizing the entire product lifecycle, from design to sustainability.

DT in Specialized Applications

Papacharalampopoulos applied DT in laser welding by combining physics-based modeling methods and sensorial data to optimize and monitor the welding process, illustrating the potential of DTs in specialized manufacturing [11].

The research on DT technology spans various domains, highlighting its potential in improving manufacturing processes, reducing costs, and enabling sustainable practices. By combining real-time data integration with virtual simulations, DT technology offers robust solutions for predictive maintenance, quality control, and lifecycle optimization. These studies provide a strong foundation for further exploration and implementation of DTs in advancing smart manufacturing systems.

3 Methodology

3.1 Overview of the Digital Twin Framework

The proposed digital twin system consists of three key components: the physical CNC machine, the digital twin, and the cloud-based platform. The physical CNC machine's real-time data (temperature, vibration, tool position) is captured using sensors, and this data is processed through the edge computing layer for real-time simulations and fault prediction.

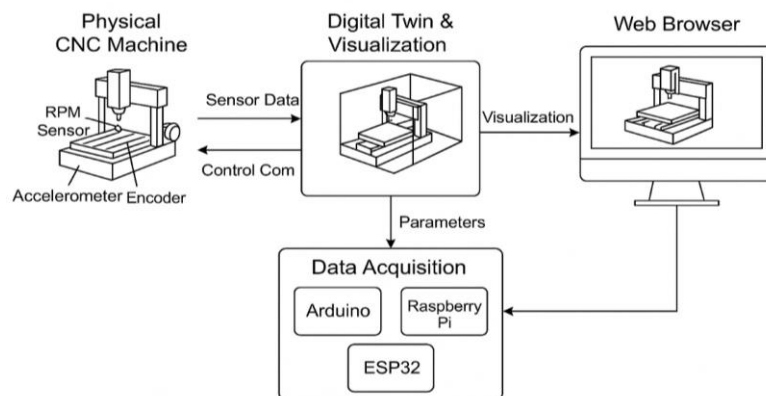


Figure 1: Digital Twin Architecture for CNC Machine

3.2 Hardware Implementation

3.2.1 CNC Machine Setup

A three-axis CNC machine was selected for the implementation of the digital twin system. The machine was equipped with stepper motors and spindle motors for controlling the motion of the cutting tool. Micro-stepping drivers were used for precision control of the axis movements, ensuring accuracy during tool operations.



Figure 2: CNC Machine

3.2.2 Embedded System Components

The core of the embedded system comprises Arduino Uno and Raspberry Pi microcontrollers. The Arduino is responsible for controlling the motor drivers and the spindle motor through the GRBL open-source software. The Raspberry Pi serves as the central hub for data processing, running the CNCJS application, and connecting the system to the network.

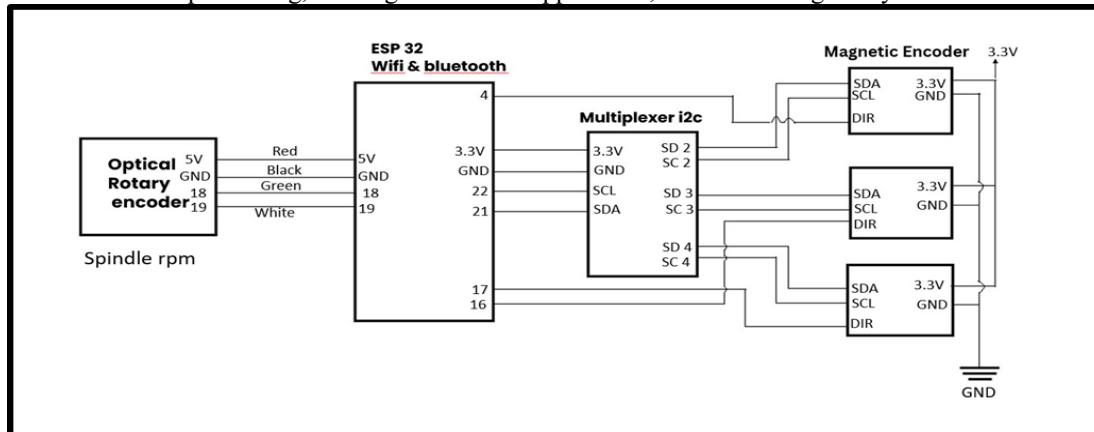


Figure 3: Hardware Architecture of the CNC Machine Prototype

3.3 Software Implementation

3.3.1 CNC Controller Software

The GRBL controller software, running on the Arduino Uno, processes G-code commands to control the CNC machine. CNCJS, running on the Raspberry Pi, provides a web-based interface for remote monitoring and control of the CNC machine.

This URDF code defines a virtual 3D model of a CNC milling machine, named "milling", for digital twin or simulation purposes in a robotic environment. The file structures the machine into various link elements—each representing a physical part (e.g., base, motors, encoders, spindle, drill bit)—and joint elements, which define the relationships and movements between these parts.

The mechanical components include:

- Linear axes: x_axis_base_1, y_axis_base_1, and z_axis_base_1
- Actuators: x_axis_motor_1, y_axis_motor_1, z_axis_motor_1
- Feedback sensors: x_axis_encoder_1, y_axis_encoder_1, z_axis_encoder_1, and spindle_encoder_1
- Spindle and tooling: spindle_1, belt_1, and drill_1

The complete assembly accurately replicates the kinematic behavior of a CNC milling machine, incorporating coordinate-based control and real-time sensing capabilities. This makes it highly suitable for applications such as digital twin visualization, real-time monitoring, and robotic simulation environments. Each component is meticulously positioned using defined origin attributes, and all mesh models are uniformly scaled for realistic representation. A Unified Robot Description Format (URDF) model was developed to digitally emulate the CNC machine within ROS-compatible platforms. Core elements like the base, spindle, and motors are defined as rigid links with associated inertial, visual, and collision properties. To simulate realistic machine behavior, prismatic joints were employed for linear axis motion, while continuous joints replicate rotational motion such as spindle and drill rotation.

3.3.2 IoT and Data Collection

IoT sensors, including accelerometers, temperature sensors, and current sensors, were mounted on the CNC machine. Data from these sensors is streamed to the Raspberry Pi for analysis. The Raspberry Pi processes the sensor data and updates the digital twin in real time. To enable remote access, the Raspberry Pi is configured to communicate over a secured ngrok tunnel, allowing users to monitor and control the machine from any location.

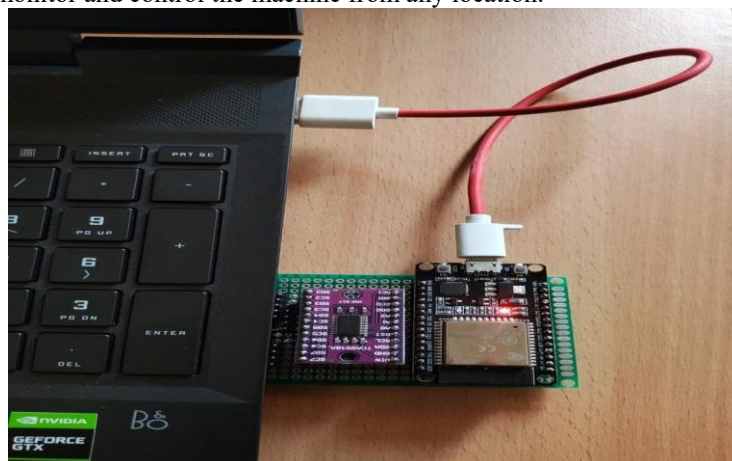


Figure 4: Sensor Integration and Data Flow

4 Real-Time Simulation and Visualization

4.1 Digital Twin Visualization

The digital twin of the three-axis CNC milling machine was created using Fusion 360 for 3D modeling and integrated with Three.js for real-time, web-based visualization. The CAD model accurately represents key machine components such as the base, spindle, motors, and tool head. This model is embedded in an interactive interface where real-time updates are reflected using data captured from the physical machine, including spindle speed, tool position, and axis displacements. Live data is streamed via an IoT interface using WebSocket communication, enabling seamless synchronization between the physical machine and its virtual counterpart. The visualization includes animated axis movements and color-coded indicators to enhance interpretability. This lightweight and scalable visualization system supports remote monitoring, operator training, and diagnostics, offering a cost-effective digital twin solution aligned with Industry 4.0 objectives.

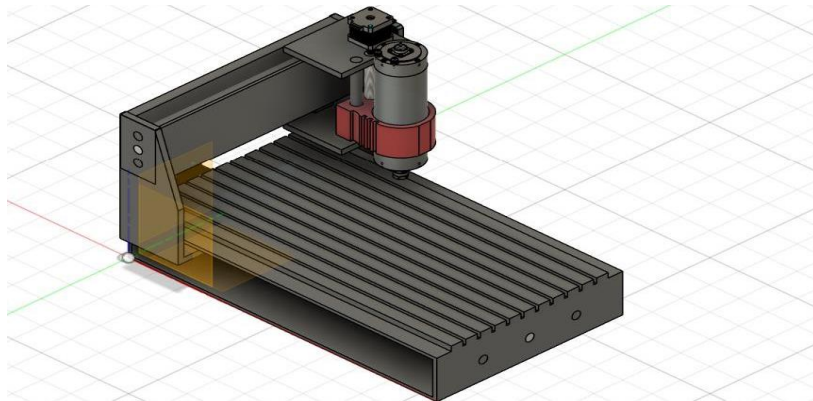


Figure 5: 3d view of three axes machine developed in fusion

4.2 Web-Based Monitoring

The developed digital twin platform is equipped with a cloud-based interface that enables seamless remote monitoring of CNC machine operations. Using secure tunneling and lightweight data protocols, live operational data—such as spindle speed, axis positions, encoder values, and system health metrics—is transmitted to the cloud from the physical machine. This data is then visualized through a browser-based dashboard, allowing users to monitor the machine in real time from any location without the need for direct physical access or specialized software.

In addition to passive monitoring, the interface supports interactive visualization of the machine's current state through the digital twin. Users can observe real-time movement of axes and the tool position, providing a virtual mirror of ongoing operations. The platform is designed to be platform-independent and device-agnostic, making it accessible via desktops, tablets, or smartphones. This web-enabled capability not only enhances operational visibility and decision-making but also supports collaborative troubleshooting, maintenance planning, and educational demonstrations, aligning with the decentralized and connected vision of Industry 4.0.

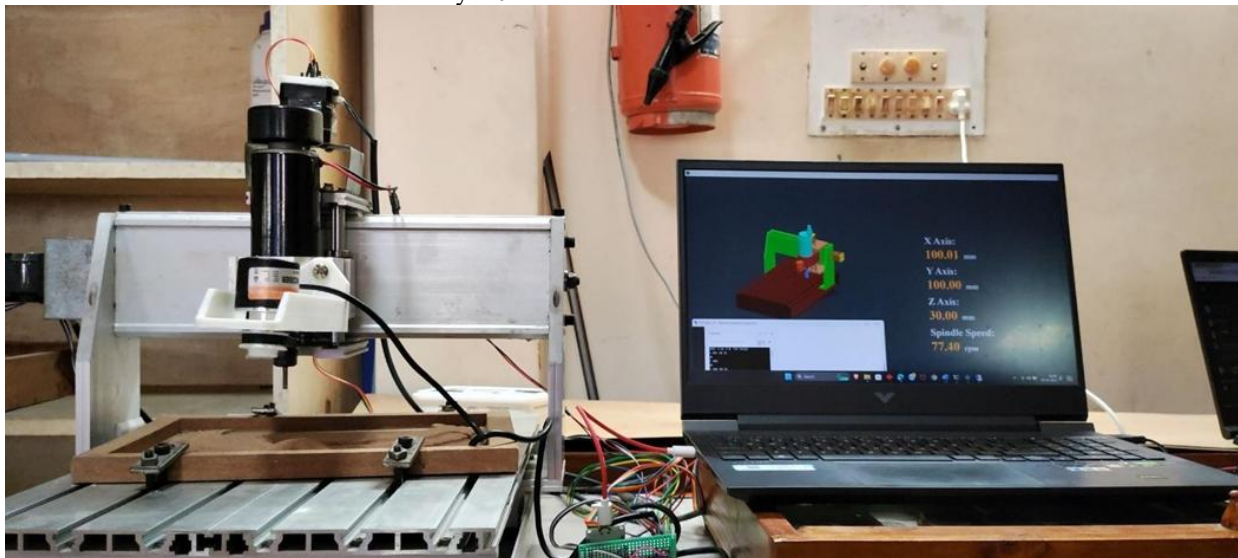


Figure 6: Digital Twin Visualization Interface

5 Experimental Results

5.1 Calibration and Testing

The CNC machine was calibrated for axis movements and spindle speeds. Initial tests were conducted to verify the accuracy of the tool positioning system and spindle motor performance. Calibration results are shown in Figure 6.

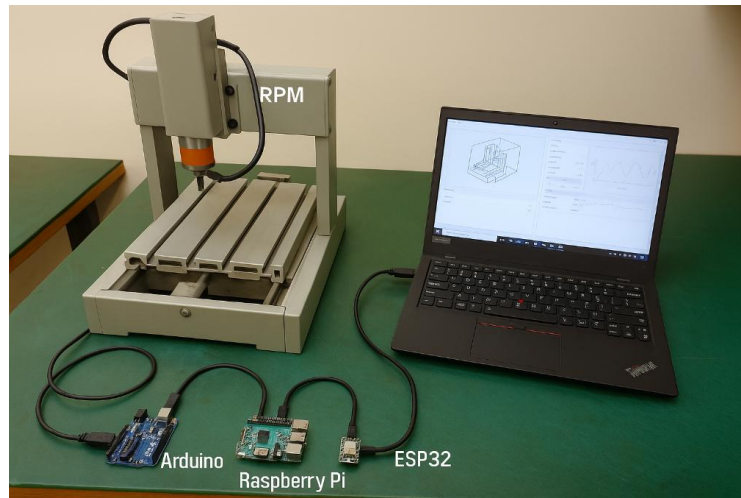


Figure 7: Calibration of Axis Movements and Spindle Speeds

6 Discussion

6.1 Advantages of Digital Twin Implementation

The implementation of the digital twin framework led to a marked improvement in machine uptime, reducing unplanned maintenance and increasing the overall efficiency of the CNC system. By continuously monitoring sensor data, the digital twin could detect potential faults early, allowing for timely interventions.

6.2 Challenges and Limitations

Some challenges encountered during the development include data latency due to network congestion and the need for high computational resources for real-time data processing. Additionally, the open-source hardware used, such as Raspberry Pi and Arduino, may not provide the robustness required for industrial-scale applications.

Future Work

Future developments could include expanding the system to accommodate more complex multi-axis CNC machines, integrating deep learning models for more accurate failure predictions, and exploring the use of blockchain for secure data transactions in the digital twin system. There is also potential for integrating augmented reality (AR) to enhance user interaction with the digital twin during the machining process.

7 Conclusion

This paper has presented a comprehensive digital twin framework for a three-axis CNC machine. By integrating IoT and cloud-based visualization, the proposed system enhances predictive maintenance and real-time simulation, resulting in significant improvements in machine performance. Future work will focus on expanding the capabilities of the digital twin system to accommodate more complex operations and further reducing system latency.

References

- [1] V. S. Vishnu, K. G. Varghese, and B. Gurumoorthy, "A Data-driven Digital Twin of CNC Machining Processes for Predicting Surface Roughness," *Procedia CIRP*, vol. 104, pp. 1065–1070, 2021, doi: <https://doi.org/10.1016/j.procir.2021.11.179>.
- [2] A. Anbalagan, B. Shivakrishna, and K. S. Srikanth, "A digital twin study for immediate design / redesign of impellers and blades: Part 1: CAD modelling and tool path simulation," *Materials Today: Proceedings*, vol. 46, pp. 8209–8217, 2021, doi: <https://doi.org/10.1016/j.matpr.2021.03.209>.
- [3] M. Dharmawardhana, A. Ratnaweera, and G. Oancea, "STEP-NC Compliant Intelligent CNC Milling Machine with an Open Architecture Controller," *Applied Sciences*, vol. 11, p. 6223, Jul. 2021, doi: [10.3390/app11136223](https://doi.org/10.3390/app11136223).
- [4] Q. Qiao, J. Wang, L. Ye, and R. X. Gao, "Digital Twin for Machining Tool Condition Prediction," *Procedia CIRP*, vol. 81, pp. 1388–1393, 2019, doi: <https://doi.org/10.1016/j.procir.2019.04.049>.
- [5] J. Wang, L. Ye, R. Gao, C. Li, and L. Zhang, "Digital Twin for rotating machinery fault diagnosis in smart manufacturing," *International Journal of Production Research*, vol. 57, pp. 3920–3934, Jul. 2019, doi: [10.1080/00207543.2018.1552032](https://doi.org/10.1080/00207543.2018.1552032).
- [6] J. Liu *et al.*, "A digital twin-driven approach towards traceability and dynamic control for processing quality," *Advanced Engineering Informatics*, vol. 50, p. 101395, Oct. 2021, doi: [10.1016/j.aei.2021.101395](https://doi.org/10.1016/j.aei.2021.101395).
- [7] X. Li, L. Wang, C. Zhu, and Z. Liu, "Framework for manufacturing-tasks semantic modelling and manufacturing-resource recommendation for digital twin shop-floor," *Journal of Manufacturing Systems*, vol. 58, pp. 281–292, Jan. 2021, doi: [10.1016/j.jmsy.2020.08.003](https://doi.org/10.1016/j.jmsy.2020.08.003).
- [8] M. Soori, B. Arezoo, and R. Dastres, "Digital twin for smart manufacturing, A review," *Sustainable Manufacturing and Service Economics*, vol. 2, p. 100017, Apr. 2023, doi: [10.1016/j.smse.2023.100017](https://doi.org/10.1016/j.smse.2023.100017).
- [9] L. F. C. S. Durão, E. Zancul, and K. Schützer, "Digital Twin data architecture for Product-Service Systems," *Procedia CIRP*, vol. 121, pp. 79–84, 2024, doi: [10.1016/j.procir.2023.09.232](https://doi.org/10.1016/j.procir.2023.09.232).
- [10] S. Ma, W. Ding, Y. Liu, S. Ren, and H. Yang, "Digital twin and big data-driven sustainable smart manufacturing based on information management systems for energy-intensive industries," *Applied Energy*, vol. 326, p. 119986, Nov. 2022, doi: [10.1016/j.apenergy.2022.119986](https://doi.org/10.1016/j.apenergy.2022.119986).
- [11] A. Papacharalampopoulos, K. Sabatakakis, and P. Stavropoulos, "Incorporating process physics phenomena in formation of digital twins: laser welding case," *Procedia CIRP*, vol. 99, pp. 490–495, 2021, doi: [10.1016/j.procir.2021.03.069](https://doi.org/10.1016/j.procir.2021.03.069).