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Quality, efficiency and sustainability improvement in machining processes using Artificial Intelligence.

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Abstract

The fourth industrial revolution is a reality and involves digitalisation and the use of artificial intelligence (AI). AI refers to techniques that enable machines or devices to learn, make decisions and optimise processes in a way that simulates human cognitive processes. These capabilities can positively influence machining processes, making them more competitive, more efficient, more sustainable and increasing the quality of the workpieces produced. While in some sectors, such as medicine, these techniques are highly developed, there is not the same level of involvement in industry, especially in the Spanish machining industry. It is necessary to take a step forward in order to be competitive in the face of increasingly high customer demands and reduce the gap between the progress of machining research and actual use in industry. In addition, these technological advances have not been welcomed by workers and citizens as optimistically as would have been desired. This paper will list all the aspects in which AI is a powerful tool for the improvement of machining processes, review the state of industry, especially in Spanish machining companies, and finally examine the social vision of its implementation.

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Keywords: Artificial intelligence; Machining processes; Social perception; Spanish Machinig Industry.

1. Introduction.

The machining industrial sector is currently in a period of global recovery, facing the shortage of raw materials and its increasing prizes. Companies must deal these constraints and improve their efficiency to be competitive. In addition, sustainability policies and the increasingly demanding requirements must be considered. The industrial environment is complex, being necessary to seek efficiency using new technologies.

Industry 4.0, increasing connectivity and digitisation of organisations, supports this last industrial transformation. To talk about the advances available is to talk about artificial intelligence (AI), which is revolutionising the world as we know it. There are many improvements that AI offers in the field of machining in terms of efficiency, quality and sustainability. In the following section the influence of the AI on the machining processes is reviewed.

2. Artificial Intelligence in machining processes.

2.1. Raw material, machining tools & equipment and machining process selection.

Determining the conditions of the machining processes even if they are conventional ones, is very complex task due to the quantity of variables to be considered. AI can make optimal decisions based on objective input data.

2.1.1. Raw Material Selection.

The right raw material selection is essential as it can improve productivity, material utilisation and the flexibility, reliability and repeatability of the process [1].

In raw material selection, there are a multitude of characteristics to consider, not only in terms of the material itself but also how that material affects the process. With the

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purpose of making a successful material selection, several authors employ the available AI methods:

Zeynali *et al.* [1] consider the selection of the combination of materials as a multiple criteria decision making (MCDM). A Fuzzy Analytical Hierarchy Process (AHP) approach is used to calculate the weight of each criterion that leads to the selection of the most suitable materials and, subsequently, the Fuzzy Technique for Order Preference by Similarities to Ideal Solution (TOPSIS) method is applied to obtain the optimised results.

Denkena *et al.* [2] propose the identification of different materials during a machining operation, which is very useful to adjust the operation parameters. The study was based on the changes in vibration and force caused by different materials. The results showed that neural networks (ANN) are able to classify materials according to the cutting parameters in turning.

2.1.2. Equipment and tools selection.

The appropriate selection of machine tools, tools and their supports are essential to obtain the desired product, in terms of forming and quality, and to achieve optimum process conditions, for example, dimensional accuracy and cycle time [3]. An inappropriate choice may lead to extra costs, negative impacts on productivity, accuracy, flexibility and responsiveness of the company.[4].

Currently, most companies make their choice based on the experience and knowledge of the people in charge. The use of AI makes it possible to consider more information objectively.

Keung *et al.* [5] decided to employ genetic algorithms for the choice of machining centre by addressing scheduling in a flexible manufacturing system. Alam *et al.* [6] use also genetic algorithms with the aim of reducing the cycle time.

Ayağ and Özdemir [4] include machine tool selection in the scope of multiple-criteria decision making (MCDM). The fuzzy AHP approach allows more accurate decision making as it serves to weight the alternatives under various attributes such as those belonging to the categories of productivity, flexibility, space, adaptability, accuracy, reliability, safety and environment, and maintenance and service. Subsequently, a benefit/cost analysis is carried out, from which the most suitable machine-tool option is obtained.

Önüt *et al.* [7] applies a two-stage model: 1-Fuzzy AHP procedure 2-Fuzzy TOPSIS for the selection of the most suitable CNC machining centre among the proposed in a Turkish company. Ic and Yurdakul [8] also applied Fuzzy AHP and Fuzzy TOPSIS logics to create a decision support system in an intuitive way for user companies.

Taha and Rostam [9] present a decision system based on a fuzzy analytic hierarchy process complemented with the Preference Ranking Organization METHod for Enrichment Evaluation (PROMETHEE). The fuzzy AHP method helps to propose the weights of each of the selection categories while the PROMETHEE method performs the final ranking.

Albertí *et al.* [10] use neural networks to model a selection system for high-speed machining centres. Starting from three types of variables related to the product, to the machine configuration and to the operation itself. Machine selection is based on accuracy/error ratio, error, time and cost of the process and machine tool cost.

Additionally, one of the characteristics that can be directly affected by choosing the wrong tool is its own wear, which influences the performance metrics. There are several factors that determine the selection of cutting tools [3] as mechanical properties, applicability, replenishment stock, accuracy and finishing requirements, type of machine-tool used, production requirements, operating conditions and costs. Several research have been used the AI to the task of tool and holder selection and sequencing:

Gjelaj *et al.* [11] propose an improvement in tool selection on CNC machining centres based on the use of genetic algorithms.

Kunaparaju *et al.* [12] propose a model that starts from a database of tools and operation data and use an adaptive neuro-fuzzy system to obtain a tools list suitable for the machining operation and genetic algorithm to optimise tool selection and machining parameters. This optimisation is based on maximising the material removal rate and tool life and minimising tool cost.

Ahmad *et al.* [13] propose a new method to obtain a cost-optimal tool sequence, by applying genetic algorithms, for 2.5-axis pocket machining. The input data considered are the geometry of the pocket and the part, the set of available tools, the cutting parameters and the geometry of the tool holder.

Lim *et al.* [14] address tool sequence optimisation by employing geometric algorithms that favour the largest tool capable of more complete volumetric clearance.

2.1.3. Machining process selection.

It should be considered that the appearance of new materials, new machining processes and the evolution of machine tools, renders the selection decision more complex, slower and less efficient. AI in this phase is crucial as it reduces human error, improves efficiency, reduces time and considers all data related. The authors have used various AI strategies to achieve an optimal process selection:

Ahmad [15] proposes a CAPP model covering from part design, feature extraction to optimisation of process parameters by means of genetic algorithms.

Ahmad and Haque [16] employ neural networks for cylindrical surface machining process selection.

Wong *et al.* [17] solve the decision of the selection and sequencing of machining processes with a hybrid approach through Fuzzy Expert System (ES) and Genetic Algorithms (GA). This approach optimized the sequencing with a cost-tolerance model.

Deja and Siemiatkowski [18] propose the use of algorithms for the selection of the machining process and its sequencing. Based on the machining characteristics and part attributes, and considering the available machine tools, the algorithm performs the selection of the most suitable operation and its sequencing.

Nallakumarasamy *et al.* [19] perform an approach using a superhybrid genetic algorithms-simulated annealing technique. The genetic algorithm provides an optimal solution to the simulated annealing technique with the aim to obtain a higher quality result and reduces the computational time.

2.2. AI to optimize the machining process.

The selection of the optimal machining process is about determining the ideal process parameters to maximise productivity and savings, reduce process cost, environmental impact and meet customer requirements. Achieving these optimum operating parameters has been the subject of many studies, as it is one of the key aspects of process efficiency:

Bakhtiyari *et al.* [20] propose AI hybrid methods, such as GA-ANN model, to achieve laser beam machining optimisation focusing on quality and performance aspects.

Boga and Koroglu [21] also employ a hybrid intelligence approach consisting in neural networks adjusted by means of a genetic algorithm to estimate the surface roughness of a fibre-carbon composite part in a milling process.

Muthuram and Frank [22] integrate the ANN technique into genetic algorithms to find the combination of parameters that maximises the Material Removal Rate (MRR) and minimises the surface roughness.

Cus and Balic [23] aimed to optimise cost and operation time by finding the best values for the cutting parameters. To this end, genetic algorithms are employed in which several objective functions and constrains are considered. D'Addona and Teti [24] also worked on turning process with genetic algorithms. The objective functions are mainly focus on minimize production cost and maximize production and profit rate.

Zuperl *et al.* [25] propose a hybrid system for this purpose. The hybrid system is developed thanks to ANN and the TOPSIS routine.

An interesting perspective is developed by La Fé-Perdomo *et al.* [26] in which, in addition to the technical-economic vision, they incorporate the environmental dimension in the selection of the ideal parameters for a multipass turning process. The decision variables chosen are based on the cutting parameters: speed, feed and depth of cut. In addition, two objective functions were considered. The first one represents the process costs while the second one reflects the environmental impact through energy consumption and tool life (tool wear). The optimisation to obtain the suitable parameters was carried out using two different techniques to be compared: the non-sorting genetic algorithm II and the multi-objective particle swarm optimization. Both provided effective results in terms of sustainable optimisation. However, the genetic algorithms presented a superior response in terms of quality as well as computational efficiency.

The new perspective of Yoo and Kang [27] on the search of optimisation of machining processes based on manufacturing cost estimation using deep learning should finally be highlighted. It is not based on the cutting parameters but in the material, final piece form and costs of the process.

2.3. Machining Process Monitoring.

The great relevance of monitoring in machining processes is evident in the large number of scientific articles and studies related to it. The scope of monitoring is the analysis of [28]: Tool, chip and process conditions, surface integrity, machine tool state, chatter detection, etc. The application of AI tools allows all data collected by sensors to be analysed more quickly, reliably and accurately.

2.3.1. Tool wear and failure monitoring.

Tool wear is a very important aspect with respect to productivity, process time, quality of the part produced and the total cost of the machining operation. There is also the possibility of premature failure, which causes unexpected material losses, production delays, etc. Tool change is mostly dependent on the knowledge and experience of the operator and those responsible for the machining process. Tool wear prediction is a very complex task due to the large number of variables involved. Several authors consider AI as a great help in this field:

Caggiano *et al.* [29] present the use of ANN in the prediction of wear and workpiece quality in a drilling process of a carbon fibre reinforced plastic. Focusing on wear and, above all, on how to maximise tool life in carbon fibre reinforced plastic drilling operations, Caggiano *et al.* [30] delve into the combination of force and cutting torque signal analysis and ANNs for condition estimation. Also studying drilling operations in composites, Zhu *et al.* [31] employ a back propagation neural network to estimate the drilling force in a SiCp/Al material by taking cutting speed and feed rate data.

If we talk about another type of machining operation such as polishing, the work of D'Addona *et al.* [32] shows that ANNs (Back propagation neural networks) present an acceptable result in terms of wear estimation of a grinding wheel, based on vibration signals.

Mention should equally be made of the works by Corne *et al.* [33] and Drouillet *et al.* [34], which also use ANNs for the prediction of tool wear. In both cases, the study is carried out using spindle power signals.

D'Addona and Teti [35] propose a methodology to determine tool wear by means of images captured by a video camera and using Back-propagation Neural Networks.

Bergs *et al.* [36] present the application of deep learning for tool wear detection from digital images. Deep learning is represented by two neural networks with two different tasks: Convolutional Neural Networks (CNN) that are used for the classification of images for the identification of tool types and Fully Convolutional Networks (FCN) that allow the detection of the tool wear area.

The work of Brili *et al.* [37] aims to estimate tool wear and possible tool failure by means of CNN in dry turning operations. A camera that provides thermographic information in addition to visual feedback has been proposed to monitor the machining process.

Based on temperature signals, He *et al.* [38] propose a Deep Learning model for tool wear prediction during CNC turning operation. As a Deep Learning technique, they use the stacked sparse autoencoders with a backpropagation neural network for regression model.

Most of the works are focused on the detection of gradual tool wear (GTW) and secondarily on catastrophic tool failure (CTF). However, Bombiński *et al.* [39] aim to identify accelerated tool wear (ATW) in turning using the cutting force in diverse time windows. To achieve its goal, pre-trained algorithms to automatically detect it are employed.

2.3.2. Quality performance monitoring.

The aim of any machining process is to achieve products that meet the technical requirements with sufficient quality to satisfy the customer in the shortest possible time and at the lowest possible cost. Even though quality is a highly relevant topic, there are a limited number of articles that directly discuss the use of AI in quality monitoring. It is true that there are a large number of articles whose aim is to monitor tool wear with the dual objective of extending tool life and ensuring workpiece quality.

Surface roughness acts as an indicator of the quality of the product obtained and also of the behaviour of the process. Some studies have the objective of controlling the quality by means of AI:

Correa *et al.* [40] tested the advantageous use of Bayesian networks over neural networks for estimating surface quality in high-speed milling processes.

Babu *et al.* [41] employ Fuzzy logic to predict surface roughness in the drilling operation of Oil Hardened Non - Shrinking Die Steel.

Moreira *et al.* [42] use an Adaptive neuro-fuzzy interference system (ANFIS) for the determination of surface roughness on a CNC machine by means of an integrated monitoring system.

Mention should also be made of the work of Chen and Kudapa [43] in which two models are presented for roughness estimation based not only on the parameters but also on the cutting current. The first is a fuzzy inference system (FIS), in which the rules are set by experts, and the second is a neuro-fuzzy system (ANFIS). The experimental result shows that the ANFIS model is more accurate in its estimation.

The work of Wang *et al.* [44] is noteworthy because it presents an unsupervised AI approach for estimating geometric quality in a wire electrical discharge machining process. Sometimes roughness is not as critical as dimensional tolerances can be. This work is novel because of the integration of these three factors: non-conventional machining, quality understood as compliance with geometric tolerances, the use of unsupervised AI in this field and the choice of the variable: distribution of ionization time instead of voltage.

2.3.3. Machine anomalies monitoring.

Typically, the monitoring of machining processes is focused on cutting parameters and tool condition, but the early detection of machine tool anomalies should not be left behind, as their malfunctioning also influences cost, lead time and workpiece quality. Netzer *et al.* [45] proposed a system based on the mean shift cluster algorithm for anomaly detection. The study showed that unsupervised techniques can be an effective tool for detecting anomalies in environments with high uncertainty since they do not have any a priori knowledge of the variable conditions or operation of the machine.

2.4. Process sustainability.

The sustainability of machining processes involves reducing their environmental impact, mainly in terms of the energy resources and toxic products consumption. In order to reduce the impact, it is necessary to carry out an adequate selection and control of the toxic products used and energy consumption.

2.4.1. Cooling and lubrication selection and control.

Lubrication and cooling are essential in machining operations as they lower the temperature, delay tool wear, protect the workpiece, increase its quality, allow chip evacuation, reduce friction and remove metal particles. There are several areas where AI can be a differentiator factor:

- Selection of the most sustainable and suitable lubrication/cooling strategy.
- Control of the consumption of cutting fluid or lubrication.
- Cooling strategy performance monitoring.
- Adjust the formulation of cutting fluids to the process.
- Possibility to combine different machining strategies in the most optimal configuration.

2.4.2. Energy consumption monitoring.

The 2030 Agenda considers the management of energy consumption as an essential target for the sustainable development. Moreover, the current price of electricity and fossil fuels makes consumption control decisive.

Kant and Sangwan [46] describe the use and comparison of two techniques for estimating electricity consumption: Artificial Neuronal Networks and Support Vector Regression.

Wang *et al.* [47] also use ANN to define the relationships between initial parameters, energy consumption and surface quality in milling processes.

Lee *et al.* [48] propose a method of optimising energy consumption in machining processes using a Virtual Machine Tool and Genetic Algorithms.

He *et al.* [49] propose the use of deep learning to estimate the amount of energy consumed in two processes: grinding and milling.

Brillinger *et al.* [50] compare three machine learning tools for the prediction of power consumption by CNC machining operation.

3. Spanish Machining Industry situation.

The Spanish machining industry is composed by more than 80% Spanish companies that only perform machining with some additional process and are subcontracted by others who manage the final product. Only 17% manufacture their own product. Only 3% of companies report more than 80% of their turnover to customers in other countries. Therefore, we are dealing with a sector of mainly national and regional consumption. 54% of companies sell less than 20% outside their region [51]. For all these reasons, Spain needs to take a step forward in terms of digitisation and strengthening of the sector, to increase its competitiveness compared to other European countries and to activate the internationalisation.

There are two factors that could determine the evolution of industrial transformation in the Spanish machining sector: machinery and workers. With regard to machinery, the data from the AVIVA project (2012) [51] show that the machines in Spanish machining companies were mainly between 2 and 10 years old at the time of the study but a high percentage had machines that were more than 10 years old. In addition, most of these companies have less than 10 workers, aged between 30 and 40 for the workers and between 40 and 50 for the management team. In relation to the training of workers, 63% of the companies confirm the difficulty of finding qualified personnel, but it is also significant that 36% do not have a training plan and 39% improvise training during the year. It is even more demonstrative that for 51% of companies, training is necessary but is not carried out due to lack of time. Looking at the data provided by the project on innovation, it can be seen that, although 65% of the companies consider R&D to be a key factor in competitiveness, its transformation into initiatives is not very significant. Only 37% of companies have invested in innovation in the last three years in machining processes and 33% in key business processes.

4. Social perception of AI.

The European Barometer 516 [52] on new technologies shows that 18% of European Union (EU) respondents believe that AI will have a very positive effect in 20 years' time, 43% quite positive while 33% think it will either have no effect or a negative effect. In Spain, 31% of respondents believe that it will have a very positive effect. It is worth noting that 25% of Spanish respondents believe that it will either have no effect or that its effect will be quite or very negative. The percentage of very negative respondents is 11%.

Concerning the opinion on the possibilities of job creation based on automation and AI, 33% of Spanish respondents believe that they will provide more jobs than they will destroy, while 60% have a neutral or negative opinion on the subject.

According to the V Survey on the social perception of innovation in Spain [53], 66% of the surveyed population is of the opinion that Spanish society is not ready to take on technological advances and in 2021, more than 80% of respondents consider that public investment in Spain is insufficient, highlighting that the percentage of people who strongly agree with this statement has increased in the last 5 years. Finally, 56.2% believe that innovation generates social inequality, and this percentage has been increasing since 2018. AI carries with it a certain personal vulnerability that generates no confidence among users and the general population. The Eurobarometer 518 [54] on digital rights and principles reflects how 87% of European respondents consider important to include protection against risk or unethical applications of digital technologies, including AI. Of that percentage, 54% consider it very important.

Nazareno and Schiff [55] stand out in the research on the possible impacts on the personal sphere of workers. While automation and AI can have an impact on stress by reducing it, it is at the cost of losing meaning, becoming more dissatisfied with work, and even making health worse. Jarrahi [56] evidences the synergy that can be created between humans and AI in decision-making and Makarius et al [57] highlights the lack of information and training of employees and managers regarding AI. This deficiency of information leads to a lack of understanding and therefore to a negative perception. Makarius *et al.* advocate for greater understanding and integration of AI so that workers and managers can focus on the opportunities that these techniques offer and create a socialisation framework for effective integration into the work environment. Ostheimer *et al.* [58] state trust as a fundamental pillar for the successful implementation and acceptance of AI.

5. Conclusions.

The virtues of artificial intelligence (AI) in machining processes have been reviewed and each of the aspects in which it can be a differentiating element to improve these processes in terms of quality, sustainability and efficiency have been explored by different authors. The advantages of adopting AI are evident, but is the Spanish machining industry and its workers ready for its adoption? The situation of the machining industry highlights that the machinery parquet is not renewed as it should be and that workers are not adequately trained. There are significant differences between academic developments and the response that the machining industry can provide today.

On the other hand, the social vision of the fourth industrial revolution or Industry 4.0, in which AI is a basic pillar, must be considered. This transformation will affect workers, organisations, and citizens. The reception of this transformation is not homogeneous and it is not as positive as it should be. Misinformation and the possibility that workers' and people's rights may be violated do not help to enhance the growth opportunities offered by AI. Much remains to be done at the academic, business, and political levels.

At academic level, studies on the use of AI in machining have not expanded to the extent that they have in other fields, such as medicine. There are future opportunities to study and develop the use of AI in machining process to improve the sustainability at less cost, the dimensional and geometrical quality, non-conventional machining processes, etc. In addition, it is necessary to bring the advances provided by these studies closer to companies, especially small and medium-sized ones.

At business level, it is necessary to link up with academic life, to be able to observe the direction in which developments are taking place and what criteria the customers of the future will demand. It is essential to create a training framework for workers to prepare them for new technologies and for the changes that their work will undergo. It is necessary to incorporate innovation and establish strategic plans in which companies set the direction of their decisions. Agreements with governments must be formulated so that small and medium-sized enterprises are not left behind. And they must definitely include sustainability in these strategic plans, not just words.

At political level, there should be four frameworks in Spain to support the adoption of AI: innovation and development, legal, training and incentive framework for industry.

The role of AI in the future is indisputable. Creating a safe and informed framework will be the key to its successful implementation.

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