LCAMP

Learner Centric Advanced Manufacturing Platform

DIGITALISATION

WPN° 3 Observatory

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GLOSSARY AND/OR ACRONYMS

AI - Artificial Intelligence

AM - Advanced Manufacturing

Cedefop - European Centre for the Development of Vocational Training

CoVE - Centres of Vocational Excellence

EAfA - European Alliance for Apprenticeships

EC - European Commission

ECVET - European Credit System for Vocational Education and Training

EntreComp - The Entrepreneurship Competence Framework

EQAVET - European Quality Assurance in Vocational Education and Training

EQF - European Qualifications Framework

ESCO - European Skills, Competences and Occupations

ETF - European Training Foundation

EU - European Union

HE - Higher Education

HVET - Higher Vocational Education and Training

I4.0 - Industry 4.0

KET - Key Enabling Technology

OECD - Organisation for Economic Cooperation and Development

SME - Small and Medium Enterprises

SWOT - Strengths, Weaknesses, Opportunities, Threats

TVET - Technical and Vocational Education and Training

VET - Vocational Education and Training

WBL - Work Based Learning

CONTENT TABLE

EXECUTIVE SUMMARY

Advanced Manufacturing (AM) and Higher Vocational Education and Training (HVET) need to update training, implement new technologies, and get quick access to data.

The causes behind these needs are technological factors (Industry 4.0), factors conditioned by education systems and education methodologies, social factors and environmental factors (the European Green Deal with its emphasis on the greening industry).

Under the CoVE initiative, the LCAMP project aims to support regional skill ecosystems and various stakeholders in providing new skills and implementing new or updated technologies in VET centres. LCAMP will tackle this by incorporating a permanent European Platform of Vocational Excellence for Advanced Manufacturing.

By collaborating across borders, LCAMP's goal is to support and empower regional Advanced Manufacturing CoVEs to become more resilient, innovative, and better equipped to train, upskill, and reskill young and adult students, to successfully face the digital and green transitions. We will help European regions and countries grow and be more competitive through their VET systems.

Therefore, the LCAMP OBSERVATORY is one of the services in the LCAMP platform. The observatory is led by the French cluster *Mecanic Vallée* and the French VET provider *Campus des Métiers et des Qualifications d'Excellence Industrie du Futur*.

This present document details the first results of the LCAMP Observatory, through the methodology that the LCAMP consortium used to set up and run the Observatory. We had set up a process cycle for the observation consisting of 5 stages:

- Stage 1: Diagnosis and priority
- Stage 2: Search and information gathering
- Stage 3: Information Analysis
- Stage 4: Creating value. Elaboration of LCAMP reports
- Stage 5: Dissemination and communication.

1. INTRODUCTION

The LCAMP observatory is one of the services of the LCAMP platform.

The LCAMP Observatory must be a reliable and easily accessible source of information and data for trainers, VET teachers, and professionals, updated on Digital / Advanced Manufacturing / Smart Industry, delivered through a multimedia and interactive platform -LCAMP platform-, that can be customized according to individual interests (Work in progress in WP8).

This observatory must feed other Work packages (WP), for instance, WP 5 on Learner Centric Training, or Open innovation Community in the WP4.

In a first document about methodology, are set up a process cycle for the observation consisting in 5 stages:

- Stage 1: Diagnosis and priority
- Stage 2: Search and information gathering
- Stage 3: Information Analysis
- Stage 4: Create value. Elaboration of LCAMP reports
- Stage 5: Disseminate-communicate.

Following this process cycle, are detailed the main aspects of the observation methodology:

- Identify reliable sources that we can find in Europe about Advanced Manufacturing.
- Classify and filter data gathered from different sources.
- Present several ways to collect data and to analyse them.
- Define the methods for the creation of annual reports.
- Validate process for those reports.

The observatory will publish periodical reports for VET and HVET target audiences about technology trends, labour market changes, skill needs, and occupations in Advanced Manufacturing. It is expected that SMEs, industry clusters and other associations will also find valuable information in the observatory.

The publication of a yearly report is planned.

- Report 1: June 2023,
- Report 2: June 2024,
- Report 3: June 2025.

This first annual report is gathering sub-reports written by around twenty different writers, from the main partners involved in the LCAMP project. 39 Topics were determined, and 22 TOPICS were analysed and worked on during this first period.

2. TECHNOLOGY TRENDS IN ADVANCED MANUFACTURING

The purpose of this chapter is to present some of the development areas related to AM.

These are topics that concern all or some of the stakeholders

- CoVEs and VETs: teachers, trainers and heads of VET schools;
- Learners: students, active workers, job seekers;
- Companies;
- Policy makers and other stakeholders

1.1 DIGITALIZATION OF MANUFACTURING PROCESSES

Adapting to increasingly digital market environments and levering digital technologies to improve operations and drive new customer value are important goals for nearly all contemporary businesses. This is the reason why companies are beginning to make the necessary changes to adapt their organisation to a digital environment. Organisations are beginning to progress digitally and that mature digitally are more likely to experiment and iterate, this experimentation and iteration are key for companies to respond to digital disruption.
Established companies must figure out how to experiment to compete in the future, while at the same time working to find the best professionals to fill those jobs.

2.1.1 INTRODUCTION

The Digital Transformation, initiated with the fourth industrial revolution, continues unstoppable in the machine tool sector and is allowing new intelligence to be incorporated into machines and generating new digital business models based on digital services that are in turn, generating new value propositions, innovative income generation models and new configurations of the digital value network. The efforts made by Basque companies and institutions to adopt the fourth industrial revolution have made it possible to place Basque machine tools in the state of art, strengthen their position in the market and grow their business and employment figures in recent years. It is a reality that digitization is increasingly present in our companies. That is why in order to face the advances that are being presented in this matter, we must train students with knowledge in these technologies through their training.
Data science, for example, is a discipline with many years of development. Despite the fact that in recent years it has gained great prominence, it is a concept that was coined in the 60s for the first time. Since the birth of the 4.0 paradigm, many companies have carried out initiatives to collect data in their workshops and plants, treat them, analyse them using advanced techniques and use them for decision making or to generate new or better ones.
However, both experts and large consultancies agree that horizontal integration in the value chain is a pending issue in the industry. The Industrie 4.0 platform itself, a forerunner of the

industry 4.0 concept, includes in one of its latest publications on Asset Administration Shell, from October 2020, the importance of exchanging information between partners in 4.0 value chains. It has even held monographic Webinars addressing how added value can be generated through collaboration between companies on topics such as Condition Monitoring of machines and components.

2.1.2 TECHNOLOGY TRENDS

Sensoring of manufacturing processes

A global deployment of 5G technology, in which data can be transmitted anywhere in the world without latency, eliminates the need for distributed edge computing, enabling lower costs for data storage and management on servers in the cloud. However, such a global deployment may take many years and a gradual 5G network deployment scenario must involve Edge Computing modules that use 5G technology locally on a machine or in a factory, and that these modules are designed in such a way that the transition to global 5G is gradual and non-traumatic. Therefore, there is a challenge to integrate new 5G sensors into Edge Computing modules, support the highest bandwidth or number of locally connected devices and ease the transition to a future global 5G network.

Assuming a higher number of connections as a higher bandwidth in an edge computing module could be realised with more powerful and expensive hardware, but a more economical solution is the inclusion of intelligence in the edge computing module so that the configuration of the bandwidths of each signal and the storage capacity is adaptively set by an artificial intelligence module. The challenge in this area will be to adapt the telecommunication network to the characteristics of the processes being controlled or monitored.

In the following, the most representative state-of-the-art advanced solutions for machine condition monitoring in the manufacturing machine sector are presented by international reference manufacturers:

Makino's Health MaximizerTM (MHmaxTM) [1]is a solution for predictive and proactive monitoring of machine health, using integrated sensors and software monitoring to help predict likely failures before they occur. The system includes the monitoring of four critical subsystems of the machine: the spindle is monitored through vibrations recorded by an integrated high frequency accelerometer; in the cooling system all lines are monitored; the hydraulic circuit is analysed for pressure and temperature; finally, for the tool change system, the actual physical position of the spindle is monitored and compared with the theoretical one. The system generates warnings and alarms in case of health incidents of the monitored components.

[1] *Predictive and Proactive Machine Health Technology - MHmax*, 2019, https://www.youtube.com/watch?v=VSkTMQw_Ubg.

The development of MHmaxTM is based on data recorded during fifteen years of customer support in different production scenarios, from which the main causes and alarm symptoms of unplanned machine stoppages were identified.

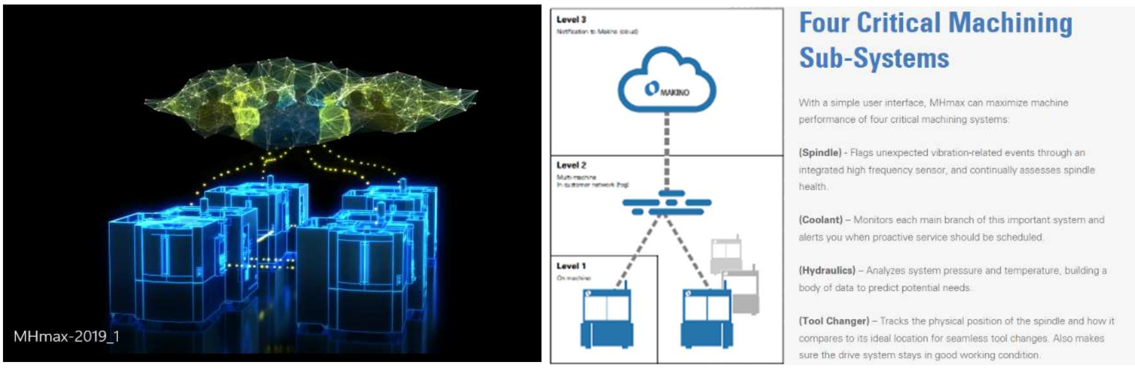

Figure 1 Health MaximizerTM (MHmaxTM) of Makino [2]

Makino offers three levels of machine connectivity for the MHmax: With no external connection, the information provided by the system remains in the machine control; With plant-level connectivity, allowing access to system information from any connected machine with permissions; With connection to the external cloud and the ability to transmit information to Makino's technical team who provide technical support and help in deciding proactive actions.

Okuma presents a solution integrated into the machine control for artificial intelligence diagnosis of the condition of the main spindle and linear axes[3]. It provides self-diagnosis of the bearing health status of these components through AI analysis of vibration recorded in specific motion cycles. The condition of the components is displayed on the machine control by means of traffic light colour coding, and the degree of normality is also provided as a numerical value.

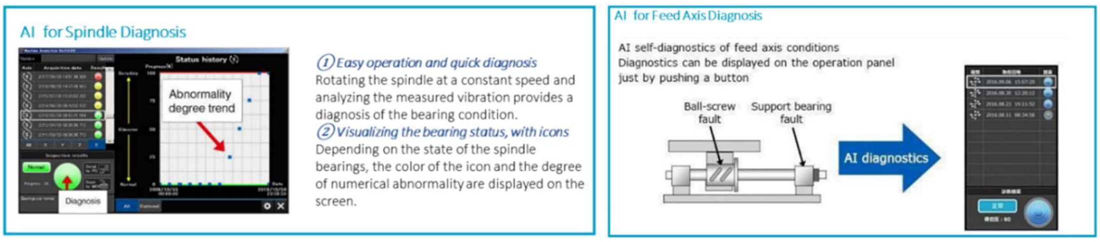

Figure 2. Diagnosis of the electro spindle and linear axes through Okuma´s AI [4]

Regarding the condition of machine geometric accuracy, Okuma has developed the Thermo-Friendly Concept[5], a control solution powered by temperature sensors distributed in the

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[2] *Predictive and Proactive Machine Health Technology - MHmax*.

[3] « The Next-Generation Intelligent CNC OSP Suite [OSP-P300A] | Technology & Solutions Okuma Smart Factory », OKUMA CORPORATION, s. d., https://www.okuma.co.jp/english/smart-factory/osp-suite/index.html.

[4] « The Next-Generation Intelligent CNC OSP Suite [OSP-P300A] | Technology & Solutions Okuma Smart Factory ».

[5] *Okuma's Intelligent Technology - Thermo-Friendly Concept*, 2015, https://www.youtube.com/watch?v=3er2OHIq9Bc.

machine, to compensate for oscillations caused by temperature and achieve high dimensional stability in long-term continuous machine use. In addition to achieving high accuracy, the system saves time and costs, as machine warm-up and manual adjustment of thermal conditions are eliminated.

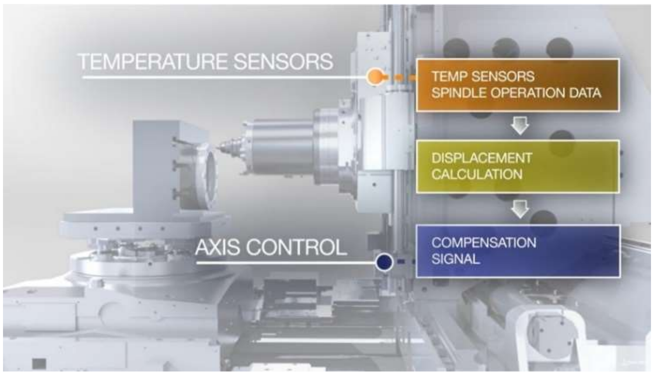

Figure 3. Thermo-Friendly Concept of Okuma [6]

In the same field of precision machine condition, Okuma's 5-Axis Auto Tuning function[7] is a solution to compensate for geometrical errors that occur during the manufacture and assembly of machines and during the life of the machine due to wear and ageing. The application detects the actual machine geometry through a touch probe and established measurement procedure, and compensates for errors through a calibration function, improving the dimensional quality of machined parts.

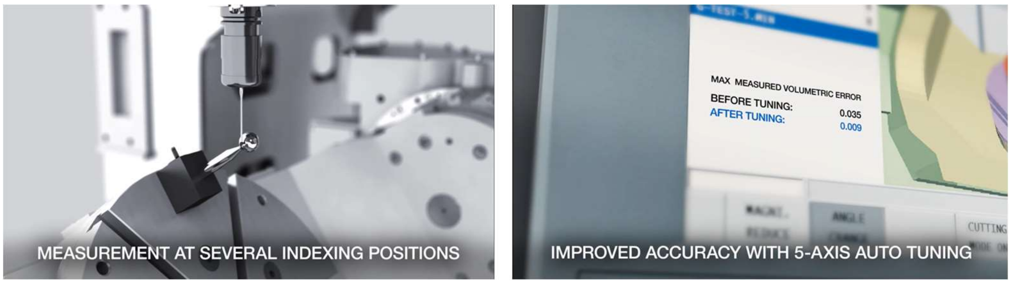

Figure 4. 5-Axis Auto Tuning of Okuma [8]

Mazak has developed the Spindle Analytics application[9], which analyses the status of the electro spindle by monitoring its temperature, vibrations and displacements, with the aim of preventing problems and reducing production stoppages. In addition, Mazak offers its customers the

[6] *Okuma's Intelligent Technology - Thermo-Friendly Concept*.
[7] *Okuma's Intelligent Technology - 5-Axis Auto Tuning System*, 2015, https://www.youtube.com/watch?v=CcGqxaFnl5M.
[8] *Okuma's Intelligent Technology - 5-Axis Auto Tuning System*.
[9] « Artificial Intelligence Makes Spindle Health Monitoring a Reality », 2019, https://www.mazakusa.com/news-events/blog/artificial-intelligence-makes-spindle-health-monitoring-a-reality/.

service of remotely monitoring the performance of the machine, in order to alert the customer of possible problems and provide technical assistance.

Figure 5. Spindle Analytics of Mazak [10]

The Condition Analyzer function of DMG MORI[11] [12] monitors the condition of certain machine components by analysing the data recorded by sensors. The results are provided both on the machine control as well as on PC, tablet or smart phone devices. The aim is to reduce unexpected machine downtime through preventive maintenance. In addition, it allows the quality of the manufactured parts to be improved thanks to the possibility of optimising processes based on the information recorded by the sensors.

The components included in the supervision are: The electro spindle, of which the unbalance, the condition of the bearings and the vibration level are monitored through an integrated accelerometer, the thermal expansion which is automatically detected and compensated, the clamping force of the tool with predefined measurement cycles and an external sensor type power check and the lubrication through automatic lubrication cycles; The cooling system to ensure that the flow rate is adequate for proper cooling; The pneumatic system to detect possible leaks.

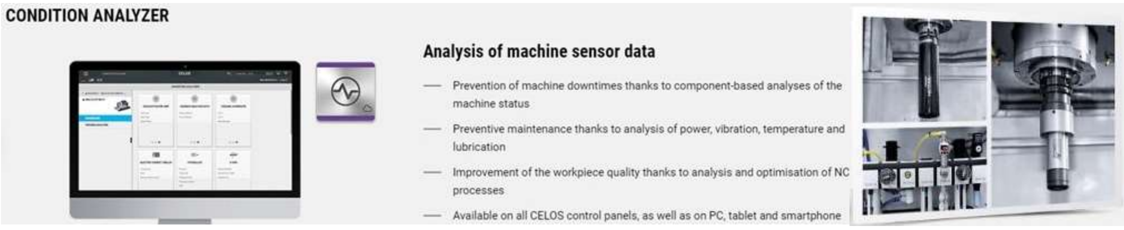

Figure 6. Condition Analyzer of DMG MORI [13] [14]

DMG MORI introduces the concept of the geometric fingerprint, or characteristic fingerprint of the machine's geometric accuracy condition. Its Volumetric Calibration System (VCS) application[15] is a solution for automated periodic checking of the machine's volumetric positioning accuracy, with the implementation of a contact inspection probe and a set measurement cycle that runs through the entire working volume. In addition to determining

[10] « Artificial Intelligence Makes Spindle Health Monitoring a Reality ».
[11] « Monitoring », s. d., https://es.dmgmori.com/productos/digitization/integrated-digitization/monitoring.
[12] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière », 2023, https://fr.dmgmori.com/.
[13] « Monitoring ».
[14] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[15] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».

accuracy, the VCS solution allows for compensation of position and angle errors through machine control.

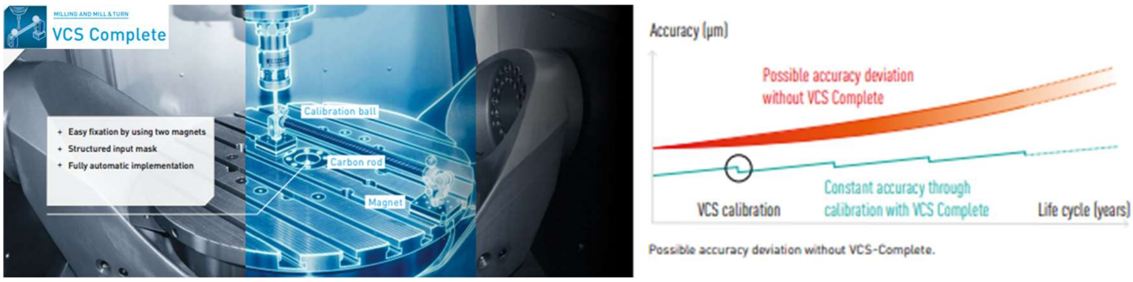

Figure 7. Volumetric Calibration System (VCS) of DMG MORI[16]

DMG MORI also offers its customers a remote technical assistance service, NETservice[17], which includes a 5G WIFI camera to transmit images of the machine in streaming, with the high-resolution rate, flexible connectivity, speed and security offered by 5G technology.

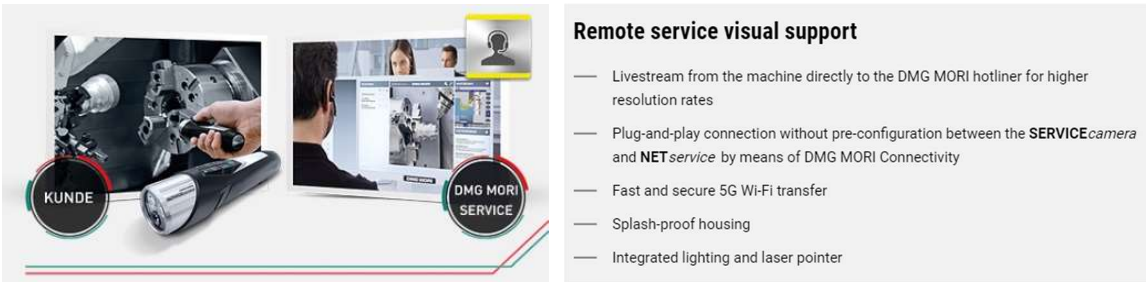

Figure 8. NETservice of DMG MORI [18]

Hermle's Wear Diagnosis System[19] includes the analysis of the feed behaviour and frequency spectrum of linear and rotary axes, the evaluation of relevant data from sensors integrated in the machine, the calculation of the vibrations of the electro spindle, the monitoring of the machine's accuracy and the monitoring of the temperatures of the drive motors. Associated with this machine condition monitoring system, Hermle offers its customers the service of analysis and diagnosis of all these data by a qualified technician.

Siemens' approach to machine condition monitoring, Analyze MyMachine/Condition[20], combines high-frequency computing at the edge with long-term trajectory monitoring in the cloud. Its solution establishes a series of dedicated tests for the acquisition of certain control

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[16] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[17] « Service », s. d., https://es.dmgmori.com/productos/digitization/integrated-digitization/service.
[18] « Service ».
[19] KMS GmbH & Co KG http://www.kms-wirkt.de, « Maschinenfabrik Berthold Hermle AG - Módulos digitales », Text, Maschinenfabrik Berthold Hermle AG (Maschinenfabrik Berthold Hermle AG, 23 mai 2023), https://www.hermle.de/es/centros_de_mecanizado/m%C3%B3dulos_digitales.
[20] « Siemens Machine Tool Days 2020 | Press | Company | Siemens », 2020, https://press.siemens.com/global/en/event/siemens-machine-tool-days-2020.

parameters under controlled machine condition conditions, parameters that are indicative of the machine health status. Among others, it includes obtaining the squareness error, friction or backlash of the machine axes. The analysis of the data consists of comparing the current values with those recorded at the time of installation of the machine, with the machine in perfect condition. The initial values form the so-called fingerprint of the machine and represent the normal reference values.

The purpose of this functionality is to perform a periodic diagnosis of the machine's condition in order to establish corrective actions. It enables early detection of problems and increases machine availability, and opens up the possibility of new remote diagnostic services from the machine manufacturer to the customer.

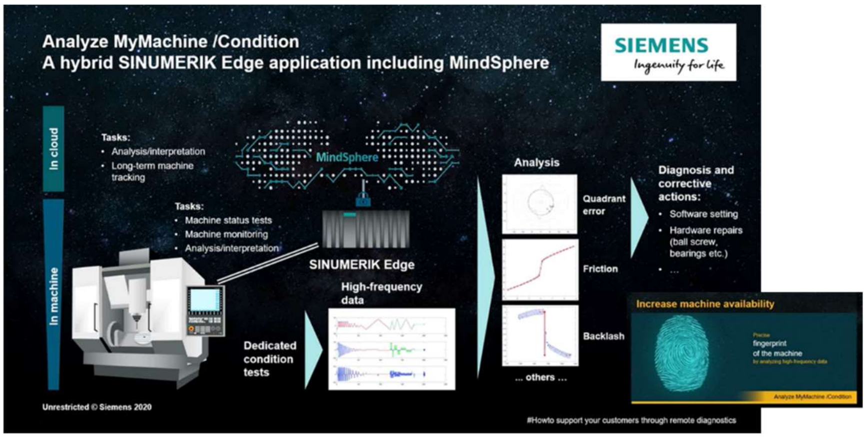

Figure 9 Analyze MyMachine/Condition of Siemens[21]

In the scientific literature there are numerous research references on the condition of particular machine components, being especially notable those related to rotating components, such as ball screws or bearings, in which solutions for predictive maintenance of components based on the monitoring of machine control signals and integrated sensors, mostly accelerometers, are analysed[22] [23].

However, there are fewer bibliographical references related to the condition of the machine as a whole, due to the fact that this is a more recent field of research:

The research work described in[24] proposes predictive machine maintenance based on Manufacturing Error Based Maintenance (MEBM), specifically by monitoring the machining backlash through machine control parameters. Also, a methodology for automated machine condition monitoring based on internal machine control parameters, without the need for

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[21] « Siemens Machine Tool Days 2020 | Press | Company | Siemens ».
[22] Li Zhang et al., « A Deep Learning-Based Recognition Method for Degradation Monitoring of Ball Screw with Multi-Sensor Data Fusion », *Microelectronics Reliability* 75 (1 août 2017): 215-22, https://doi.org/10.1016/j.microrel.2017.03.038.
[23] María Navarro Carmona, « Diagnóstico de fallos en rodamientos », 2016, https://ingemecanica.com/tutorialsemanal/objetos/tutorial215.pdf.
[24] Shengyu Shi et al., « Manufacturing-error-based maintenance for high-precision machine tools | SpringerLink », 2017, https://link.springer.com/article/10.1007/s00170-017-1070-y.

external sensors, is described in[25]. It is based on periodic comparison of machine axis parameters with reference values. The research work described in [26]proposes the development of a predictive maintenance system for a milling machine based on web-services, with data acquisition from the CNC-PLC of the machine and statistical analysis of the variables. It introduces the concept of the no-load check cycle. Two research works[27] [28] propose the analysis of the health of the machine's spindle and linear axes through the analysis of electrical signals. They propose the use of an eMaintenance web platform to benefit from the exploitation of information from many machines. It introduces the concept of machine fingerprinting during the execution of a check cycle. The research work described in [29]discusses the industrial applications of Machine Learning and presents a use case on the predictive maintenance of a machine head, based on its fingerprint. This other[30] presents eMaintenance as a potential service of machine data access, explains how to use sensor-based tools and control data to increase the efficiency of diagnosis, prognosis and decision making in maintenance, and describes methods to solve the challenges of massive data recording and processing.

In the field of EDM and additive manufacturing, machine condition has not been as high a priority as process control, because machines suffer less than with start-up processes. However, a recent work[31] stands out in which the condition of some of the consumables of a wire EDM machine (filters, resins, contacts) is monitored by adapting new sensors with the aim of predicting their useful life.

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[25] A. Verl et al., « Sensorless Automated Condition Monitoring for the Control of the Predictive Maintenance of Machine Tools », *CIRP Annals* 58, nº 1 (2009): 375-78, https://doi.org/10.1016/j.cirp.2009.03.039.

[26] Luca Fumagalli et Marco Macchi, « Integrating Maintenance within the Production Process through a Flexible E-Maintenance Platform », *IFAC-PapersOnLine*, 15th IFAC Symposium onInformation Control Problems inManufacturing, 48, nº 3 (1 janvier 2015): 1457-62, https://doi.org/10.1016/j.ifacol.2015.06.292.

[27] Susana Ferreiro et al., « Industry 4.0: Predictive Intelligent Maintenance for Production Equipment », 2016, https://www.researchgate.net/publication/317066007_Industry_40_Predictive_Intelligent_Maintenance_for_Production_Equipment.

[28] Augustin Prado et al., « Health and Performances Machine Tool Monitoring Architecture » (International Workshop and Congress on eMaintenance : 17/06/2014 - 18/06/2014, Luleå tekniska universitet, 2014), 139-44, https://urn.kb.se/resolve?urn=urn:nbn:se:ltu:diva-40402.

[29] Pedro Larranaga et al., *Industrial Applications of Machine Learning*, 2018, https://doi.org/10.1201/9781351128384.

[30] Diego Galar et Uday Kumar, *eMaintenance: Essential Electronic Tools for Efficiency*, 1st éd. (USA: Academic Press, Inc., 2017), https://dl.acm.org/doi/book/10.5555/3161422.

[31] G. Wälder et al., « Smart Wire EDM Machine », *Procedia CIRP*, 19th CIRP Conference on Electro Physical and Chemical Machining, 23-27 April 2017, Bilbao, Spain, 68 (1 janvier 2018): 109-14, https://doi.org/10.1016/j.procir.2017.12.032.

Data collection, analysis of data

Over the last 5 years and in the context of Industry 4.0, almost all manufacturing companies have, to a greater or lesser extent, undertaken actions aimed at integrating functionalities based on digital technologies. Today, there are many solutions available on the market for the acquisition and recording of machine data on which to build new services and new functionalities. Both machine manufacturers and component manufacturers have incorporated sensors into their products to increase the nature and type of data from machines and the processes they run, and have developed and incorporated functionalities based on this data.

The application of AI techniques in manufacturing has made it possible to formalise complex multivariate knowledge of machine and process conditions. These tools enhance the work of the operator, which also increases his value as a technician.

Continuous learning based on the experiences of machine use is a reality that is applied to strategies for continuous process improvement.

The worker is provided with many more tools for assistance, diagnosis and optimisation, and can focus his efforts on increasing the value of the component and freeing himself from tasks that may not have a direct impact on production. It is also a fact that the incorporation of new technicians can be accelerated in a more efficient way. In short, more reliability, workers who see their jobs valued, increased overall machine safety and an impact on overall well-being.

The massive generation of data through the IIoT and is giving Artificial Intelligence (AI) a huge boost in the industrial sector. Artificial Intelligence currently offers tremendous potential for industry, making production more efficient, more flexible and, above all, more reliable.

An important lever in favour of AI deployment in industry has been the advent of high computing power as an asset available to all. This capability makes it possible to disentangle knowledge from massive ingestions of sensor data and new sources of unstructured data (images, text, video, etc.). All these new functionalities are a perfect fit in a sector with such varied needs as advanced manufacturing.

As stated in the European Communication Artificial Intelligence for Europe, Artificial Intelligence refers to systems that display intelligent behaviour by analysing their environment and take actions with some degree of autonomy to achieve specific objectives. AI does not refer to a single technology, but refers to a set of different approaches, methods and technologies that demonstrate behaviour in different contexts. AI-based systems can be solely software-based, acting in the virtual world, or embedded in hardware devices. Machine Learning can be considered as a branch of AI, and is defined as "the set of methods that can automatically detect patterns in a data set and use them to predict future data, or to make other types of decisions in uncertain environments". In turn, Deep Learning is a branch of Machine Learning that, defined in its most basic aspect, can be explained as a probability system that allows computational models that are composed of multiple layers of processing to learn about data with multiple levels of abstraction.

Currently, there are multiple machine learning techniques in the advanced manufacturing environment, depending on the type of information (structured or unstructured information) and the learning paradigm used. The choice of the technique to be applied depends, among others, on the objective of the model to be built, as well as on the type of information available. Furthermore, it seems that the solution is probably not the use of a single technique for each of the problems, but rather combinations of several techniques. For intelligent environments, this has been the approach that has been adopted.

One of the main advantages of AI is optimisation based on prescriptive analysis based on decision models. The use of machine learning for autonomous machine decision-making is one of the main goals of AI today. To date, developments have mainly focused on descriptive analytics and predictive maintenance tasks. Several of the techniques used in industry in this field are outlined below:

- Fuzzy logic: for symbolic knowledge management and process diagnosis; this is a reasoning system based on logical expressions describing the membership of fuzzy or fuzzy sets. The diagnosis of the system is based on fuzzy rules and the detection of events of interest from fuzzy rules and fuzzy sets, defined from the available data. Its main utility is to manage easily interpretable symbolic knowledge, very close to natural language. It is compatible with automatic rule generation systems and can be useful for detecting faults or symptoms of future faults (corrective and predictive maintenance). This method allows predictive maintenance to be carried out if the input data used refer to the state of health of the system. Regarding its application in data diagnosis and prognosis, this article[32] presents a diagnostic method based on fuzzy logic applied to the manufacturing sector. The results show better results in noisy data than standard models. In the work carried out by this work [33], diagnosis and fault detection is performed with the aim of reducing the number of false positives generated in an engine.

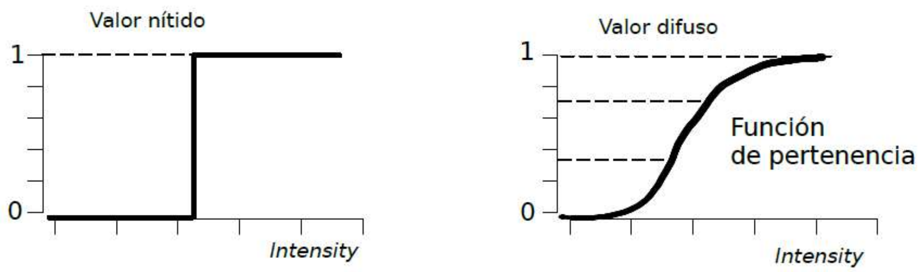

Figure 10. Classic Logic vs Fuzzy Logic[34]

[32] Tung-Hsu (Tony) Hou et Chun-Chi Huang, « Application of Fuzzy Logic and Variable Precision Rough Set Approach in a Remote Monitoring Manufacturing Process for Diagnosis Rule Induction », *Journal of Intelligent Manufacturing* 15, nº 3 (1 juin 2004): 395-408, https://doi.org/10.1023/B:JIMS.0000026576.00445.d8.

[33] Erick Rocha et al., « A fuzzy type-2 fault detection methodology to minimize false alarm rate in induction motor monitoring applications », *Applied Soft Computing*, 1 mai 2020, 106373, https://doi.org/10.1016/j.asoc.2020.106373.

[34] Azzam Sleit, Maha Saadeh, et Wesam Almobaideen, « A Two-Phase Fuzzy System for Edge Detection », 2016, https://www.researchgate.net/publication/311068958_A_Two-Phase_Fuzzy_System_for_Edge_Detection.

- Artificial neural networks: for the characterisation of non-linear behaviour in industrial processes; these models are non-linear multivariate mathematical models that use iterative procedures with the aim of minimising a certain error function and thus classifying the observations. Their main disadvantage is their "black box" nature, i.e. the difficulty in interpreting the results and the limitation in incorporating the physical sense of the element or process. This technique has been used many times for fault classification and diagnosis. For example, this research[35] uses neural networks for fault detection in industrial rotating equipment. This other[36] presents a new methodology based on neural networks for failure mode detection applied to rotating machinery. In unbalanced data, the methodology presented presents substantial improvements over traditional techniques applied in this field. This work37, presents a robust convolutional neural network capable of performing real-time diagnosis for gas turbines. In turn, this other[38] has diagnosed bearing failures using convolutional neural networks.

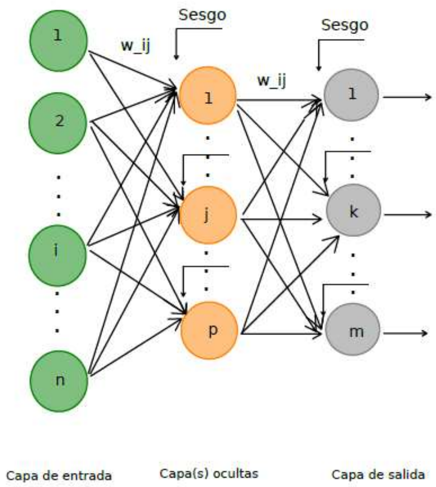

Figure 11. Structure of neural network[39]

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[35] Xianzhen Xu et al., « Application of neural network algorithm in fault diagnosis of mechanical intelligence », *Mechanical Systems and Signal Processing* 141 (1 juillet 2020): 106625, https://doi.org/10.1016/j.ymssp.2020.106625.
[36] Quan Zhou et al., « A Novel Method Based on Nonlinear Auto-Regression Neural Network and Convolutional Neural Network for Imbalanced Fault Diagnosis of Rotating Machinery », *Measurement* 161 (1 septembre 2020): 107880, https://doi.org/10.1016/j.measurement.2020.107880.
[37] Dengji Zhou et al., « Fault Diagnosis of Gas Turbine Based on Partly Interpretable Convolutional Neural Networks », *Energy* 200 (1 juin 2020): 117467, https://doi.org/10.1016/j.energy.2020.117467.
[38] Zhuyun Chen et al., « A Deep Learning Method for Bearing Fault Diagnosis Based on Cyclic Spectral Coherence and Convolutional Neural Networks », *Mechanical Systems and Signal Processing* 140 (1 juin 2020): 106683, https://doi.org/10.1016/j.ymssp.2020.106683.
[39] Amin Hedayati, Moein Hedayati, et Morteza Esfandyari, « Stock Market Index Prediction Using Artificial Neural Network », SSRN Scholarly Paper (Rochester, NY, 17 juillet 2017), https://papers.ssrn.com/abstract=3004032.

- Support Vector Machine or SVM: these are classification models that try to solve the difficulties that complex data samples can pose, where relationships need not be linear. In other words, the aim is to classify observations into various groups or classes, but these are not separable via a hyperplane in the dimensional space defined by the data. The goal is to find the hyperplane that separates the classes and that is most distant from the observations of the classes simultaneously. SVMs have been widely used in the field of failure mode classification. This study[40] presents a comparison of several techniques for failure diagnosis in a centrifugal pump including the SVM model. The results show a higher capability of SVM using a smaller number of features. This work[41] proposes a new methodology based on SVM for the detection and identification of multiple bearing failure modes. The results obtain high accuracy for different operating conditions.

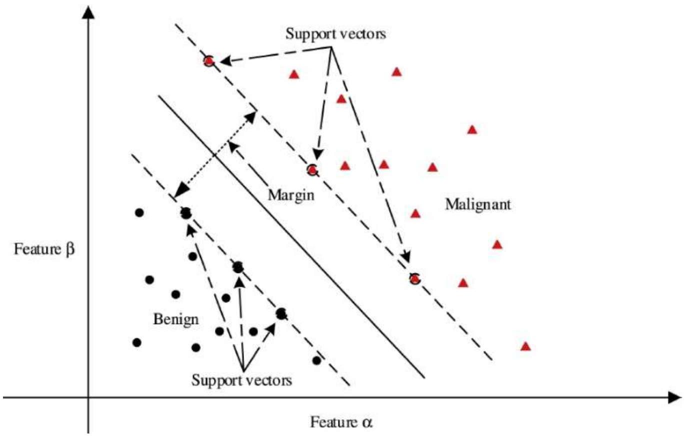

Figure 12. Illustrative image of the operation of SVM for linear cases[42]

- Clustering techniques: these clustering techniques are unsupervised techniques that group data according to their similarity. In the field of diagnosis, clustering techniques make it possible to detect the state of health of a system at a given moment based on a history of data that has been previously trained. The classification of a piece of data is established by its belonging to a specific grouping. These techniques are frequently used today in the field of maintenance, especially for the diagnostic part. This study[43] presents

[40] Maamar Ali Saud ALTobi et al., « Fault Diagnosis of a Centrifugal Pump Using MLP-GABP and SVM with CWT », *Engineering Science and Technology, an International Journal* 22, nº 3 (1 juin 2019): 854-61, https://doi.org/10.1016/j.jestch.2019.01.005.
[41] Xiaoan Yan et Minping Jia, « A Novel Optimized SVM Classification Algorithm with Multi-Domain Feature and Its Application to Fault Diagnosis of Rolling Bearing », *Neurocomputing* 313 (3 novembre 2018): 47-64, https://doi.org/10.1016/j.neucom.2018.05.002.
[42] Haifeng Wang et al., « A Support Vector Machine-Based Ensemble Algorithm for Breast Cancer Diagnosis », *European Journal of Operational Research* 267, nº 2 (1 juin 2018): 687-99, https://doi.org/10.1016/j.ejor.2017.12.001.
[43] Xiang Li, Xu Li, et Hui Ma, « Deep Representation Clustering-Based Fault Diagnosis Method with Unsupervised Data Applied to Rotating Machinery », *Mechanical Systems and Signal Processing* 143 (1 septembre 2020): 106825, https://doi.org/10.1016/j.ymssp.2020.106825.

a fault diagnosis for real data associated with rotating machinery. The results obtained are really good in the exploration of these faults for unsupervised data. This work[44] performs an approach for on-line fault diagnosis based on clustering and fuzzy logic techniques. This approach incorporates a machine learning mechanism that allows excellent results to be obtained.

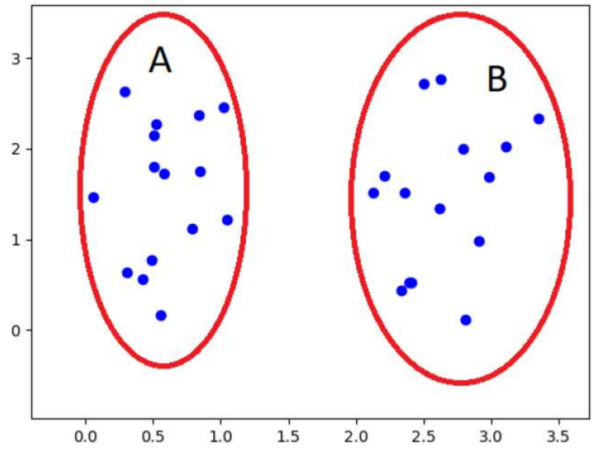

Figure 13. Clustering of 2 Dimesional signals[45]

- Hidden Markov Model (HMM): is a concept developed within the theory of probability and statistics that establishes a strong dependence between an event and a previous state. This type of technique is used for irreversible repetitive systems of long duration, where the evolution in the states of the chain allows establishing a distance to the event under study. This work[46] performs bearing fault detection and demonstrates its superiority over conventional methods. This work[47] also generates a fault detection model applying Markov models based on the data acquired from the fluids of the machinery associated with the process.
- ARIMA: these are statistical models that use variations and regressions of data to detect patterns and predict future values over time. It is a dynamic time series model, i.e. future estimates are explained by previously collected data. For prognostics, it allows the prediction of future values based on the latest available data in an adaptive way, which gives a great potential in those systems with a small margin of error such as the prediction of tool wear in fast mechanical processes. This technique has become very

[44] Adrián Rodríguez-Ramos, Antônio José da Silva Neto, et Orestes Llanes-Santiago, « An Approach to Fault Diagnosis with Online Detection of Novel Faults Using Fuzzy Clustering Tools », *Expert Systems with Applications* 113 (15 décembre 2018): 200-212, https://doi.org/10.1016/j.eswa.2018.06.055.
[45] Amit Saxena et al., « A Review of Clustering Techniques and Developments », *Neurocomputing* 267 (6 décembre 2017): 664-81, https://doi.org/10.1016/j.neucom.2017.06.053.
[46] Zefang Li et al., « Data-Driven Bearing Fault Identification Using Improved Hidden Markov Model and Self-Organizing Map », *Computers & Industrial Engineering* 116 (1 février 2018): 37-46, https://doi.org/10.1016/j.cie.2017.12.002.
[47] Pasquale Arpaia et al., « Fault Detection on Fluid Machinery using Hidden Markov Models », *Measurement* 151 (1 octobre 2019): 107126, https://doi.org/10.1016/j.measurement.2019.107126.

important in time series prediction. This work[48] performs the estimation of remaining tool life for the turning of a part in the automotive sector.

- Gaussian Regressive Processes (GPR): is a collection of random variables that satisfy that any physical subset of the collection has a Gaussian distribution. It can be likened to an infinite-dimensional multivariate Gaussian distribution. Within this distribution, prior knowledge about the function space can be incorporated through the selection of the mean and covariance functions. This study[49] generates a surface roughness prediction model for compacted graphite cast iron using GPR. The results show that the shear rate significantly affects the surface roughness. This study[50] presents an application of the GPR method for the prediction of the RUL (remaining useful life) of low-speed bearings based on acoustic emission signals. The results show very low errors in low-speed bearings.
- Survival methods: these techniques are part of studies in which the objective is to study the times until an event of interest occurs. Once this event is fixed, the times until the event occurs are observed, which in maintenance is known as time to failure (TTF), and the study focuses on modelling these times. This type of analysis aims at modelling the survival function and the risk function of the event. This study[51] presents a predictive maintenance model using the Cox model. The data used has been real data in which the proposed method has improved the existing one. This stydy[52] applies the survival model for the estimation of the RUL in a turning system.
- Decision trees and extensions, for the inference of diagnostic rules and detection of malfunctioning symptoms in industrial assets; this method consists of using efficient and easily interpretable classification and regression algorithms that divide the problem search space into tree models. It is a classifier whose interpretability is reduced in tree rules and has high computational efficiency. This method allows mixing continuous and categorical data, and there are multiple extensions with state-of-the-art performance such as Random Forest, AdaBoost, etc.
- Novelty detection: this type of Machine Learning algorithms from the world of robotics have become widespread in industrial realities where training with anomalous cases is not an option. This type of algorithm is an evolution of anomaly detection with the difference of being able to label these anomalies as they happen, in order to learn as

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[48] Alberto Jimenez-Cortadi et al., « Predictive Maintenance on the Machining Process and Machine Tool », *Applied Sciences* 10, nº 1 (janvier 2020): 224, https://doi.org/10.3390/app10010224.

[49] Juan Lu et al., « Effect of Machining Parameters on Surface Roughness for Compacted Graphite Cast Iron by Analyzing Covariance Function of Gaussian Process Regression », *Measurement* 157 (1 juin 2020): 107578, https://doi.org/10.1016/j.measurement.2020.107578.

[50] S. A. Aye et P. S. Heyns, « An Integrated Gaussian Process Regression for Prediction of Remaining Useful Life of Slow Speed Bearings Based on Acoustic Emission », *Mechanical Systems and Signal Processing* 84 (1 février 2017): 485-98, https://doi.org/10.1016/j.ymssp.2016.07.039.

[51] Chong Chen et al., « Predictive Maintenance Using Cox Proportional Hazard Deep Learning », *Advanced Engineering Informatics* 44 (1 avril 2020): 101054, https://doi.org/10.1016/j.aei.2020.101054.

[52] Lucas Equeter et al., *Estimate of Cutting Tool Lifetime through Cox Proportional Hazards Model*, 2016, https://doi.org/10.13140/RG.2.2.15305.13927.

they go along. Novelty Detection has been largely driven by applications in nuclear energy and aerospace technologies. In addition, such algorithms have the ability to learn from data streams, so that they can process them as they arrive, in some cases, and depending on the underlying algorithm, they can work in real time. Another fundamental characteristic is its capacity to detect and measure the degradation of the system being measured, which is very interesting for different types of industrial applications where the remaining useful life of the different components is to be measured.

With regard to process optimisation algorithms, genetic algorithms, inspired by the theory of evolution, make it possible to find optimal solutions to a problem. These algorithms try to optimise an objective function by recombining and mutating the existing population of solutions. The use of evolutionary methods in optimisation problems has introduced important improvements with respect to traditional methods in various domains and applications: mathematics, industry, applied engineering, etc. It allows ad-hoc solutions to be defined, establishing complex relationships between variables, constraints and objectives[53].

Industrially, Artificial Intelligence appears especially in Asian manufacturers. The Japanese machine tool manufacturer Okuma has integrated a set of applications called Intelligent Technologies into the numerical controls of its machines, including the "Machining Navi" application. Among other things, this application recommends optimal spindle speeds to avoid vibrations during machining and increase productivity. The system leverages Okuma's advanced OSP control and sensors to monitor vibrations[54].

Siemens' "Analyze MyMachine/Condition" application[55] uses AI-based statistical models to analyse and ensure the quality and stability of the workpiece process, and improve productivity while saving resources, by analysing machine data acquired at high frequency

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53 Zuntong Wang, Zhanqiang Liu, et Xing Ai, « Case Representation and Similarity in High-Speed Machining », *International Journal of Machine Tools and Manufacture* 43, nº 13 (1 octobre 2003): 1347-53, https://doi.org/10.1016/S0890-6955(03)00152-4.

54 « Intelligent Technology // OKUMA Europe GmbH », Okuma Europe GmbH, s. d., https://www.okuma.eu/es/tecnologia/corte/intelligent-technology/.

55 « Analyze MyMachine /Condition », s. d., https://documentation.mindsphere.io/resources/html/Analyze-MyMachine-condition-opman/en-US/114549568779.html.

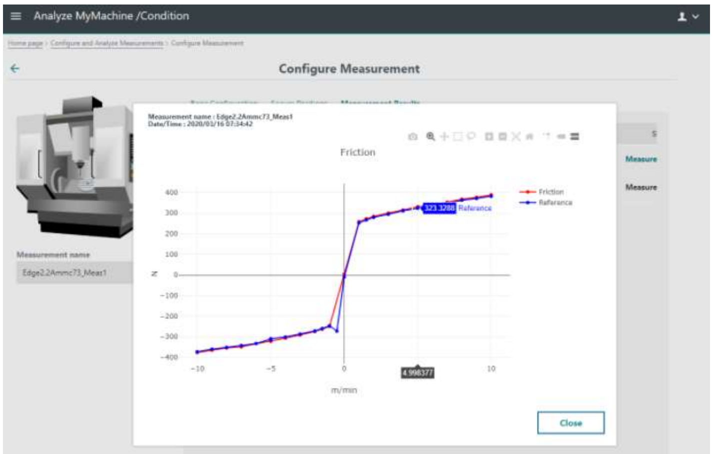

Figure 14. "Analyze MyMachine/Condition" application of Siemens[56]

In turn, DMG MORI focuses on the optimisation and acceleration of procurement and manufacturing processes based on Artificial Intelligence: from quotation and order entry, through job preparation and CAM programming, to machine planning. The core of the software solution is Artificial Intelligence, which analyses the geometry of each component in a matter of seconds on the basis of machine learning algorithms and human knowledge. The result is a concrete work plan and the manufacturing price of the component. With each component, the AI 'learns', optimising its algorithms independently and continuously. One example is the "Machine Vibration Control" application, which aims to assist the user in the operational phase of the machine by means of tools that range from monitoring the parameters of the machining processes to the automatic and intelligent correction of the different geometric errors and deviations detected from the programmed trajectories[57].

Makino, for its part, has developed the "MHmax" software based on Machine Learning techniques for predictive machine status monitoring which, by means of automatic learning of the sensors integrated in the machine, predicts problems before they occur, taking measures to avoid unplanned downtime[58].

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[56] « Analyze MyMachine /Condition ».
[57] « CELOS Machine & Manufacturing », s. d., https://es.dmgmori.com/productos/digitization/celos.
[58] « Makino Health Maximizer (MHmax) Tutorial | Makino », s. d., https://www.makino.com/en-us/digital-makino/mhmax/mhmax-tutorial.

Figure 15. "MHmax" Software of Makino to determine the spindle status[59]

Finally, Mazak has incorporated the term "AI powered" into its machines. Two Machine Learning applications are worth highlighting, a CAM assistant for turning that is able to learn from operator corrections, and an application that records vibration levels in operation in order to create a pattern of positions and cutting conditions where machine vibrations are generated in order to assist the operator in controlling cutting conditions[60].

Figure 16. "Smooth AI Spindle" system of Mazak[61]

In the EDM environment, a review of the most recent scientific literature shows the increasing trend towards intelligent manufacturing systems, with autonomy to detect/collect data, control the erosion process, diagnose faults and "learn" to improve their performance using AI techniques. An example in the field of wire EDM is the application of AI techniques, such as unsupervised learning algorithms, to process machine signals and detect deviations in part

59 « Makino Health Maximizer (MHmax) Tutorial | Makino ».
60 « Smooth Ai », s. d., https://www.mazakeu.com/smooth-ai/.
61 « Smooth Ai ».

accuracy[62] [63]. Another example is the work done by Guisti et al. This work[64] based on a convolutional neural network (CNN) that, given as input a small image of the surface (thanks to a machine vision system) returns the roughness value. In the specific case of "Fasthole" penetration machines, many of the works focus on the detection of the "break out" or exit of the hole based on the machine data and the detected patterns[65]. Finally, one of the Keynotes of the most prestigious conference on EDM, ISEM XX (Conference on Electro Physical and Chemical Machining), held in early 2021, mentions how the use of enabling technologies such as the Internet, 5G, IoT, Edge Computing or AI are overcoming the frontier of technical limitations for the development of modern smart manufacturing systems[66].

GF Machining Solutions is one of the leading manufacturers of EDM machines in the use of AI for process control and improvement. During Matlab Expo 2019 it presented a Keynote showcasing some applications where AI algorithms could be useful. For example, the application of neural networks to detect anomalies in the process in advance and correct them (Zero Defect Manufacturing) or the optimisation of the Fasthole process for turbine blades. This process is notable for the large number of variables involved, and GF proposes the application of stochastic optimisation algorithms to find the optimum of the process.

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[62] J. Wang et al., « Artificial Intelligence for Advanced Non-Conventional Machining Processes », *Procedia Manufacturing*, 8th Manufacturing Engineering Society International Conference, MESIC 2019, 19-21 June 2019, Madrid, Spain, 41 (1 janvier 2019): 453-59, https://doi.org/10.1016/j.promfg.2019.09.032.

[63] Jun Wang et al., « Unsupervised Machine Learning for Advanced Tolerance Monitoring of Wire Electrical Discharge Machining of Disc Turbine Fir-Tree Slots », *Sensors* 18 (8 octobre 2018): 3359, https://doi.org/10.3390/s18103359.

[64] Alessandro Giusti et al., « Image-Based Measurement of Material Roughness Using Machine Learning Techniques », *Procedia CIRP*, 20th CIRP CONFERENCE ON ELECTRO PHYSICAL AND CHEMICAL MACHINING, 95 (1 janvier 2020): 377-82, https://doi.org/10.1016/j.procir.2020.02.292.

[65] Wei Liang et al., « Feasibility Research on Break-out Detection Using Audio Signal in Drilling Film Cooling Holes by EDM », *Procedia CIRP*, 20th CIRP CONFERENCE ON ELECTRO PHYSICAL AND CHEMICAL MACHINING, 95 (1 janvier 2020): 566-71, https://doi.org/10.1016/j.procir.2020.02.271.

[66] Wansheng Zhao et al., « Reconstructing CNC Platform for EDM Machines towards Smart Manufacturing », *Procedia CIRP*, 20th CIRP CONFERENCE ON ELECTRO PHYSICAL AND CHEMICAL MACHINING, 95 (1 janvier 2020): 161-77, https://doi.org/10.1016/j.procir.2020.03.134.

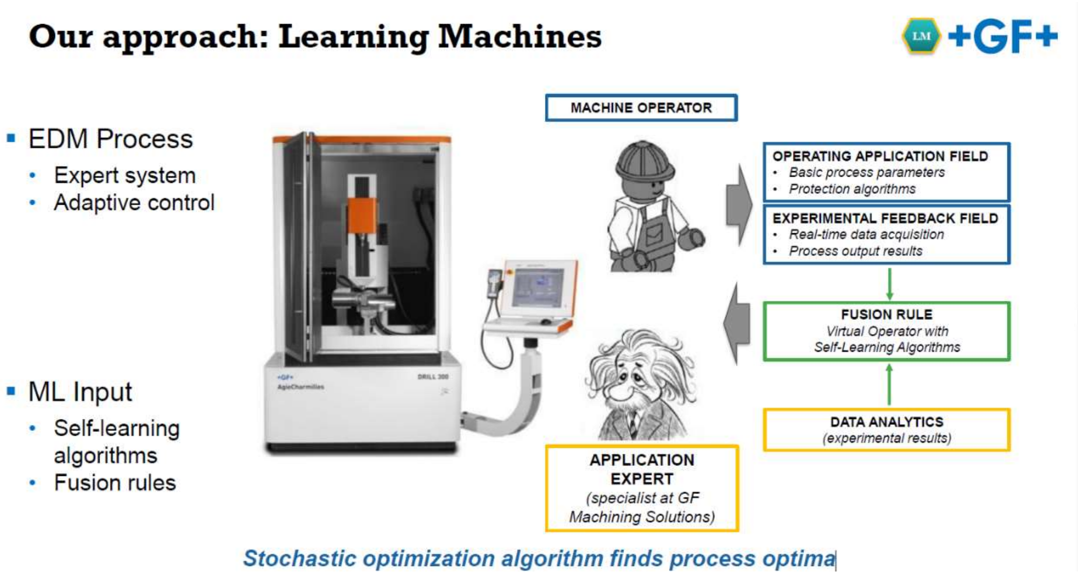

Figure 17. Example of Fasthole EDM process parameter optimisation using ML techniques.

GF.MITSUBISHI Electric has applied its wireless communication system for automatic optimisation thanks to AI called Maisart (Mitsubishi Electric's AI creates the State-of-the-art in Technology) in its SV12P die sinking EDM machine. This technology monitors the process and thanks to AI adapts it to obtain better results such as an ultra-fine finish, faster machining speed or less wear on the electrodes when working with PCD and CBN type materials. In addition, they promise to predict erosion times more accurately, traditionally a difficult task[67].

With respect to Machine Vision, it can be defined as a field of Artificial Intelligence that, by using the appropriate techniques, allows obtaining, processing and analysing any type of special information obtained through digital images. Artificial Vision is made up of a set of processes aimed at carrying out image analysis. These processes are: image capture, information storage, processing and interpretation of the results.

Machine vision excels at quantitative measurement of a structured scene due to its speed, accuracy and repeatability. For example, on a production line, a machine vision system can inspect hundreds, or even thousands, of objects per minute. A Machine Vision system built around the right camera resolution and optics can easily inspect details of objects too small to be seen by the human eye. Some of the applications of Machine Vision in industry are as follows:

Industrially, in recent years there has been a growing number of companies that have installed automated systems in their workshops using Machine Vision. For example, one of the problems of DMG MORI's customers who use automation systems is stopping the machine due to faults caused by chips generated during machining. The "AI Chip Removal" function developed by DMG MORI analyses the state of chip accumulation using Machine Vision and Machine

[67] « Electroerosionadora Mitsubishi SV12P con tecnología de inteligencia artificial », 31 décembre 2020, https://www.mms-mexico.com/productos/electroerosionadora-mitsubishi-sv12p-con-tecnologia-de-inteligencia-artificial.

Learning techniques and removes the chip automatically to reduce problems and help maximise the production output of automation systems[68].

Figure 18. "AI Chip Removal" application from DMG MORI for the removal of chips by Artificial Vision[69]

Siemens offers a wide range of Edge applications for a variety of use cases. Its "Analyze MyWorkpiece/Vision" application analyses the quality of the workpiece using a camera image and AI-based software to increase machine tool productivity. The application is able to determine the correct position of the workpiece in the machining area and can also monitor tool wear throughout its life[70].

Figure 19. "Analyze MyWorkpiece/Monitor" for the analysis by Artificial Vision[71]

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[68] « "AI Chip Removal" Developed for Automatic Removal of Chips Generated during Machining | News/topics | DMG MORI », s. d., https://www.dmgmori.co.jp/en/trend/detail/id=5484.
[69] « "AI Chip Removal" Developed for Automatic Removal of Chips Generated during Machining | News/topics | DMG MORI ».
[70] « Analyse MyWorkpiece /Toolpath », fw_Routing, siemens.com Global Website, s. d., https://www.siemens.com/global/en/markets/machinebuilding/machine-tools/cnc4you/fokus-digitalisierung/analyse-myworkpiece-tp.html.
[71] Ibid

Regarding the maintenance of machine components, researchers at the Karlsruhe Institute of Technology (KIT) have developed a system for fully automated monitoring of ball screws in machine tools. A camera integrated directly into the disc nut generates images that artificial intelligence continuously monitors for signs of wear, which helps to reduce machine downtime through the use of machine vision[72].

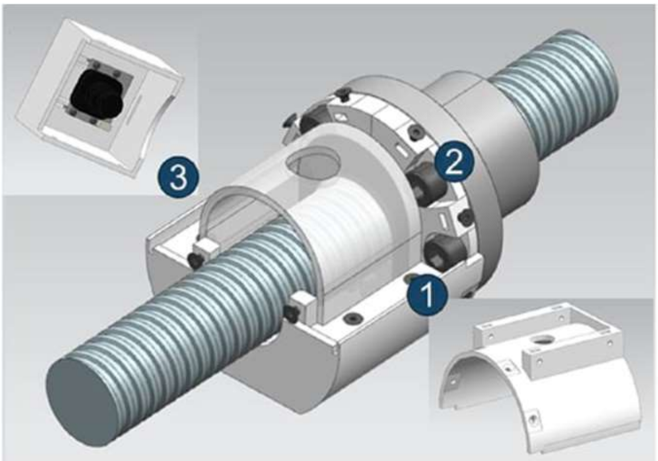

Figure 20. Artificial Vision for intelligent monitoring of the ball screw (KIT)[73]

The Makino i-Assist robot features a host of advanced functions for manufacturing parts using machine vision. For example, it finds its own way to the machine it needs to feed, avoiding any obstacles, picks up parts even if they are not in the correct position, and loads tools into a pre-setting machine.

Figure 21. Robot i-Assist by Artificial Vision of Makinol

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[72] Tobias Schlagenhauf et al., « Integration of machine vision in ball screw drives – Integrated system for condition monitoring of ball screw drives », *wt Werkstattstechnik online* 109 (1 août 2019): 605-10, https://doi.org/10.37544/1436-4980-2019-07-08-95.

[73] Ibid

Multitask and hybrid machines, flexible systems

The industrial capacity of the Basque Country is undoubtedly one of the most important in Spain, and it is also one of the most advanced regions in Europe. Within Basque industry, it is worth highlighting the machine tool sector, which is widely consolidated and is considered strategic for the Basque Country, not only because of the volume it represents, but also because of the pull effect it generates on the entire Basque economy. The Basque machine tool sector is characterised by its high competitiveness, continuous innovation and high rate of internationalisation, with more than 90% of its sales being exported to all corners of the world.

One fact that reflects the importance of the machine tool sector in the Basque Country is that, with Spain being the third largest exporter of machine tools in Europe and the ninth largest in the world, 90% of its machine tool companies are located in the Basque Country. It is therefore clear that the Basque Country is one of the most important machine tool regions in the world and where most technology and added value is being generated.

Due to the great depth and importance of the machine tool sector in the Basque Country, there are numerous entities and administrations that continually propose common actions related to new activities for the sector

More efficient and flexible processes and their effect in terms of productivity gains.

- Predictive Maintenance of Machinery

  The state of the machine condition will be diagnosed continuously and unattended at the customer's site without interfering with production. Normality patterns and supervised learning of the machine's condition will allow the parameters of the machine and its systems to be adapted to the state of the machine and its cabin at any given moment. Continuous modification of the tuning parameters will ensure optimal operating conditions and prolong the service life of the machines.

- Second Best

  The learning of the process executed during the manufacturing of the first part will allow the learning and formulation of prescriptions to improve the manufacturing of the second part according to objective functions selected by the machine operator: reduce times to increase productivity, reduce vibrations and deflections in the tool to improve precision and surface quality, eliminate impacts on the tool and keep the load on the cutting edge constant, reduce the flow of the input material in areas of overgrowth or similar.

- Continuous Dynamic Adjustment of the Machines

  As opposed to an adjustment for a fixed weight and inertia that impairs the dynamics in case of reduced part weight and inertia by finding a compromise solution for any weight and inertia, the continuous adjustment of the machine dynamics will increase the process speed and substantially reduce process times. Parts can undergo drastic weight changes through processing: weight reduction in start-up processes of up to 90% and weight increase in additive processes (up to 100%).

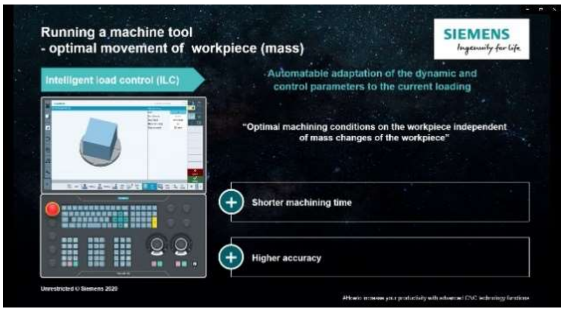
Automation of processes

As with machine condition monitoring and optimisation, including the condition of major components and geometric accuracy, access to machine control and integrated sensor data opens up a world of possibilities related to the condition of the manufacturing processes carried out on the machine. Access to data enables the development of advanced functions aimed at optimising process quality and productivity.

Recently, the most advanced machine manufacturers have been incorporating functionalities for monitoring the condition of the processes carried out on their machines and functionalities for self-adjustment of process control parameters, giving rise to adaptive processes that seek to optimise quality and productivity, as well as facilitating the work of machine operators.

Some of the advanced solutions for process condition monitoring, representative of the state of the art in the manufacturing machine sector, are presented below:

As standard the machines are delivered with the drive parameters set to the highest foreseeable part weight. The Load Adaptive Control (LAC) functions from Heidenhain[74], Intelligent Load Control (ILC) from Siemens[75] and Servonavi from Okuma[76] adapt the settings of the machine axis control according to the weight of the workpiece to be machined. This allows the machine dynamics to be optimised for each workpiece, resulting in shorter process times and greater precision. The adjustment is made possible by the automated calculation of the workpiece weight by means of control parameters recorded in a specific axis movement.



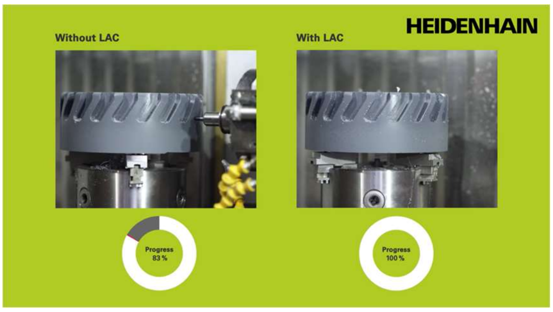


Figure 22. Intelligent Load control of Siemens (left)[77] and Load Adaptive control of Heidenhain (right)[78]

During the high-performance machining process, the high forces generated by the tool can cause vibrations in the machine structure (chatter). In extreme situations, this can lead to damage to the tool, workpiece or machine. DMG MORI, Heidenhain, Mazak, Okuma and Soraluce offer intelligent control solutions to reduce these vibrations.

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[74] « DynamicPrecision.pdf », Heidenhain, 2013, https://www.heidenhain.us/lp/controls/DynamicPrecision.pdf.
[75] « Siemens Machine Tool Days - October 14th, 2020 », siemens.com Global Website, 2020, https://new.siemens.com/global/en/company/fairs-events/events/machine-tool-days.html.
[76] *Okuma's Intelligent Technology - SERVONAVI*, 2016, https://www.youtube.com/watch?v=k4bHmpFui-Y.
[77] « Siemens Machine Tool Days - October 14th, 2020 ».
[78] « DynamicPrecision.pdf ».

DMG MORI's Machine Vibration Control (MVC) function[79] registers vibrations during machining by means of an accelerometer integrated in the electrospindle and detects whether chatter is occurring, in which case the system algorithm proposes new cutting conditions that avoid vibrations. More productive cutting conditions are obtained with less vibration, it provides automatic suggestions of suitable process parameters and allows the vibration status to be monitored by means of different indicators that serve as guidance for the machine operators.

Figure 23. Machine Vibration Control (MVC) of DMG MORI[80]

Heidenhain has developed the Active Chatter Control (ACC) function[81], which calculates a compensation signal based on the number of inserts in the tool and the spindle speed, thus reducing vibrations. This makes it possible to achieve higher feed rates, feed rates and process times, which helps to increase productivity and reduce costs.

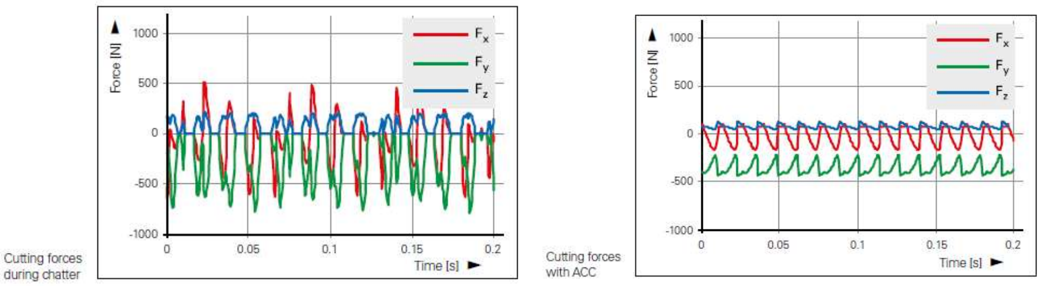

Figure 24. Active Chatter Control (ACC) of Heidenhain[82]

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[79] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[80] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[81] DR JOHANNES HEIDENHAIN GmbH, « Dynamic Efficiency », s. d., https://www.heidenhain.us/lp/controls/DynamicEfficiency.pdf.
[82] GmbH.

Mazak's chatter control solution, Smooth AI Spindle83, detects when chatter is occurring during machining, and using AI techniques searches for optimal machining conditions to reduce or eliminate chatter to improve part quality and enable increased productivity.

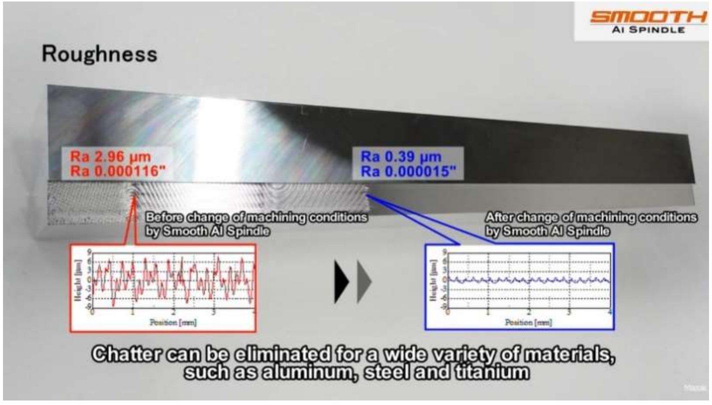

Figure 25. Smooth AI Spindle of Mazak[84]

Okuma's Machining Navi system[85] uses accelerometers to monitor the vibrations of the electro spindle during the cutting process. If necessary, the intelligent control application recommends or automatically adapts the spindle speed, improving machining surface quality and process times.

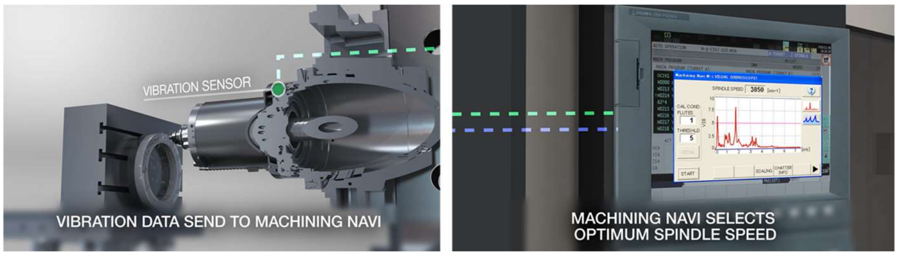

Figure 26. Machining Navi of Okuma[86]

DMG MORI presents Machine Protection Control (MPC)[87], a solution that prevents tool breakage and protects the machine against damage caused by overloads and collisions during machining. With an accelerometer integrated in the machine head, the vibrations produced during machining are recorded and compared live with the reference values for the respective process, values that were obtained in a teaching or learning cycle. The solution monitors the vibrations continuously and generates alarms and machine stops when set thresholds are exceeded.

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[83] *Smooth AI Spindle : Automatic compensation by AI*, 2018, https://www.youtube.com/watch?v=K0pjVRsS2hI.
[84] *Smooth AI Spindle*.
[85] *Okuma's Intelligent Technology - Machining Navi*, 2016, https://www.youtube.com/watch?v=wXfsKomM_tE.
[86] *Okuma's Intelligent Technology - Machining Navi*.
[87] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».

MPC Graph: current and learned process values.

MPC Diagnostics: stock condition, number of impact and crash.

Figure 27. Machine Protection Control (MPC) of DMG MORI[88]

DMG MORI also offers a complementary solution for the prevention of damage due to tool breakage or overloading, which does not require external sensors as it is based on the machine's internal control parameters. Easy Tool Monitoring 2.0[89] consists of an advanced evaluation algorithm with self-learning capability of load limits and efficient control after the first workpiece.

Figure 28. Easy Tool Monitoring 2.0 of DMG MORI[90]

Another solution from the same manufacturer, DMG MORI, is the Tool Control Center[91] for force and bending detection of the cutting head, with sensors integrated in the nose of the electro spindle and wireless data transfer by induction from the rotor to the stator. It allows detection of chips in the bearing and tool taper, monitoring of the tensile force, in-process control of the cutting tool cutting edge by symmetrical tracking of the bending moment per cutting edge and monitoring of the bending moment by history graph. It provides tool and workpiece protection and optimises tool life.

[88] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[89] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[90] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[91] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».

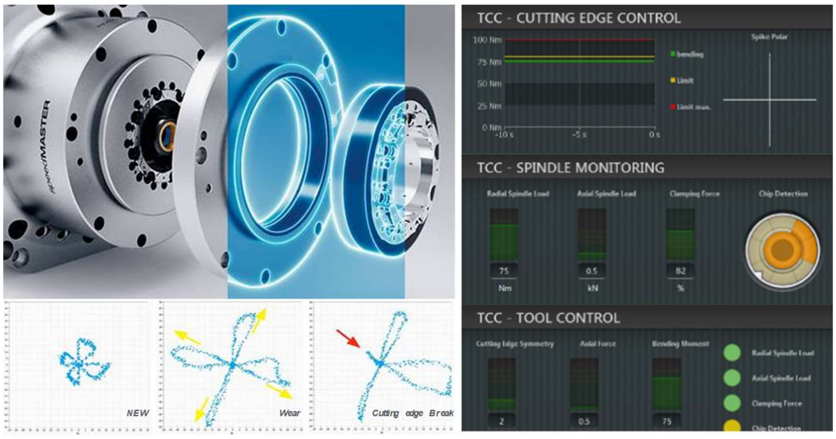

Figure 29. Tool Control Center of DMG MORI[92]

Along the same lines of cutting tool protection, Okuma incorporates Dynamic Tool Load Control in its machines, with the aim of reducing cutting tool wear, achieving stable machining for difficult-to-cut materials. Okuma's Dynamic Tool Load Control[93] compensates for tool deflection by varying the feed rate. Deflection is measured, ensuring a constant load during machining. It increases tool life, improves the quality of machined parts and reduces downtime for tool changes.

To protect the machine against excessive power values and optimise productivity, Heidenhain offers the Adpative Feed Control function[94]. The feed rate in machining operations is usually set depending on the material to be machined, the tool and the depth of cut. If the cutting conditions change during the process, e.g. due to fluctuations in the depth of cut, tool wear or variations in the hardness of the material, the feed rate is usually not changed, so that the process is not optimised because the values are usually set for the worst-case scenario. The AFC function adapts and optimises the machining feed rate in real time, depending on the spindle power. The function continuously compares the momentary power of the process with the reference values and varies the feed rate to keep the power at the reference values. In this way, it increases the productivity of the process while protecting the machine from exceeding excessive power values.

In order to avoid collisions between tool and workpiece during machining, Okuma's Collision Avoidance System (CAS)[95] installed in the machine control monitors the cutting process through a virtual application (with 3D models of the machines, workpieces and tools) that measures the exact shape of the material milliseconds before the machining operation. Potential collisions are detected in time for the control to stop the machine before they occur. It protects the machine,

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92 « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
93 *Okuma's Intelligent Technology - SERVONAVI*.
94 GmbH, « Dynamic Efficiency ».
95 *Okuma's Intelligent Technology - Collision Avoidance System*, 2015, https://www.youtube.com/watch?v=ViONSkhC3SU.

workpiece and tools against collisions and greatly reduces machining setup time as it can also be used in the manual mode of the control.

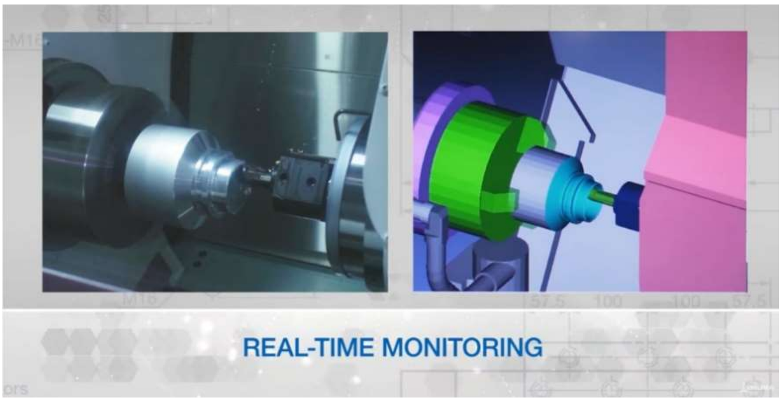


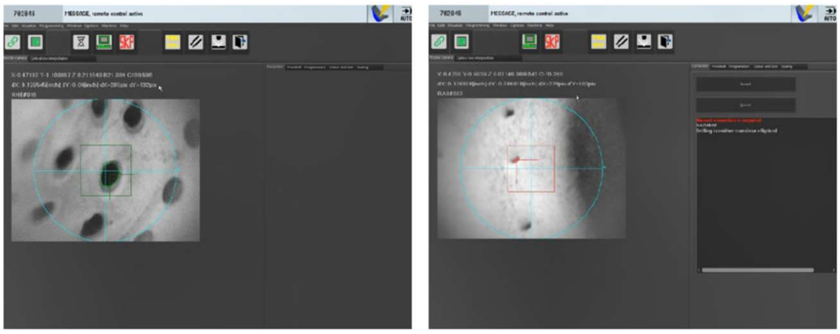
Figure 30. Collision Avoidance System (CAS) of Okuma[96]

In turn, Siemens proposes a solution that integrates a vision camera that monitors the machining process and protects the machine and workpiece from possible collisions through artificial intelligence[97].

Figure 31. Solution to avoid collisions with Artificial Vision of Siemens[98]

Another example of solutions based on machine vision is DMG MORI's Automatic Hole Detection (ADH)[99], for recognition of reference holes in the part (features), comparison with the virtual part and automated translation of the part program on the machine. It reduces the work of positioning and adjusting the part prior to machining, eliminating possible errors and reducing process times.

[96] *Okuma’s Intelligent Technology - Collision Avoidance System.*
[97] « Siemens Machine Tool Days - October 14th, 2020 ».
[98] Ibid
[99] « DMG MORI France - Machines-outils CNC pour toutes les applications de l’enlèvement de matière ».



Automatic detection and position compensation of round and elliptical drill holes

Possibility for manual correction of hardly detectable or partially closed drill holes

Figure 32. Automatic Hole Detection (ADH) of DMG MORI[100]

Taking a particular look at EDM, this process requires a great deal of variable control to achieve a stable cut, which has forced machine manufacturers to develop digital generators capable of controlling and acting on individual discharges. The control of discharges influences the achievement of priority objectives such as increasing removal rates or improving the surface integrity of the parts, but also opens an opportunity to adapt the process to specific part characteristics or working conditions, such as detecting part cutting thickness, avoiding wire breakage, predicting wear, estimating component life, etc. If this is combined with the information acquired from the CNC itself and the use of new sensors on the machine, its environment or the part itself, it is possible to acquire enough information from the process to apply techniques with predictive and decision-making capabilities.

Thanks to this, manufacturers of EDM machines have begun to integrate intelligent systems into the machines to facilitate the user's work. GF Machining Solutions has integrated the optional Spark Track system into its wire EDM machines[101]. Although the principle of this system has been known for more than 30 years, it could not be implemented until now due to the absence of the necessary electronics for signal processing. GF integrates state-of-the-art sensors in its machines that detect in real time where each discharge occurs along the wire and its intensity, and then process all this data and generate application modules to better control the cutting process. The processing is done using FPGAs (Field Programmable Gate Arrays), programmable devices to extract from the electrical signals the most significant characteristics for the process in real time.

The first module presented is the Intelligent Spark Protection System (ISPS), which prevents wire breakage thanks to constant monitoring of discharges in variable-section parts and adaptive control of process parameters. This results in an increase in performance. In addition to this module, according to GF, the Spark Track system opens the way for further innovation in wire EDM and the implementation of research carried out more than 30 years ago thanks to

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[100] « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
[101] « ISPS - Intelligent Spark Protection System », GF Machining Solutions Sales Switzerland SA - Suisse, s. d., https://www.gfms.com/fr-ch/machines/edm/wire-cutting/intelligent-spark-protection-system.html.

the capabilities of new sensors, the processing speed of signal acquisition and processing systems and the application of AI algorithms[102].

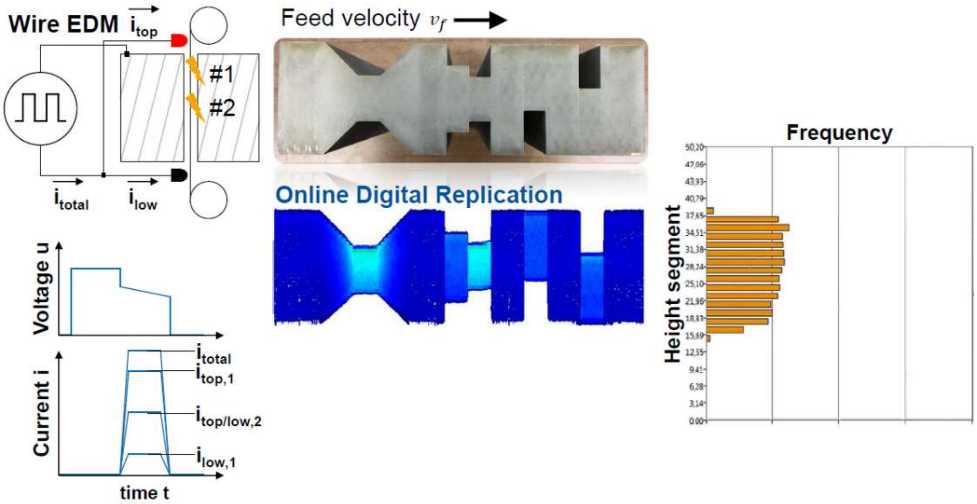

Figure 33. SparkTrack system of GF Machining Solutions[103]

Other manufacturers, such as Makino, have recently presented a paper showing the development of a system for online analysis of machine signals in wire EDM using FPGAs for process performance control[104]. They also mention that the developed control system can be implemented in other applications such as wire breakage control.

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[102] M. Boccadoro, R. D'Amario, et M. Baumeler, « Towards a Better Controlled EDM: Industrial Applications of a Discharge Location Sensor in an Industrial Wire Electrical Discharge Machine. », *Procedia CIRP*, 20th CIRP CONFERENCE ON ELECTRO PHYSICAL AND CHEMICAL MACHINING, 95 (1 janvier 2020): 600-604, https://doi.org/10.1016/j.procir.2020.02.266.

[103] Boccadoro, D'Amario, et Baumeler.

[104] Ugur Küpper, Tim Herrig, et D. Welling, « Evaluation of the Process Performance in Wire EDM Based on an Online Process Monitoring System », *Procedia CIRP* 95 (2 février 2021): 360-65, https://doi.org/10.1016/j.procir.2020.02.325.

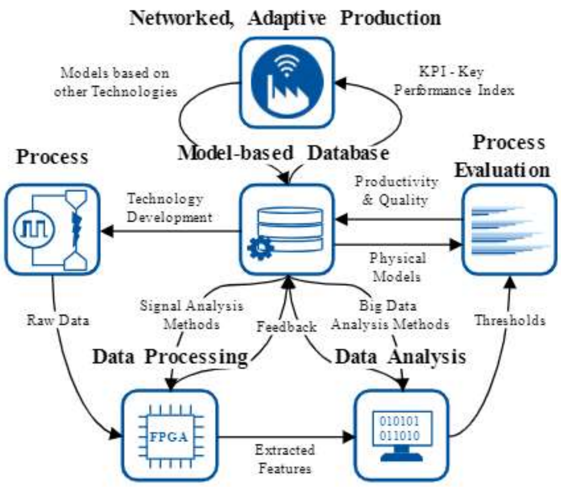

Figure 34. Process data analysis system of Makino[105]

In the field of additive manufacturing, in order to obtain a reliable and efficient industrial input process, it is of vital importance to monitor the process by acquiring internal signals.

An example of this is the DMG MORI AM-Evaluator[106] solution for data logging of the additive manufacturing process. It provides a detailed analysis of relevant process data, in 3D model format, as well as in time graphs. It allows comparisons of different processes to be made for user support, enabling processes to be optimised and quality to be improved. Data logging also provides traceability of the manufacturing of each part.

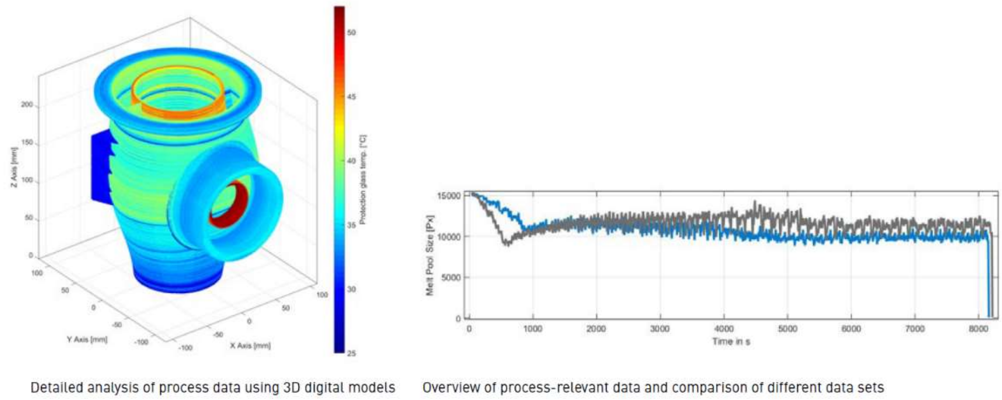

Figure 35. AM-Evaluator of DMG MORI[107]

Additive Manufacturing

In Additive Manufacturing it is also necessary to include closed loop control systems within the process that act on the main parameters (power, powder feed and flow/wire feed, etc.) adapting automatically according to the data recorded during the process. Recent studies in additive

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105 Küpper, Herrig, et Welling.
106 « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».
107 « DMG MORI France - Machines-outils CNC pour toutes les applications de l'enlèvement de matière ».

technologies have incorporated process monitoring and control systems in machines dedicated to additive manufacturing and have developed control algorithms to diagnose the process during input. This is essential to ensure the quality of the parts and to prevent errors such as pores, non-fusion zones or deformations. The inclusion of these systems implies integrating more systems into the process that interact with the rest of the machine and with the casting paths.

More specifically, regarding Laser Cladding technology, the most frequent monitoring parameters in the state of the art are the geometry of the molten bath, defects in the structure (porosities and cracks), height of the deposited material or simply temperature[108]. Most efforts have focused on monitoring temperature, molten bath size and deposited layer height in addition to the subsequent dimensional control of the deposited geometry.

The following is a description of the work focused on monitoring and controlling the main process parameters in additive manufacturing by Laser Cladding, which are the molten bath, the layer height, powder flow and the final delivered geometry:

- **Melting bath:** Temperature is a relevant parameter that affects the metallurgical structure[109] and the dimensional accuracy of the input material. As material is added, the substrate heats up, so if you continue to add material in the same area, the process will reach higher temperatures. This will increase the molten pool and dilution causing dimensional differences, differences in structure and mechanical characteristics in the different layers of input material. It will also increase the fluidity of the input material and may cause loss of shape and, if the temperature reached is too high, evaporation of material as in a laser cutting process.
  The control of the temperature and size of the molten bath is done by reducing the power in a closed control during the process. Control of the molten bath can be done with a CMOS camera and a closed-loop control algorithm controlling the dilution and hardness of the coatings by keeping the values constant[110]. The temperature is controlled by pyrometers or thermographic cameras. However, measurements in this process are characterised by the noise caused by the injected powder[111], making it difficult to obtain a clean reading of the temperature and geometry of the molten bath.

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[108] Adrita Dass et Atieh Moridi, « State of the Art in Directed Energy Deposition: From Additive Manufacturing to Materials Design », *Coatings* 9 (29 juin 2019): 418, https://doi.org/10.3390/coatings9070418.
[109] Mohammad H. Farshidianfar, Amir Khajepouhor, et Adrian Gerlich, « Real-Time Monitoring and Prediction of Martensite Formation and Hardening Depth during Laser Heat Treatment », *Surface and Coatings Technology* 315 (15 avril 2017): 326-34, https://doi.org/10.1016/j.surfcoat.2017.02.055.
[110] J. T. Hofman et al., « A Camera Based Feedback Control Strategy for the Laser Cladding Process », *Journal of Materials Processing Technology* 212, nº 11 (1 novembre 2012): 2455-62, https://doi.org/10.1016/j.jmatprotec.2012.06.027.
[111] Ahmad Mozaffari et al., « Optimal Design of Laser Solid Freeform Fabrication System and Real-Time Prediction of Melt Pool Geometry Using Intelligent Evolutionary Algorithms », *Applied Soft Computing*, Hybrid evolutionary systems for manufacturing processes, 13, nº 3 (1 mars 2013): 1505-19, https://doi.org/10.1016/j.asoc.2012.05.031.

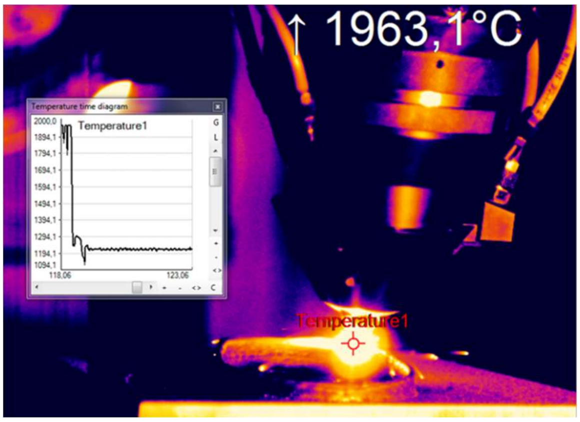

Figure 36. Image of temperatura measurement with a thermal camera.

However, alterations in the mean noise amplitude have been related to process instabilities such as damage to the laser head protective lens[112] or oxidation and dilution problems[113]. Aligning the chamber coaxially is strongly recommended as the lateral arrangement, although simpler, can lead to measurement errors.

This type of control improves the profile of the deposited material by reducing its waviness and therefore stabilises the cutting forces to which the tool is subjected in subsequent machining. It also makes it possible to monitor defects such as lack of fusion or porosity[114]. However, it is not clear what effect power control has on the efficiency of the process and whether the deposited layer height remains constant using this type of control.

Power control is critical in thin substrate coating applications such as pipelines for the petrochemical sector. In such cases the temperature rise with process time is excessive and leads to severe damage to the substrate. An example of this control is the CLAMIR system for the control of coatings manufactured by DED [New Infrared Technologies].

- **Layer height:** Controlling the height of the applied layer is also critical. If the deposited layer grows less than calculated, after several layers the deposition distance between

[112] Pedro Ramiro et al., « Characteristics of Fe-Based Powder Coatings Fabricated by Laser Metal Deposition with Annular and Four Stream Nozzles », *Procedia CIRP*, 10th CIRP Conference on Photonic Technologies [LANE 2018], 74 (1 janvier 2018): 201-5, https://doi.org/10.1016/j.procir.2018.08.094.
[113] Guijun Bi et al., « Identification and Qualification of Temperature Signal for Monitoring and Control in Laser Cladding », *Optics and Lasers in Engineering* 44, nº 12 (1 décembre 2006): 1348-59, https://doi.org/10.1016/j.optlaseng.2006.01.009.
[114] Zhong Yang Chua, Il Hyuk Ahn, et Seung Ki Moon, « Process Monitoring and Inspection Systems in Metal Additive Manufacturing: Status and Applications », *International Journal of Precision Engineering and Manufacturing-Green Technology* 4, nº 2 (1 avril 2017): 235-45, https://doi.org/10.1007/s40684-017-0029-7.

the laser head and the substrate will be greater, causing a poor deposition process and generating a dimensionally defective structure[115].

This layer control can be performed during the deposition process by triangulating a coaxial laser beam of a different wavelength than the deposition laser[116] and varying the deposition rate[117] so that the layer grows as much as required. Height control can also be performed by stopping the process between layers, obtaining the actual input geometry using structured light and adapting the trajectories to the differences with the programmed geometry[118].

It is important to point out that both the laser height control and the control of the molten bath and temperature are carried out coaxially. This fact, together with the fact that they influence different process parameters, can cause space problems to integrate all the necessary sensors and incompatibilities in the control strategies if they are not developed as a joint control.

The height control developed within the European PARADDISE project by Siemens using a Precitec sensor based on interferometry [Siemens, Height control] for the laser beam process is a clear example[119].

- **Powder Flow:** One of the problems with monitoring the flow in laser sputtering processes is the low powder flow rate (between 5 and 20 g-min-1) compared to other processes such as thermal spraying. Monitoring systems based on the weight of gravimetric feeders are often not effective in generating a uniform flow in these cases and this can result in a deposition process with significant variations in the amount of material deposited[120]. This is why, to monitor the powder flow in the laser deposition process, optical sensors are often used in the flow path due to the direct impact that the powder in the flow has on the intensity of the light that can be detected [MEDICOAT, Flow Watch]. A photoresistor transforms this light intensity into a voltage that allows the

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115 Andrew J. Pinkerton et Lin Li, « The Significance of Deposition Point Standoff Variations in Multiple-Layer Coaxial Laser Cladding (Coaxial Cladding Standoff Effects) », *International Journal of Machine Tools and Manufacture* 44, nº 6 (1 mai 2004): 573-84, https://doi.org/10.1016/j.ijmachtools.2004.01.001.
116 Simone Donadello et al., « Monitoring of Laser Metal Deposition Height by Means of Coaxial Laser Triangulation », *Optics and Lasers in Engineering* 112 (1 janvier 2019): 136-44, https://doi.org/10.1016/j.optlaseng.2018.09.012.
117 « Additive Manufacturing: New Process Improves Speed and Reliability », fw_Inspiring, siemens.com Global Website, s. d., https://www.siemens.com/global/en/company/stories/research-technologies/additivemanufacturing/additive-manufacturing-laser-metal-deposition.html.
118 Iker Garmendia et al., « Structured Light-Based Height Control for Laser Metal Deposition », *Journal of Manufacturing Processes* 42 (1 juin 2019): 20-27, https://doi.org/10.1016/j.jmapro.2019.04.018.
119 « ADDITIVE MANUFACTURING APPARATUS AND METHOD - US20210039167 », 2020, https://patentscope.wipo.int/search/es/detail.jsf?docId=US317629321.
120 Vishnu Thayalan et Robert G. Landers, « Regulation of Powder Mass Flow Rate in Gravity-Fed Powder Feeder Systems », *Journal of Manufacturing Processes* 8, nº 2 (1 janvier 2006): 121-32, https://doi.org/10.1016/S1526-6125(06)80007-1.

flow to be monitored and to act directly on the powder feeder depending on the signal generating a closed-loop control.

As the flow is carried several meters to the injectors in the die, a control system with short response times is complicated, so these control systems are used to ensure a stable flow during the process. Powder characteristics such as size, density or surface area have a direct effect not only on the flow provided by the feeder but also on the response of the sensor.

- **Verification of the geometry obtained**: The low dimensional accuracy of the process coupled with the uncertainty of the final geometry obtained makes an inspection prior to the machining stage necessary. In repair and coating applications there is also an uncertainty of the initial substrate geometry so the substrate must also be inspected before the additive process.

  This inspection stage is more critical in hybrid additive manufacturing machining as its main advantage is to incorporate both processes without the need to move the part. This eliminates errors associated with geometry manipulation and mismatch. However, for this solution to be fully realised, an in-situ measurement system must also be incorporated.

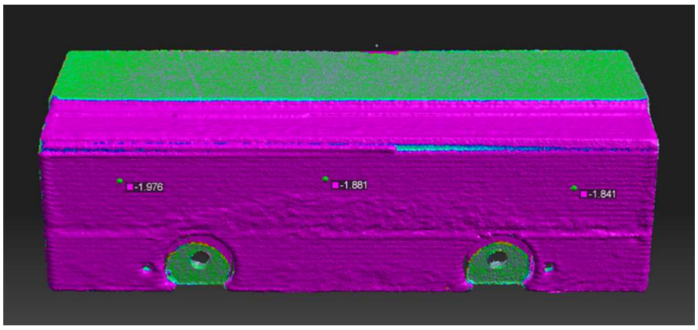

Figure 37. Measurement of a coating applied by laser using structured light.

Although various methods have been studied in other additive technologies[121], not many alternatives have been studied for laser cladding processes. Siemens has incorporated into its NX software the inspection of additive parts using a stylus to validate quality[122] and other work

121 Magdalena Cortina et al., « Latest Developments in Industrial Hybrid Machine Tools That Combine Additive and Subtractive Operations », *Materials* 11, nº 12 (décembre 2018): 2583, https://doi.org/10.3390/ma11122583.

122 « Tecnomatix Digital Manufacturing Software | Siemens Software », Siemens Digital Industries Software, s. d., https://plm.sw.siemens.com/en-US/tecnomatix/.

has focused on 3D laser scanning[123] or structured light measurement systems[124] integrated into the machine itself.

In the case of WAAM - Wire Arc Additive Manufacturing technology, the main process parameters to be controlled are the signal intensity, voltage, wire feed, speed of the moving system, etc.

The following figure shows the monitoring of the energy used during the WAAM process in the manufacture of a single aeronautical hardware and in the manufacture of three aeronautical hardware in matrix form.

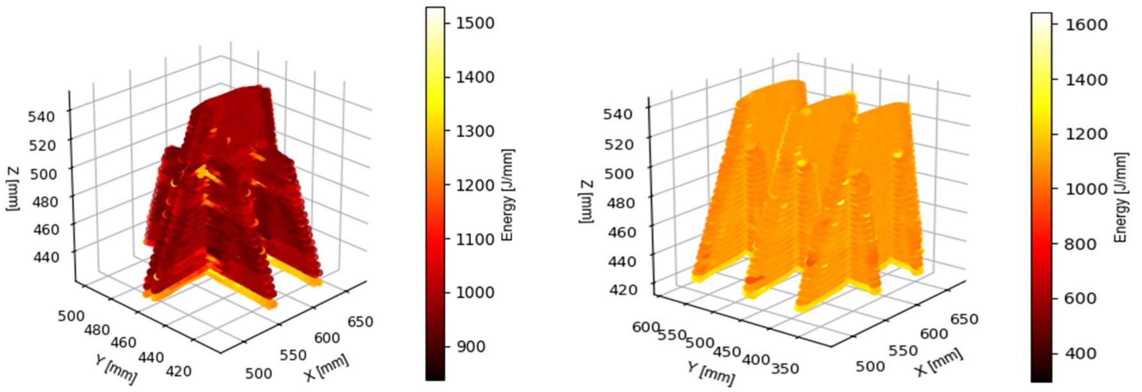

Figure 38. Monitored energy during the manufacture of a single aeronautical fitting (left) and during the manufacture of three matrix-shaped aeronautical fittings (right).

On the other hand, elements such as vision systems, geometric lasers, pyrometers, etc. have sometimes been integrated:

- **Visual control systems:** Several studies have shown that in order to reduce defects in the parts, the most important thing is to control the width and height of the wall, and

[123] Yuan Liu, Thomas Bobek, et Fritz Klocke, « Laser Path Calculation Method on Triangulated Mesh for Repair Process on Turbine Parts », *Computer-Aided Design* 66 (1 septembre 2015): 73-81, https://doi.org/10.1016/j.cad.2015.04.009.

[124] Amaia Alberdi et al., « Egituraturiko argiaren aplikazioak fabrikazio hibridoaren bidez pieza metalikoak ekoizteko », *EKAIA EHUko Zientzia eta Teknologia aldizkaria*, 2 avril 2019, https://doi.org/10.1387/ekaia.19829.

for this, on-line monitoring of the melt pool is an essential part of the control. In these cases, visual control systems are commonly used for this application[125] [126] [127].

- **Geometric laser:** Another control strategy for WAAM processes is often the scanning of each layer after deposition with a geometric laser. This provides three-dimensional information of the deposited weld beads in the form of a point cloud and allows the deviation in the height and width of each layer to be monitored and the parameters of the next layer to be adjusted to compensate for this[128].
- **Oxygen level gauges:** Oxygen level gauges are used for materials that require an enclosed space with a controlled atmosphere for deposition to ensure the quality of the manufacturing atmosphere[129].
- **Pyrometers:** Another control method is the monitoring of the melting pool temperature by means of pyrometers[130], since, in the WAAM process, temperature is a fundamental parameter due to the complicated thermal history of the parts manufactured by this method.

As an example, at Chalmers University they are working on WAAM technology using a robot and a table with an additional rotation for LMD technology. The most characteristic feature of their system is that it focuses on an exhaustive monitoring of the process, with up to 3 cameras in the head, as can be seen in the figure below[131]. In addition, the latest version of the system incorporates a laser scanner mounted on a protective housing. In the latest version of the system, a laser scanner mounted on a protective housing has been incorporated.

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[125] Zengxi Pan et al., « Arc Welding Processes for Additive Manufacturing: A Review », in *Transactions on Intelligent Welding Manufacturing*, éd. par Shanben Chen, Yuming Zhang, et Zhili Feng, Transactions on Intelligent Welding Manufacturing (Singapore: Springer, 2018), 3-24, https://doi.org/10.1007/978-981-10-5355-9_1.
[126] Y. M. Zhang, H. S. Song, et G. Saeed, « Observation of a Dynamic Specular Weld Pool Surface », *Measurement Science and Technology* 17, nº 6 (mai 2006): L9, https://doi.org/10.1088/0957-0233/17/6/L02.
[127] Jun Xiong et al., « Vision-Sensing and Bead Width Control of a Single-Bead Multi-Layer Part: Material and Energy Savings in GMAW-Based Rapid Manufacturing », *Journal of Cleaner Production* 41 (1 février 2013): 82-88, https://doi.org/10.1016/j.jclepro.2012.10.009.
[128] Almir Heralić, Anna-Karin Christiansson, et Bengt Lennartson, « Height Control of Laser Metal-Wire Deposition Based on Iterative Learning Control and 3D Scanning », *Optics and Lasers in Engineering* 50, nº 9 (1 septembre 2012): 1230-41, https://doi.org/10.1016/j.optlaseng.2012.03.016.
[129] T. Artaza et al., « Design and Integration of WAAM Technology and in Situ Monitoring System in a Gantry Machine », *Procedia Manufacturing*, Manufacturing Engineering Society International Conference 2017, MESIC 2017, 28-30 June 2017, Vigo (Pontevedra), Spain, 13 (1 janvier 2017): 778-85, https://doi.org/10.1016/j.promfg.2017.09.184.
[130] Artaza et al.
[131] Almir Heralic, « Monitoring and Control of Robotized Laser Metal-Wire Deposition », 2012, 82, https://www.semanticscholar.org/paper/Monitoring-and-Control-of-Robotized-Laser-Heralic/76527b9a6ea6a1c8256e1b23884d991de56759e0.

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4. INDEX OF IMAGES

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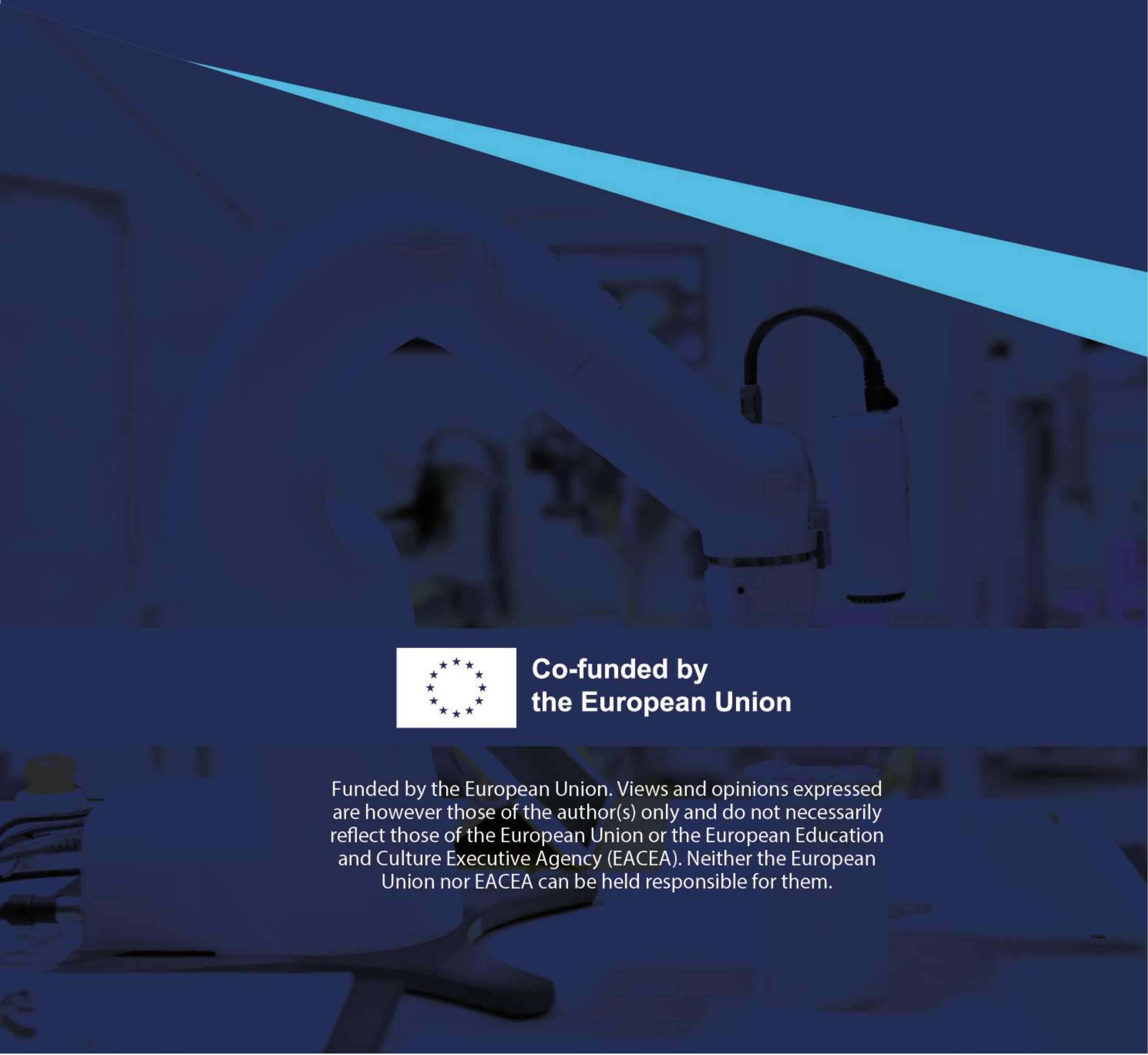

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