Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

Digital upgrade of a bandsaw machine through an innovative guidance system based on the digital shadow concept

Federico Scalzo[1,a *], Davide Bortoluzzi[1,b], Giovanni Totis[1,c], Marco Sortino[1,d]

[1]Polytechnic Department of Engineering and Architecture, University of Udine, Via Delle Scienze 206, 33100 Udine, Italy

[a]federico.scalzo@uniud.it, [b]davide.bortoluzzi@uniud.it, [c]giovanni.totis@uniud.it, [d]marco.sortino@uniud.it

Keywords: Man-Machine System, Digital Shadow, Sensors

Abstract. Nowadays, there is an increasing trend towards advanced CNC machine tools having a high level of automation. Nevertheless, manually operated equipment is still playing an important role in many industrial workshops. Operators' experience is still essential in the perspective of increasing productivity, enhancing product quality, reducing manufacturing costs related to tool wear, waste and maintenance. Thus, even manual operations that are apparently less important in terms of product added value may deserve attention and need to be improved according to the principles of the digital transformation era. This paper introduces a structured approach for design, development and implementation of an operator guidance system for a manual bandsaw machine, based on the digital shadow concept and additional feedback sensors. This provides an actual example of how the digital transformation of a small-scale equipment may improve the manufacturing performance and ergonomics as well.

Introduction

Advances in saw technology and blade materials have significantly improved the effectiveness, versatility, and cost-efficiency of sawing. In the past, sawing was regarded as a secondary step in the machining process and saws were mainly utilized for cutting bar stock in preparation for further machining operations. However, thanks to the recent technological advancements, bandsaws are now being used as the primary tool for shaping many metal components. The benefits of using band sawing include minimal material loss (low kerf loss) and process efficiency [1].

Observing modern manufacturing shopfloors, the growing trend towards highly automated advanced CNC machine tools is obvious. Nevertheless, manually operated equipment still holds significant importance in many industrial settings. In such cases, the expertise of operators is still crucial for increasing productivity, improving product quality, and reducing costs associated with tool wear, waste, and maintenance. The application of the principles of the digital transformation era can therefore give a significant contribution, providing support to technical operators, improving the performance of the production process.

The fusion of Cyber-Physical Systems (CPS) and the Internet of Things favored the evolution of smart manufacturing in the context of Industry 4.0. Nowadays at the core of CPS is Digital Twin (DT) technology, which is capable of accurately sensing and reflecting the behavior and real-time state of the production system, thereby enabling the analysis, simulation, prediction, and optimization of processes [2]. In particular, the ability to perform data-driven simulations executed on real-time gathered data, thanks to the availability of adequate hardware and software tools, should be highlighted. Numerous studies have tackled the challenge of providing a comprehensive categorical overview of the existing literature on Digital Twin, as demonstrated by the works of Kritzinger et al. [3] and,Jones et al. [4]. The plethora of review works underscores the growing interest of the research community in this subject matter. Nevertheless, most of the literature

Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

focuses mainly on theoretical foundation and conceptual aspects pertaining to DT, while concrete implementation and case studies are still at an early stage. One of the first examples of manufacturing digital twin applied at the shop-floor level was proposed by SIEMENS in 2015 [5]. A Cyber-Physical Production System (CPPS) comprised of four Cyber-Physical Production units was under investigation: a Robotic Cell for handling loading and unloading operations, a Drilling Machine, a Milling Machine, and a Transport System, all were managed by a Manufacturing Execution System (MES). However, the model proposed was merely an illustrative example, and only preliminary work was conducted to implement it. Further implementations of DT can be observed in the aerospace [6], additive manufacturing [7], injection molding [8] and end-of-life [9]. DT was also applied to machining process design. A new method for process optimization driven by a DT for fast reconfiguration of automated manufacturing systems was proposed by Liu et al. [10]. A novel model-based methodology for tactical and strategical decisions in manufacturing systems, applied to a real case study of o a manufacturing company producing axles for the railway sector was proposed in [11]. Digital twins for operation and maintenance are especially beneficial for managing complex equipment such as aircraft, ships, and wind turbines that are susceptible to performance degradation from environmental factors. Some applications of DT in operation and maintenance were developed for prognostic and health management of wind turbines [12], damage accumulation and remaining useful life [13]. DT applications were developed also in the manufacturing sector. An active fixture prototype was developed to detect and mitigate the level of chatter vibrations in general rough-milling operations [14]. A survey of the state of the art and of relevant standards of Digital Twins in Industrial IoT can be found in [15]. Chatter vibrations arising during machining operations are particularly detrimental when appropriate strategies cannot be applied [16], leading to high production cost and extended pre-production runs. In order to optimize the thin-walled part manufacturing process, a Digital Twin-driven framework for thin-walled part manufacturing was proposed in [17]. DT of dynamic mechanical systems could be used for experimental setup design and optimization purposes, since as demonstrated in [18] the influence of external disturbances has to be taken into account to enhance dynamic characterization accuracy.

Since this study involves a one-way flow of data from the physical counterpart to the digital object, the attention is focused on the Digital Shadow characteristics. On the basis of the level of data integration between the physical and digital counterpart, a comprehensive classification of Digital Model (DM), Digital Shadow (DS) and Digital Twin is drawn by Kritzinger et al. [3]. In a manufacturing environment a Digital Shadow requires data harvesting from each machine, product or component. The data flow includes operation and condition data, process data, and other information. The Digital Shadow is continuously linked to the manufacturing system and generates a database. Hence, a real-time, accurate representation of the production system is available for optimization purposes. Data collected can be analyzed, labeled and linked to their appropriate context. The Digital Shadow is a prerequisite for application of methods and models of data analysis and evaluation in a manufacturing environment, and it serves as the foundation for additional applications that utilize the aggregated data for smart manufacturing applications.

As previously mentioned, the literature review has demonstrated that the majority of research papers on digital twin and digital shadow is theoretical, with only a few examining applications or actual case studies. To address this gap, this study introduces a structured approach for design, development, and implementation of an operator guidance system (OGS) for a manual band saw machine. The initial section examines the selection and installation of sensors required for generating the digital shadow, followed by the analysis of the infrastructure created for collecting, analyzing, and visualizing the gathered data. Finally, results of cutting tests performed with and without the operator guidance system are presented, demonstrating that the OGS allows for a quick evaluation and control of the actual process efficiency.

Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

This case study provides an actual example of how the digital transformation of a small-scale equipment may be beneficial for ergonomics and manufacturing performance improvement.

Machining efficiency evaluation in band sawing

The cutting process efficiency can be evaluated considering several factors such as tool wear, cutting forces, material removal rate (MRR), chip ratio, chip characteristics and temperature. Surface finish, sound and vibrations can also indicate the efficiency of machining. Nevertheless, none of these indicators are suitable for a quantitative measurement of the machining efficiency when different combinations of machining process, tool and workpiece are under investigation. A more effective way of quantitatively measuring the workpiece machinability is the specific cutting energy u_c [1]. Assuming that the material properties of the blank to be cut are almost constant, the initial machining performance corresponds to the cutting behavior of a brand-new blade, then u_c tends to increase with tooth wear. The wear rate can be determined by the slope of the u_c curve plotted against the blade's life, expressed in terms of the number of workpieces cut. The specific cutting energy is the energy required to remove a specific volume of material. Therefore, it can be calculated as the ratio between the cutting power P_c to the material removal rate MRR, as follows:

$$u_c = P_c/MRR \quad [\mathrm{J/mm^3}] \tag{1}$$

Another useful parameter to characterize the cutting process is the average, uncut chip thickness h. This parameter is the average chip thickness perceived by each cutting edge when it is engaged with the workpiece. Specifically, for a band saw the average, uncut chip thickness can be calculated as follows:

$$h = \frac{v_f p}{1000\, v_c}\ [\mathrm{mm/tooth}] \tag{2}$$

where v_f [mm/min] is the instantaneous feed speed perpendicular to the band saw, v_c [m/min] is the cutting speed parallel to the bandsaw and p is the average pitch between subsequent teeth (which are generally not equally spaced along the bandsaw). It has to be highlighted that this parameter depends on the instantaneous feed speed, which does further depend on the feed control strategy. Ideally, the chip thickness should be almost constant – within a given range recommended by the bandsaw manufacturer – to reduce the risk of a rapid tool wear or cutting edge chipping. In the current case (manual band saw), in order to keep the uncut chip thickness constant, the force applied by the operator should be adapted throughout the cutting process.

Materials and experimental setup

The machine on which the operator guidance system based on the digital shadow concept was implemented is a BIANCO 370 M horizontal pivot style manual bandsaw installed at the Laboratory for Advanced Mechatronics (LAMA FVG) of the University of Udine. The machine is powered by a SIEMENS three-phase electric motor. The use of star and delta connections enables the selection of two distinct rotational speeds. The machine is equipped with a bimetal band saw blade with variable raker tooth setting (6/10 teeth/in, alternating right-left-straight teeth). The blade's edge is made of HSS AISI M42 alloy (8% Co) while the body is made of spring steel, ensuring an optimal balance between flexibility and resistance to fatigue, tensile and torsional stresses. The material selected to perform the cutting tests is a 40 mm diameter Al 7075 aluminum alloy rod.

The BIANCO 370 M band saw is not equipped with sensors for process monitoring. In order to analyze the cutting process, some low-cost sensors were chosen and installed. The design choice to limit the cost of the sensors is appropriate to the type of machine being studied. The quantities monitored are the force exerted by the operator who manually controls the feed, the power absorbed by the three-phase electric motor, the cutting speed and the blade angle.

Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

The force exerted by the operator is calculated starting from the data acquired from two active HBM 120LY41 120 Ω strain gage elements glued to the actuating lever, positioned where the maximum deflection is expected. The first one mounted in the direction of axial strain on the top side of the lever and the other mounted in the direction of axial strain on the bottom side (bending configuration). The half bridge is connected to a National Instruments (NI) Data Acquisition System (DAQ) NI-9986 bridge adapter, connected in turn with a NI-9218 that allows the analog signal acquisition. Calibration was performed using known masses fixed at the end of the actuation lever. Through this procedure it was possible to correlate the sensors' output in volts with the force applied to the operating lever. Hence, the calibration coefficients were obtained by linear regression.

The power absorbed by the electric motor is measured with a Montronix PS200-DGM power sensor. The amount of current in each phase conductor is measured by means of three Hall effect sensors. Via current and voltage, the PS200-DGM determines the effective power and creates a corresponding analog voltage output signal. Future developments will include replacement with an economy class industrial power sensor.

The cutting speed is calculated starting from the data acquired from an OMRON E2E-S05S12-WC-B1 proximity sensor that picks up the transit of the spokes of the rotating driven pulley. A tailor-made 3D printed pulley inspection cover was designed in order to facilitate the proximity sensor installation. The passage of a spoke triggers the sensor that outputs a "high" logic state. Knowing the geometry of the driven pulley and the number of "high" pulses from the proximity sensor in a certain period of time, it is possible to calculate the rotation speed and therefore the cutting speed.

The blade angle is calculated using a 10 kΩ VISHAY potentiometer mounted close to the rotation axis of the cutting head. To increase the resolution of the potentiometer, the coupling with the axis of rotation was achieved by means of a pair of straight-toothed gear wheels with a 5:1 gear ratio. As the blade angle changes, the potentiometer acts as a voltage divider, outputting a variable voltage proportional to the angle of rotation. Similarly to the case of the strain gage, the calibration was performed through linear regression using the data acquired from the potentiometer and comparing them with those obtained through direct measurements of the pivot angle.

The potentiometer and the proximity sensors are powered by a TRACO POWER TPP 15-109-J 9V stabilized power supply, while the power sensor is powered by a KERT 24V stabilized power supply. The NI-9218 provides the 2V excitation voltage to the half bridge strain gage. The analog voltage outputs of power sensor, proximity sensor and potentiometer are acquired by means of a NI-9215 four channel voltage input module. Fig. 1A shows the upgraded band saw, evidencing the sensors installed to acquire the cutting process data.

The digital signals are acquired, displayed, recorded, and analyzed using a tailor-made system created using MATLAB and NI LabVIEW. In order to determine the volume of chips removed during a specific time frame, two essential data have to be known: the starting blank's geometry and the blade angle.

A MATLAB-based application was developed to calculate the volume of chip removed during the cutting process. This application necessitates the loading of the STL 3D model of the workpiece to be cut. Hence, the blank needs to be positioned in the virtual space using the appropriate keys to perform translations and rotations, see Fig. 2A. The software allows to clearly view the blank and its position relative to the band saw with a three-dimensional, side and frontal views. The virtual cutting plane is indicated by the blue transparent plane with a red outline. Selecting from the top menu the "Slice & Cut" tab it is possible to perform the virtual cutting operation and calculate some process parameters, according to the angular position of the blade (e.g. number of engaged teeth, contact length and cut area), see Fig. 2B.

Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

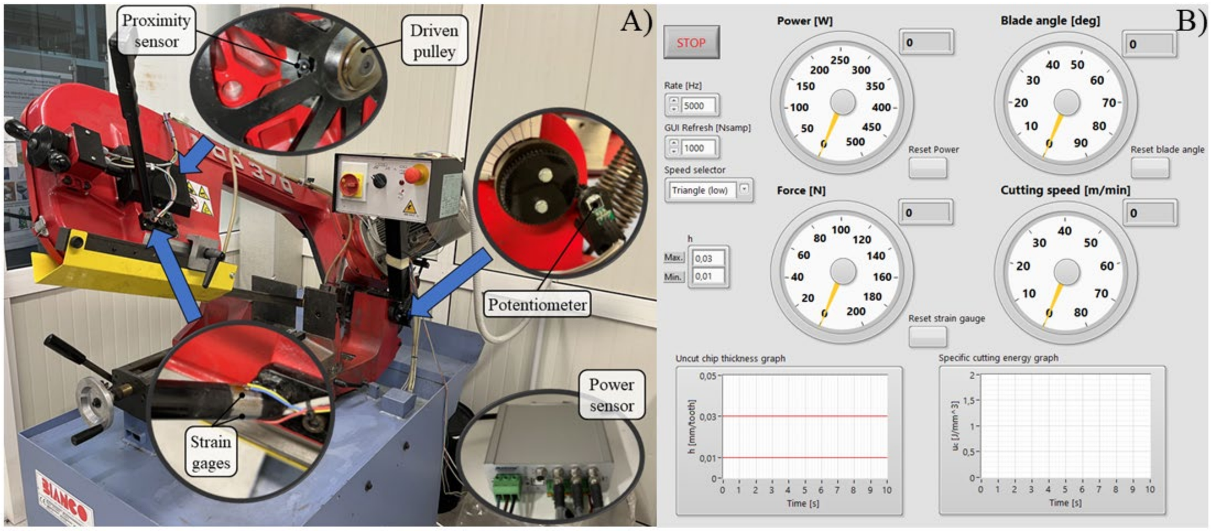

Figure 1 Upgraded band saw and dashboard for data acquisition and visualization (OGS).

The blue outline indicates the edge of the areas involved in the cutting process, while the red circles represent the engaged teeth. The volume of the removed material is easily calculated multiplying the cut area (expressed as a function of the blade angle) by the mean blade thickness. The data table generated by the virtual cutting process is then stored in a spreadsheet, which is subsequently imported into the LabVIEW application to allow real-time u_c and h calculations. The data visualization and control dashboard of the operator guidance system is shown in Fig. 1B. Fig. 3A shows a diagram that summarizes the tasks performed by the MATLAB app. On the left side, the dark blue boxes highlight the virtual 3D environment initialization and the blank's STL file import and positioning. The light blue boxes in the center show the cutting process slicing and simulation stages. These phases allow working teeth number, contact length and cut area estimation. On the right side a spreadsheet containing the calculated parameters is generated (green box), ready for import into NI LabView (yellow box). Similarly, Fig. 3B shows a diagram that summarizes the tasks performed by the LabVIEW VI. The dark blue boxes on the left side highlight the preliminary operations to be performed prior to the main loop start. Local variables are initialized and analog input channels, sample clock and shift registers are configured. Hence, the cutting process data calculated by the MATLAB app are imported by means of the aforementioned spreadsheet. The main loop starts (light blue boxes), analog input data acquisition, filtering and elaboration is performed allowing real-time cutting process data calculation and visualization. Therefore, acquired data are stored in a LabVIEW measurement file (green boxes).

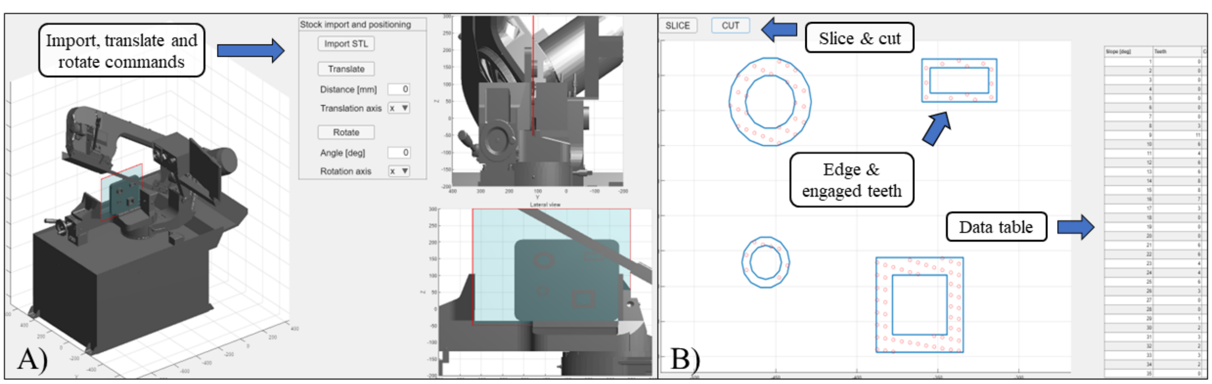

Figure 2 MATLAB application for virtual cut data calculation.

Materials Research Proceedings 35 (2023) 286-294 https://doi.org/10.21741/9781644902714-34

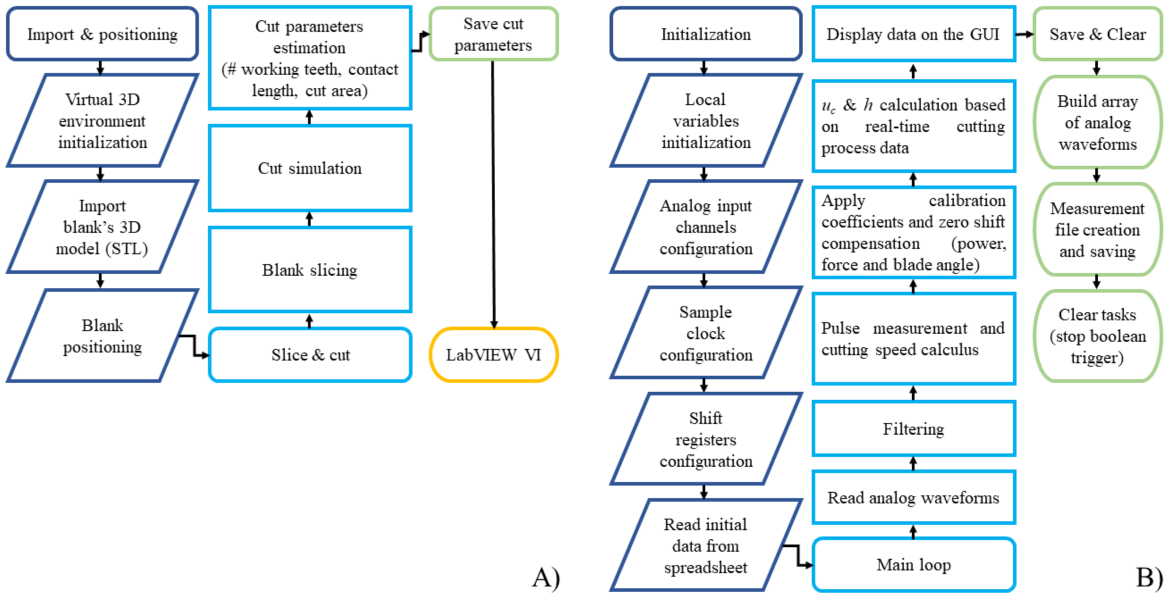

Figure 3 MATLAB app and LabVIEW VI operation diagrams.

Results and discussion

The conceived operator guidance system provides the operator with the cutting process data required for a quick evaluation and control of the actual process efficiency, see OGS of Fig. 1B. The program allows to set the sampling frequency, the refresh rate of the GUI, the cutting speed and the uncut chip thickness max.\min. values. Furthermore, the absorbed power, the blade angle, the force applied by the operator and the actual cutting speed are shown for in-process evaluation. The power is calculated taking into account the existence of a contribution due to friction and machine efficiency (no-load operation). The reset keys next to the power, blade angle and force gauges allow the sensors zeroing to eliminate any offsets due to electrical noise or changes in environmental conditions. Finally, two graphs allow the in-process evaluation of cutting process efficiency by means of u_c and h. To evaluate the effectiveness of the OGS, cutting tests were performed on a 40 mm Al 7075 rod. The tests were repeated 3 times, carrying out the measurements with and without OGS, for a total of 6 data sets. Comparing the results obtained with and without OGS, see Fig. 5 and Fig. 6, it can be observed that the developed system allows to keep the specific cutting energy almost constant, at the same time the uncut chip thickness is kept within the optimal range, avoiding rubbing phenomena and excessive tooth load. This helps extend the tool life and improve the cutting process efficiency. These results are confirmed observing the u_c standard deviation (Fig. 4) and the uncut chip thickness average values (Fig. 5).

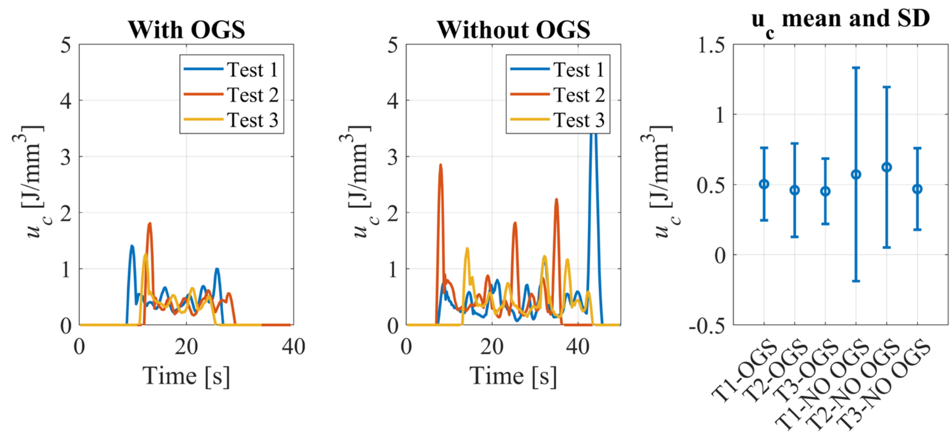

Figure 4 Measured specific cutting energy, with and without OGS.

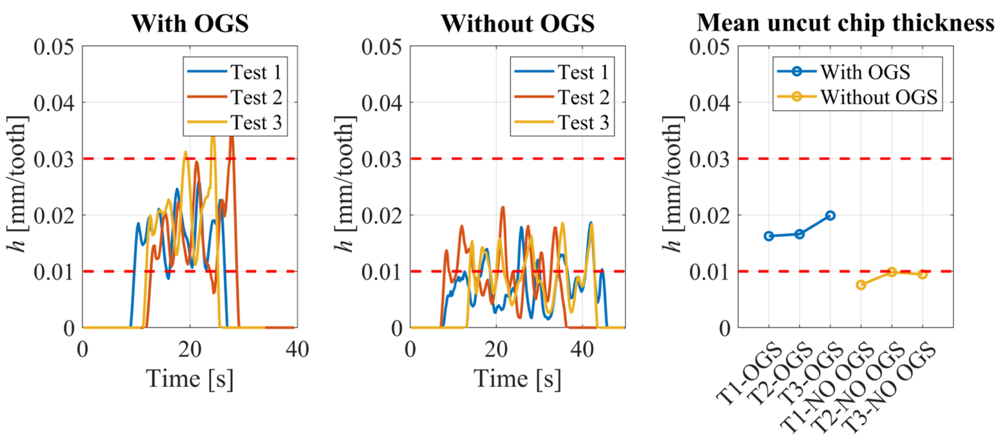

Figure 5 Measured uncut chip thickness, with and without OGS.

Conclusions

The operator guidance system (OGS) based on the digital shadow of a bandsaw machine presented in this paper demonstrated the effectiveness of digital innovation for machining processes performance improvement. The cutting process parameters measurement was made possible through the design and on-board deployment of a tailor-made measurement system made mostly by low-cost sensors. In-process data acquisition, visualization and elaboration were performed by means of NI DAQ devices and a specifically devised NI LabVIEW application. Preliminary geometrical data required to calculate the real-time specific cutting energy u_c were computed by means of a MATLAB app that performed the cut simulation. The combination of these systems made it possible to develop an OGS which allows the operator to view real-time process parameters such as power, cutting speed, blade angle and applied force. These parameters are then processed to obtain the specific cutting energy and the uncut chip thickness, allowing for real time cutting process optimization, avoiding rubbing and excessive tooth load. To evaluate the effectiveness of the OGS, a series of cutting tests were performed on a 40 mm Al 7075 rod with and without the support of the OGS. These tests demonstrated the effectiveness of the OGS, allowing the operator to keep the u_c stable and maintaining the uncut chip thickness within optimal limits throughout the cutting operation. The OGS utilizes high-performance DAQ and power sensor. By using industrial PLC and I/O, it is possible to contain costs within 15% of the market price of the bandsaw. A further development of the system can be achieved by implementing an automatic feed rate control, effectively obtaining a digital twin.

Acknowledgements

This study was carried out within the Interconnected Nord-Est Innovation Ecosystem (iNEST) and received funding from the European Union Next-GenerationEU (PIANO NAZIONALE DI

RIPRESA E RESILIENZA (PNRR) – MISSIONE 4 COMPONENTE 2, INVESTIMENTO 1.5 – D.D. 1058 23/06/2022, ECS00000043). This manuscript reflects only the authors' views and opinions, neither the European Union nor the European Commission can be considered responsible for them.

References

[1] Sarwar, M., Persson, M., Hellbergh, H., & Haider, J., Measurement of specific cutting energy for evaluating the efficiency of bandsawing different workpiece materials. International Journal of Machine Tools and Manufacture 49 12-13 (2009), pp. 958-965. https://doi.org/10.1016/j.ijmachtools.2009.06.008

[2] Lu, Y., Liu, C., Kevin, I., Wang, K., Huang, H., & Xu, X., Digital Twin-driven smart manufacturing: Connotation, reference model, applications and research issues. Robotics and Computer-Integrated Manufacturing 61 (2020), 101837. https://doi.org/10.1016/j.rcim.2019.101837

[3] Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W., Digital Twin in manufacturing: A categorical literature review and classification. Ifac-PapersOnline 51 11 (2018), pp. 1016-1022. https://doi.org/10.1016/j.ifacol.2018.08.474

[4] Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B., Characterising the Digital Twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology 29 (2020), pp. 36-52. https://doi.org/10.1016/j.cirpj.2020.02.002

[5] Lattanzi, L., Raffaeli, R., Peruzzini, M., & Pellicciari, M., Digital twin for smart manufacturing: A review of concepts towards a practical industrial implementation. International Journal of Computer Integrated Manufacturing 34(6) (2021), pp. 567-597. https://doi.org/10.1080/0951192X.2021.1911003

[6] Li, C., Mahadevan, S., Ling, Y., Choze, S., & Wang, L., Dynamic Bayesian network for aircraft wing health monitoring digital twin. Aiaa Journal 55(3) (2017), pp. 930-941. https://doi.org/10.2514/1.J055201

[7] Knapp, G. L., Mukherjee, T., Zuback, J. S., Wei, H. L., Palmer, T. A., De, A., & DebRoy, T. J. A. M. Building blocks for a digital twin of additive manufacturing. Acta Materialia 135 (2017), pp. 390-399. https://doi.org/10.1016/j.actamat.2017.06.039

[8] Liau, Y., Lee, H., & Ryu, K., Digital Twin concept for smart injection molding. In: IOP Conference Series: Materials Science and Engineering 324(1), IOP Publishing, 2018. https://doi.org/10.1088/1757-899X/324/1/012077

[9] Wang, X. V., & Wang, L., Digital twin-based WEEE recycling, recovery and remanufacturing in the background of Industry 4.0. International Journal of Production Research 57(12) (2019), pp. 3892-3902. https://doi.org/10.1080/00207543.2018.1497819

[10] Liu, J., Zhou, H., Tian, G., Liu, X., & Jing, X., Digital twin-based process reuse and evaluation approach for smart process planning. The International Journal of Advanced Manufacturing Technology 100 (2019), pp. 1619-1634. https://doi.org/10.1007/s00170-018-2748-5

[11] Magnanini, M. C., & Tolio, T. A. M., A model-based Digital Twin to support responsive manufacturing systems. CIRP Annals 70.1 (2021), pp. 353-356. https://doi.org/10.1016/j.cirp.2021.04.043

[12] Tao, F., Zhang, M., Liu, Y., & Nee, A. Y., Digital twin driven prognostics and health management for complex equipment. Cirp Annals 67(1) (2018), pp. 169-172. https://doi.org/10.1016/j.cirp.2018.04.055

[13] Sivalingam, K., Sepulveda, M., Spring, M., & Davies, P., A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In: 2018 2nd international conference on green energy and applications (ICGEA), IEEE, 2018, pp. 197-204. https://doi.org/10.1109/ICGEA.2018.8356292

[14] Sallese, L., Tsahalis, J., Grossi, N., Scippa, A., Campatelli, G. & Tsahalis, H. Case Study 1.3: Auto-adaptive Vibrations and Instabilities Suppression in General Milling Operations. In: Intelligent Fixtures for the Manufacturing of Low Rigidity Components. Lecture Notes in Production Engineering. Springer, Cham., 2018. https://doi.org/10.1007/978-3-319-45291-3_3

[15] Vuković, M., Mazzei, D., Chessa, S., & Fantoni, G. Digital Twins in Industrial IoT: a survey of the state of the art and of relevant standards. 2021 IEEE International Conference on Communications Workshops (ICC Workshops). IEEE, 2021. https://doi.org/10.1109/ICCWorkshops50388.2021.9473889

[16] Scalzo F, Totis G, Vaglio E & Sortino M. Passive Chatter Suppression of Thin-Walled Parts by Means of High-Damping Lattice Structures Obtained from Selective Laser Melting. Journal of Manufacturing and Materials Processing 4(4):117 (2020). https://doi.org/10.3390/jmmp4040117

[17] Zhu, Z., Xi, X., Xu, X., & Cai, Y. Digital Twin-driven machining process for thin-walled part manufacturing. Journal of Manufacturing Systems 59 (2021), pp. 453-466. https://doi.org/10.1016/j.jmsy.2021.03.015

[18] Scalzo, F., Totis, G. & Sortino, M. Influence of the Experimental Setup on the Damping Properties of SLM Lattice Structures. Exp Mech 63 (2023), pp. 15-28. https://doi.org/10.1007/s11340-022-00898-8