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MANUFACTURING EMPOWERED BY DIGITAL TECHNOLOGIES AND TWINS

Smart manufacturing platform based on input-output empirical relationships for process monitoring

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Abstract
Intelligent monitoring and maintenance protocols are undoubtedly crucial for improving manufacturing processes. Accordingly, machine learning techniques and predictive control models have been customized and optimized to account for the specific characteristics of the processes under investigation. In this context, the management of manufacturing processes in a "smart way" requires the development of specific models based on input-output empirical data. The aim of the proposed research was to develop an easily customizable application integrated into a milling process executed at the laboratory level. The application was designed to identify and record the operator, the order and the specific work sequences. It also supports the operator in setting processing parameters according to the type of work sequence to be performed. The application analyses specific process outputs, such as the wear growth on the inserts of the cutter in relation to the main input process parameters: depth of cut, feed rate, and spindle speed. This analysis is implemented by leveraging empirical evidence.

Keywords Smart manufacturing · Digital twin · Machining · Milling · Wear

Introduction

The increased focus on data and the opportunities created by digitization have highlighted the potential of digital twins (DTs) in the manufacturing industry [1]. DTs simulate real-time working conditions, facilitating intelligent decision-making [2]. This approach is particularly relevant in process monitoring within smart factories, where dynamic and responsive production environments are critical [3]. This concept aligns with Industry 4.0's aim to meet the requirements of a Smart Factory [4].

Recently, Chen and Huang [5] examined the use of DT technologies across different sectors, focusing on remanufacturing processes within the construction industry. They found that process monitoring via DTs helps manage construction waste and supports sustainability by enabling efficient circular economy practices. Additionally, Mostafa et al. [6] presented a novel architecture for DT systems based on a structured multi-layer model, incorporating critical components for process monitoring. This practical model was implemented in production and mining environments, demonstrating the feasibility and applicability of DTs in real-world settings.

Given the widespread digitization in industrial sectors, the development of DTs is promising for various manufacturing categories [7]. For example, Castelló-Pedrero et al. [8] suggested integrating DTs with additive manufacturing technologies using an innovative multi-scale approach. Ren et al. [9] proposed a DT model for the roll forming field to control forming quality and enable advanced data analysis in the forming process. Uribe et al. [10] developed a surrogate model for predictive control in single-blow upsetting using Proper Orthogonal Decomposition to facilitate model construction and reduce dimensionality. Zi et al. [11] introduced a DT-driven ensemble learning milling tool for online wear monitoring. Furthermore, DTs have been proposed to investigate the properties of specific materials, such as

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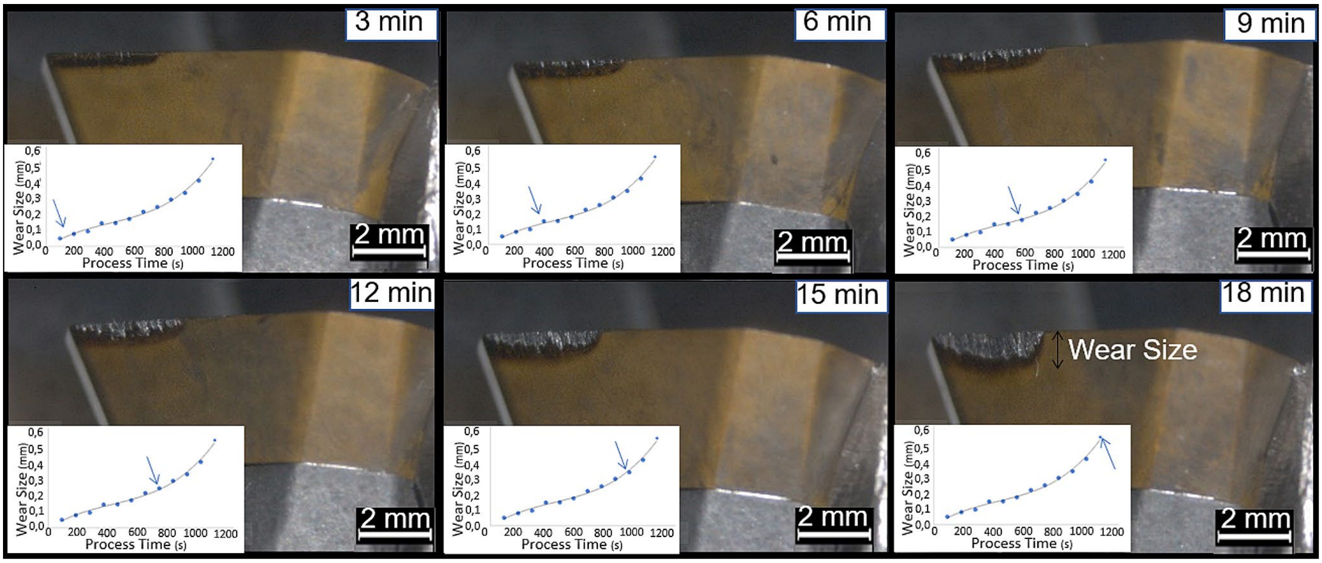

Fig. 1 The wear evolution at passing of the process time

composite materials, relating these properties to the production parameters [12].

Collectively, these studies illustrate the diverse applications of DT technology in process monitoring, from smart manufacturing to construction and material characterization. DTs can also be integrated into process optimization strategies, ensuring enhanced sustainability and efficient resource management [13].

In the proposed research, a customized platform was developed to oversee a milling process within a smart manufacturing framework. This platform incorporates input-output empirical relationships and communicates with the employed machine to improve maintenance, product quality, and machining efficiency through preventive analyses. The goal is to provide a tool that supports the operator during the manufacturing process, including the selection of operating sequences and optimal working ranges for each process variable. The platform records production steps and anomalies, and monitors inserts' wear to predict severe conditions.

The experimental campaign for the construction of the input-output process relationship

A milling sequence was planned to study the process under specific working conditions by monitoring the growth of inserts' wear over time. The experimental tests were conducted in a laboratory setting using a Mazak Nexus Model 410 A CNC Vertical Machining Center and a CoroMill 245 face milling cutter. Different experimental campaigns were performed, with the main process variables fixed for each campaign and new cutters used at the start of each configuration. The depth of cut (DoC), feed rate (FR), and spindle speed (SS) were the input parameters set up. Given the cutter diameter (CD), it is also straightforward to calculate the cutting velocity (CV), a parameter commonly used by technicians:

Table 1 The investigated ranges of the investigated milling variables

Campaign number	DoC (mm)	FR (mm/min)	SS (rev/min)
1	3	1600	1400
2	3	800	1400
3	3	800	700
4	4.5	800	1400

$$CV = \frac{\pi SSCD}{1000}\left[\frac{m}{min}\right] \quad (1)$$

A single full immersion movement of the milling cutter was tested. Specifically, at predefined process intervals, the milling was stopped and the cutter was removed from the spindle of the machining center. Micrographs of the insert shapes were then captured using a Leica DM400M metallographic optical microscope. This allowed for the detection of inserts' wear (Fig. 1).

Each experiment concluded when clear catastrophic wear was observed. This was the monitored criterion, used as an indicator for determining when to replace the inserts. Four different process configurations were tested to analyse the influence of the investigated process variables. The tests, conducted within the range of the manufacturer's recommendations, are summarized in Table 1.

By doing so, a preliminary input-output relationship was obtained for implementation in the proposed platform to construct a smart manufacturing approach, reaching a TRL of 6 according to the EU definition [14]. To enhance the platform's performance at an industrial level, these variable relationships must be strengthened using data derived from real production, thereby improving the consistency of the empirical model for predicting inserts' wear under varying process conditions.

The proposed methodology

In the proposed research, a customized application was developed to achieve an integrated smart manufacturing solution, incorporating the previously discussed input-output relationship. This application can be considered as one of the tools within a comprehensive smart manufacturing software suite, usable in a multi-process manufacturing plant. The prototype was designed as an integrated solution that can be easily customized to account for a company's specific needs. The access point to the user interface is shown in Fig. 2.

The application begins with a landing page that outlines all the processes executed in a typical manufacturing company. This page serves as the "level 0" of the proposed architecture. In Fig. 2, the displayed screen illustrates, as an example, two manufacturing routes. Upon selecting the milling process, the subsequent "Level 1" interface appears, presenting details specific to the milling process (Fig. 3). Here, the first required information identifies the operator performing the test, the order, and the specific work-in-process (WIP) sequence. This structure is designed to enable centralized supervision within the company, allowing the operator to identify the order by accessing information from the engineering sector.

By doing so, the order to be processed is registered, and the application's "Level 2" interface appears, as shown in Fig. 4. At this level, all processing variables to be set are displayed, with recommended ranges for each variable based on the cutter manufacturer's specifications. For the milling process under analysis, information on the type and size of the cutter for the specific operation is provided, along with the recommended ranges for DoC, FR and SS, considering the loaded part program. Additionally, there is a column where the operator can input the desired values. Finally, the application is connected via intranet to the milling machine, reporting the actual values of the monitored variables.

Filling-in the Cutter Diameter, the Cutting Velocity in m/min is automatically calculated according to Eq. (1).

Based on the recorded data, the wear growth forecast is represented in real-time by a graph. This wear prediction is derived from the empirical law established through the experimental tests described in Sect. 2. Wear growth is evaluated only when the input values of the monitored process variables match those specified in the part program for material removal. The prediction model can be customized for each cutter-material pair, updated and enriched with data

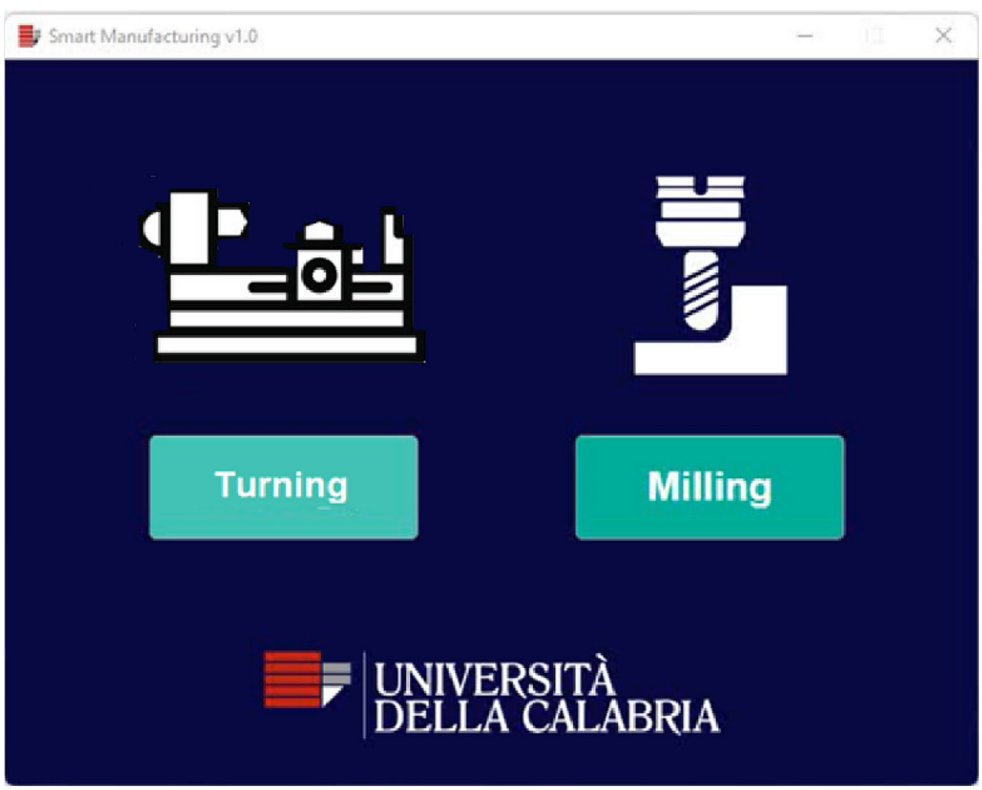

Fig. 2 The access window of the integrated smart manufacturing solution (Level 0)

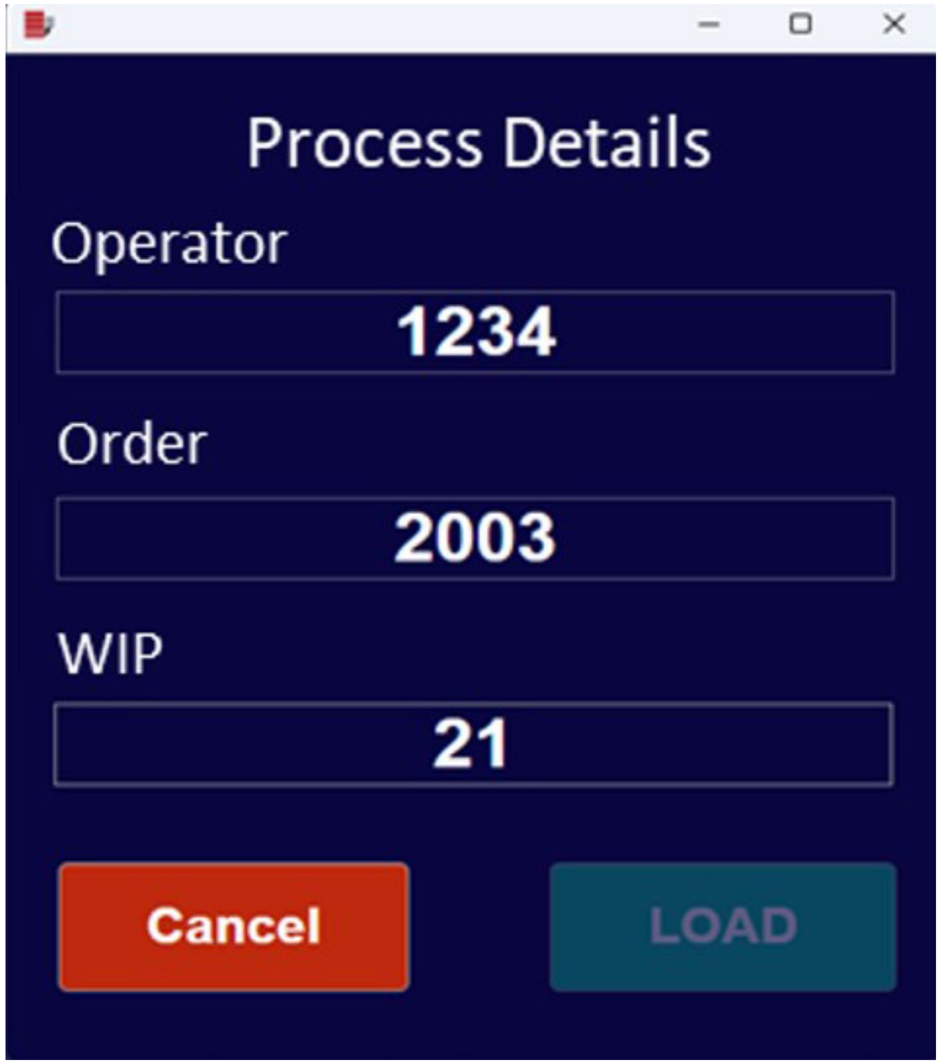

Fig. 3 System identification on the integrated smart manufacturing solution (Level 1)

Fig. 4 Digital twin interface for milling process (Level 2)

collected during industrial production. This helps prevent unexpected machine downtime.

At the same level, general working information is displayed in a text log window, which automatically compiles a report. This report can be manually enhanced by the operator, who, using their expertise, can detect "chatter" phenomena or other process anomalies through sound or vibration variations. This procedure can be further improved by integrating a "chatter" detection system to identify irregular process conditions. Once the manufacturing phase is complete, the operator finalizes the information and exports the file, which can then be saved in the company database.

Discussions on the platform strengths

The advantages of implementing the proposed Digital Twin (DT) platform in an industrial setting, specifically in a generic manufacturing factory focused on machining processes, can be summarized as follows:

1. **Enhanced Collaboration**: the DT facilitates seamless communication and collaboration among design engineers, manufacturing engineers and machine operators by providing a direct interface and integration platform.
2. **Process Optimization**: the digital manufacturing environment, as a "virtual replication" of real-world processes, offers insights into optimal process parameters, thereby improving efficiency and production quality.
3. **Improved Process Control**: enhanced control over the machining process and workforce activities ensures better traceability of operator actions and adherence to company protocols.
4. **Validation of Decisions**: real-time data monitoring allows operators to validate their decisions against optimal process values, ensuring consistent and reliable outcomes.
5. **Streamlined Data Management**: simplified data flow and integrated knowledge management facilitate efficient decision-making and resource allocation.
6. **Enhanced Production Efficiency**: comprehensive monitoring of process parameters and defect tracing minimizes waste and optimizes resource utilization, thereby increasing production effectiveness.
7. **Cost Reduction and Maximization of Production**: the platform enables more effective cutter changes and optimal resource use, leading to reduced costs and maximized production.
8. **Performance Analysis**: detailed log files enable in-depth analysis of both personnel performance and product quality, supporting continuous efforts to improve products and processes.

Summarising, the above advantages highlight the multifaceted benefits of leveraging DT technology for a typical milling process, resulting in improved collaboration and decision-making among workers, as well as enhanced process efficiencies and cost savings.

Conclusion

Amidst the complexities of Industry 4.0 and the advent of smart manufacturing, digital twins emerge as a disruptive technology, empowering organizations to adapt, innovate and excel in an increasingly competitive landscape. From expediting time-to-market for new products to fostering sustainable practices and facilitating agile decision-making, the transformative power of digital twins in manufacturing is boundless. As we venture further into this technological frontier, the path toward digital transformation promises to reshape the essence of modern industry, ushering in a new era characterized by efficiency, resilience and value creation.

The platform proposed in this work exemplifies how smart manufacturing strategies can enhance industrial efficiency by streamlining information flow for data management and boosting product competitiveness in production, without increasing costs.

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Declarations

Conflict of interest The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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