Optimising CNC Machining Processes through Artificial Neural Networks: A Case study in a machine tool company.

Mateo Del Gallo*, Fabrizio Defant, Giovanni Mazzuto*, Filippo Emanuele Ciarapica*, Maurizio Bevilacqua***

* *Department of Industrial Engineering and Mathematical Science, Università Politecnica delle Marche Ancona (AN), Italy (m.delgallo@pm.univpm.it, g.mazzuto@staff.univpm.it, f.e.ciarapica@staff.univpm.it, m.bevilcqua@staff.univpm.it)*

** *R&D Department, Pama S.p.A Rovereto (TN), Italy (Fabrizio.Defant@pama.it)*

Abstract: In modern manufacturing environments, production site efficiency is crucial to sustain competitiveness in an ever-changing market. The imperative to reduce rework operations is crucial to improve productivity, reduce operating costs and maximise resource utilisation. This requirement becomes particularly critical when machining large components, which can take a long time, sometimes several days, to complete. To address this challenge, our study presents two single-layer Artificial Neural Networks, each configured with different hyperparameters and number of neurons, designed to accurately determine the material removal volumes required to produce cast iron columns of different lengths. The first model predicts the amount of material to be stripped from the column guides in order to ensure a parabolic profile of the component. The second, on the other hand, predicts the amount of cast iron to be removed on the sides of the column in order to respect parallelism values. In a real industrial context, the algorithm was evaluated on a three-axis CNC machine at the company PAMA S.p.A., which is part of the AIDEAS European project consortium. The effectiveness of the solution was demonstrated by the high score value in predicting the removal parameters (score of both models ≈ 0.9) and was also validated by the previous experience of the company's production manager.

Keywords: Optimising manufacturing, Artificial Neural Networks, Predictive Model, Case Study

1. Introduction

The current market environment is very competitive, placing significant pressure on enterprises to produce components with exceptional accuracy and adhere to tight timelines [1]. This requirement is especially evident in the context of Industry 4.0, where enterprises are compelled to enhance and perfect their manufacturing procedures, with a strategic emphasis on optimising crucial production stages [2]. There has been a notable increase in the development of Artificial Intelligence (AI) algorithms within the scientific community, specifically aimed at enhancing different stages of the manufacturing cycle. These algorithms are characterised by their capacity to identify complex patterns and relationships within large datasets [3][4], leading to significant enhancements in production efficiency. AI covers a wide range of tools and techniques, including machine learning (ML), deep learning (DL), natural language processing (NLP) and computer vision. Each of these tools has distinct applications in various fields. For example, ML and DL are widely used in predictive maintenance, quality control and optimisation of production processes. NLP has applications in automated customer service and sentiment analysis, while computer vision is crucial in defect detection and automated inspection systems. AI tools have been used in the manufacturing sector to optimise supply chain management, predict demand and improve operational efficiency. Techniques such as reinforcement learning have been applied to develop adaptive control systems and convolutional neural networks have been used for real-time image processing in quality control. The proposed research introduces two Artificial Neural Networks (ANN) to forecast the specific material quantities that need to be removed from cast iron columns in a 3-axis CNC machine. This study aims to develop a model that maximises production efficiency by ensuring the required tolerance levels and minimising the need for rework. The algorithm was tested in a real industrial environment at PAMA S.p.A., a renowned global firm specialising in manufacturing massive boring and milling machines. This study focused on examining the cast iron column that serves as the sliding surface for the headstock of big boring machines, ranging from 4500 mm to 8500 mm in height. Several outside factors influence the machining process of the columns under evaluation due to the high level of precision needed. Consequently, the business had to repeatedly remove material from the column's guides and sides in order to adhere to extremely exact technical criteria, which were on the scale of microns. The paper is structured as follows: Section 2 presents the state of the art about the utilization of ANN to solve manufacturing issues. Section 3 will present the case study, the problem of the company under investigation, methodology and algorithm design to solve the industry problem. The results and discussions are argued in 4 and the conclusion chapter is presented in section 5.

2 State of the art

The ever-increasing amount of data available from production processes supports the development of data-based models [5]. This has enabled the ever-increasing development of AI and ML algorithms that support production managers in making data-driven decisions [6]. ML comprises a range of algorithms, including supervised learning, unsupervised learning and reinforcement learning and each category has unique applications and advantages in industry. Among the various ML techniques, the use of ANN is gaining considerable momentum in the literature, especially for the prediction of anomalous or unexpected phenomena that slow down production [7] or efficiency [8]. ANNs are computational models inspired by the network of neurons in the human brain and are particularly effective in identifying patterns and relationships within large datasets. There are several fields of industrial use where ANNs have found success and increased productivity, such as in the case of High Speed Machines presented by Dimla [9] or in the management of production orders for stencil printing processes [10] [11]. Wang et al. [12] employ ANN to optimise the parameters of the milling process, specifically the energy consumption and surface roughness, in order to manufacture a single component. ANN is utilised to represent complex non-linear relationships between important process factors and the measured data of energy consumption and surface quality. Azab et al [13] devised a system that integrates commercial software tools for production scheduling with an ML technique to anticipate machine faults in scheduling programmes. The suggested methodology was implemented and evaluated at a pharmaceutical company, where many AI approaches were scrutinised. The NN algorithm outperformed the decision forest algorithm in accurately forecasting machine failure time. Simeunović et al. [14] developed a model that utilises ANN to manage the staffing schedule of a corporation. The algorithm's objective was to forecast the number of employees for future days by considering many criteria, including consumer demands and working hours. As a result of this contribution, the waiting time experienced by the employees of the firm was decreased, resulting in an improvement in the company's productivity and a greater level of customer satisfaction. Previous research has explored various approaches to achieve similar goals in manufacturing. Techniques such as regression analysis, decision trees and support vector machines have been used to predict machining parameters, optimise tool paths and improve overall process efficiency. However, ANNs offer a distinct advantage due to their ability to model non-linear relationships and handle complex, high-dimensional data.

With the following article, the authors aim to explore the use of ANNs, in particular, the use of MLPRegressor [15] models, in an as-yet unexplored field of the machining of large cast iron components subject to very tight design constraints, with the intention of minimising the number of re-machining steps.

3 Research Approach

This research employs a structured methodology comprising several key steps to improve the accuracy and efficiency of large component machining processes. The main steps include data collection, correlation analysis and the construction and validation of ANN models. The approach aims to predict the specific amounts of material to be removed from cast iron columns, optimising the production process and minimising the number of re-manufacturing steps. The case study presented in the papers concerns the company PAMA S.p.A., an Italian machine tool manufacturer with over 90 years of experience constructing big and medium-sized machines for all industries that demand optimum stiffness, precision, and efficiency. This research examines a specific method for producing huge components for boring machines. Specifically, the headstock of the boring machine moves over cast iron columns that can vary in length from 4500 mm to 8500 mm, depending on the specific models being produced. Figure 1 displays an example of a cast iron column that must adhere to extremely strict standards.

Figure 1: Cast iron columns

The cast iron columns undergo machining on a 3-axis CNC machine while positioned horizontally as shown in Figure 1. Following the completion of processing, the component is positioned vertically for a minimum duration of 24 hours. Subsequently, measurements are conducted on the component's guides and sides, which are subject to deformation caused by gravity, temperature, and other factors. The dimensions of the guides and sides, along which the headstock of the boring machine will move, must be carefully measured and adhere to extremely precise tolerances, often in the range of microns. Measurements are collected at intervals of 500 mm from the top of the column for both guides and sides. The approach proposed in this paper is structured into 4 steps. Initially, all the data which came from the production plant and from the measurement of the pillar were collected into 2 separate datasets, one for the guides and the other for the sides. A total of 43 tests were collected for the guides and 54 for the sides. That highlights that in the data store, the process under investigation is more critical for the side of the column instead of the guides. For both, rails and sides, the operator performs two sets of measurements, one on the front of the column and the other on the rear at 500mm intervals. Therefore, the number of measurements will vary for columns of different lengths. To ensure consistency in the amount of measures for each test, the measurements were converted into percentages with a 5% increment. For every test, there will be a total of 21 data points collected for the front and 21 data points collected for the rear. In that way, each row of the dataset contains information about the 21 data points for the rear and the 21 for the guides, Product ID, Order ID, the length of the column, the weight of the column, type of column section, the total number of re-machining processes, temperature, the season of the test (1 = winter, 2 = autumn, 3 = spring, 4 = summer) and the quantity of material to be removed as a percentage of length. Only for the guide dataset are reported also the ideal curve of the profile according to the technical specification and the twisting value. Meanwhile, for the side's dataset are reported also the tolerance range and the parallelism value.

Once the dataset including all pertinent information for each production process has been established, it is crucial to comprehend the elements that impact the quantity of re-machining procedures. Correlation analysis was performed using Excel, revealing that only temperature exhibits a moderate association (ranging from 0.3 to 0.7) with the number of re-manufacturing processes (Figure 2).

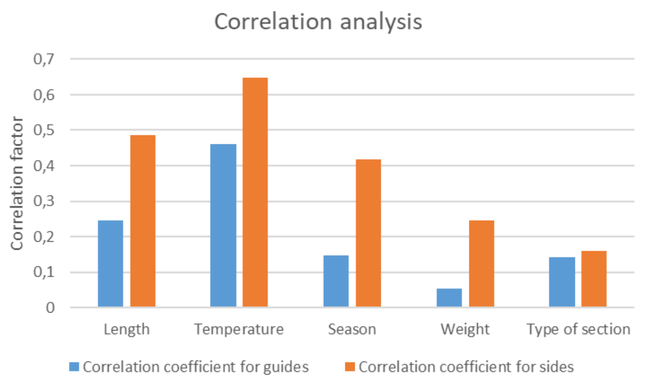

Figure 2: Correlation analysis results

The issue with this particular form of analysis is its reliance on a substantial quantity of tests. The dataset in the proposed case study is rather small, which makes it susceptible to mistakes. Nevertheless, the correlation analysis is used to provide an early understanding of which parameters have the most significant impact on the number of reprocesses.

3.1 ANN Realization

Once the dataset was created and the results of the correlation analysis were examined, the data were imported into Python and made ready for the ANN model. The data manipulation method involved utilising the Pandas and NumPy libraries to import and alter the data from the dataset. Due to the significant variation in the units and orders of magnitude of the information in the dataset, it was determined that standardisation was necessary. The SciKit-learn library's StandardScaler function was utilised for the purpose of standardising.

The Formula 1 was adopted to establish a standardised framework for all classes of components.

$$S = (V - \mu) / \sigma \qquad (1)$$

The formula represents the relationship between the standardised value (S), the actual value (V), the mean of variable V (μ), and the standard deviation of variable V (σ). Now all the components are prepared to construct the ANN models for forecasting the correction parameters.

The aim of this study is to determine the corrected parameters required as input for a 3-axis CNC machine in order to minimise the need for re-machining. Therefore, two ANN models were developed. The first model predicts the correction parameters to be removed from the guides, while the second model focuses on the sides of the cast-iron column. The ANN models were constructed via the MPLRegressor function from the SciKit-learn package [14]. The MPLRegressor is a regression tool that utilises NN to identify intricate connections between input and output variables. This tool is particularly valuable for solving numerical prediction issues.

The MLPRegressor employs a feedforward NN, characterised by unidirectional information flow from the input layers, via one or more hidden layers, to the output layer. During the training process, the neural network endeavours to acquire the most advantageous weights and biases that reduce the disparity between the predicted and actual values of the training data. The MLPRegressor is a type of model that can handle many input variables and generate a single output value, making it a member of the Multiple Input Single Output model group. In this case study, two ANN models were constructed utilising a single hidden layer.

A set of common input data for both models where identified. In particular, Figure 3 shows the input parameters for the algorithms, the hyperparameters of both ANN and the output value.

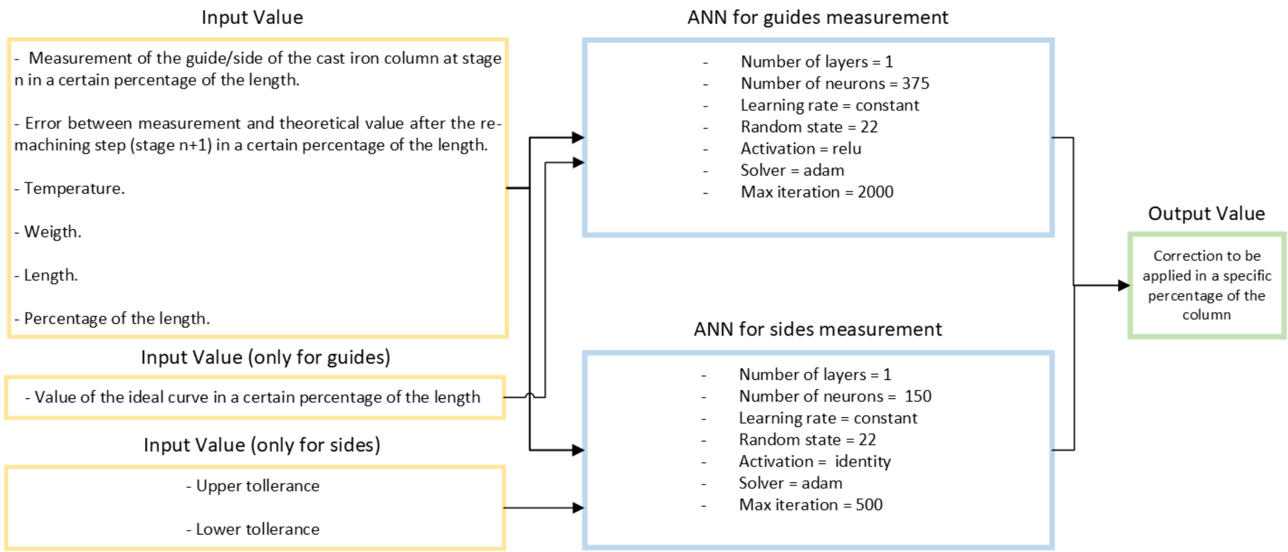

Figure 3: Input structure and ANN models characteristics

The main distinction in the input structure between the two models is that the guides model incorporates the input values of the ideal curve, whilst the sides model includes the tolerance ranges, which consist of two values. For the sides model, one additional column of data will be included to account for the reason previously mentioned. The remaining variables are of the same kind for both models.

The first stage in creating the ANN models is to determine the hyperparameters that best represent the current scenario with the highest accuracy. During the hyperparameterization process, a wide range of values is explored for each hyperparameter in order to get the optimal combination that maximises the model's performance. For the present case study, the grid search method was used to discover the hyperparameters for both models and the results are shown in Figure 3.

3.2 Train and test results

A total of 43 measurement samples were obtained for the guides and 54 for the sides of the columns throughout the training and testing phase. For each sample, a total of 42 measurement points are obtained by taking 21 measurements for the front of the guide/side and 21 measurements for the rear. The pre-processing phase yields 1806 measurement points for the training and testing of the guide-corrected ANN, and 2268 measurement points for the side-corrected ANN. Both models utilised 75% of the available data for the training phase and allocated the remaining 25% for testing. At this stage, due to the limited number of samples that indicated successful processing among those given by the company, a decision was made to randomly choose measurement points from different samples to train the models. The findings from this phase indicate that the mean disparity between the correction projected by the model and the quantity of material eliminated by the company is 3.02 µm during the training phase and 3.19 µm during the test phase in the guide model. Conversely, in the sides model, the discrepancy between the predicted and actual values is 0.67 µm in the training data and 0.77 µm in the test data. Based on these first findings, it is evident that the model recommends deleting varying quantities of content compared to the previous method employed by the organisation being evaluated. This difference is particularly noticeable in the guidelines.

4 Results and Discussion

4.1 Results

In order to provide a more comprehensive description of the two models, the authors opted to input the complete set of samples individually into the models, encompassing all measurement values ranging from 0% to 100% for the front and rear of the guide, as well as the sides. This approach allows for the assessment of whether the two models indicate varying quantities of material eliminated in various regions of the columns. Figure 4 shows the difference between the quantity of material to be removed recommended by the models and that applied by the company under investigation for each percentage of the length of the uprights.

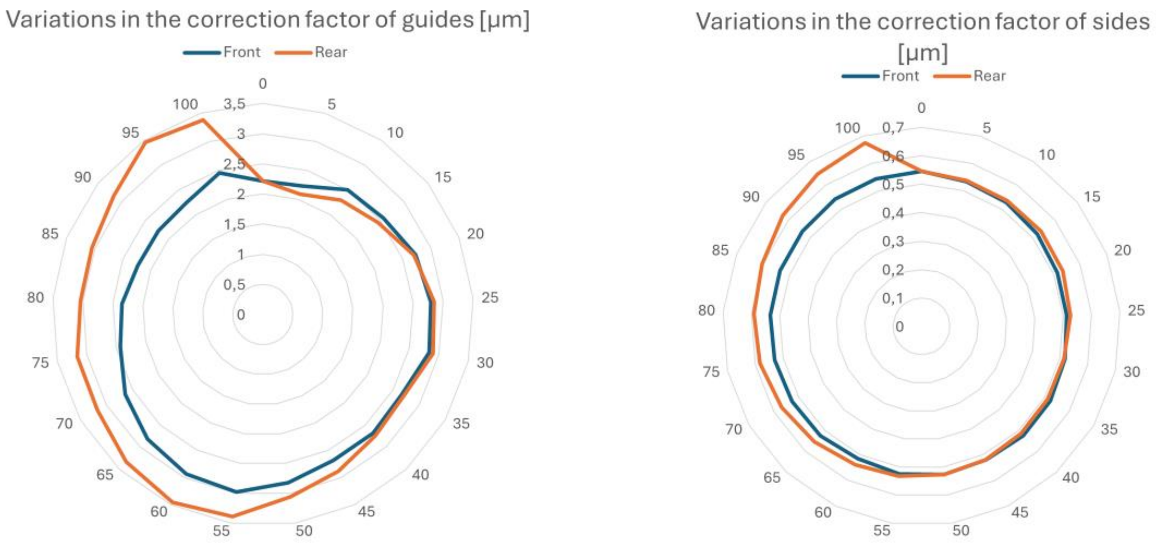

Figure 4: Test results for guide and side model

From the graphs it can be seen that the amount of material to be removed recommended by the models is greater in the case of guides and also more irregular according to the percentage of column height. For the sides, on the other hand, the difference recommended by the model compared to the company's approach is smaller and, above all, more even across the entire profile of the component. To use the two models in an actual industrial environment, 17 more measurement data were utilised to authenticate the result. These samples consist of previously unprocessed data sets with varying column lengths. During this phase, it is necessary to have access to and be aware of all the parameters depicted in Figure 3, with the exception of the number representing the "Error between measurement and theoretical value after the re-machining step (stage n+1)" expressed as a particular percentage of the length. The value in question should be adjusted to zero in order to minimise the discrepancy between the measured value at a specific point on the column and the anticipated value. Figure 5 illustrates the disparities between the proposed adjustments from the two models and the actual corrections implemented by the firm for each percentage of the columns examined.

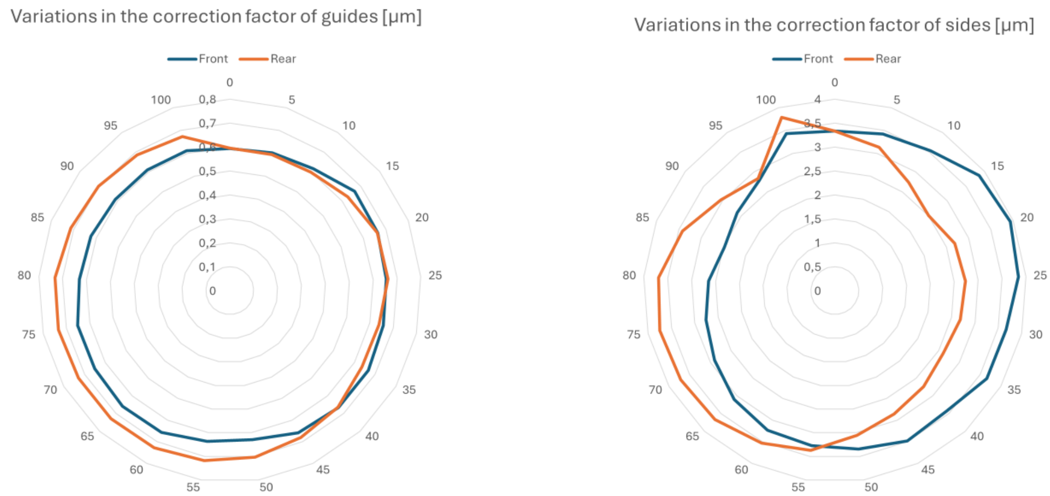

Figure 5: Validation results for guide and side model

4.2 Discussion

The primary objective of this work is to develop an AI tool that enables the company to decrease the number of remanufacturing processes involved in a certain production process. Two ANNs were developed to accurately forecast the adjustments required for a 3-axis CNC machine. The first ANN was designed to predict the necessary corrections for the guide profile of the cast iron column, while the second ANN was utilised to forecast the amount of material that needs to be removed from the side profile. The results, when compared to the old technique employed by the company, indicate that the ANN models propose the elimination of a little discrepancy in the material. The disparity in the implementation process of the two models (train-test-validation) can be observed in Figure 4 and Figure 5. Upon studying the graphs, it is evident that both models propose deleting a little greater quantity near the back of the column. Additionally, it is evident that the guides model often suggests deleting a larger quantity on average compared to the sides model. A crucial factor to take into account in this study is the data's trustworthiness, given that the operators manually carry out the procedure of measuring the columns. This results in a diminished level of consistency in the measurement conducted on the component. Furthermore, obtaining information on the profiles of the guides and sides at the exact instant they began machining in the horizontal position was not feasible. Nevertheless, it was noted that in 85% of the examples employed for model validation, the findings indicated a reduction in material removal compared to the company's previous strategy. The company's managers were presented with these results, and based on their professional analysis of the topic under study, they deemed the values produced from the two models to be correct and pertinent to the situation.

Hence, the subsequent course of action is assessing the proposed solution at the production site to see whether the company would experience a decrease in the number of machining operations as a result of the adjustments recommended by the model. During the initial stage, more data will be gathered to maximise the number of samples and enhance the precision of the model tailored to the company's requirements.

5 Conclusion

This study focuses on a crucial part of modern manufacturing processes, which is the improvement of machining operations to increase efficiency and competitiveness. The research involved the development of two ANNs to predict material removal parameters for cast iron columns in a 3-axis CNC machining process. The objective of the research was to limit the need for rework steps while ensuring that stringent tolerance levels are maintained. The generated artificial neural network (ANN) models provide encouraging outcomes, suggesting their capacity to substantially diminish the requirement for rework in industrial environments. The models provide a data-driven method to optimise machining operations for cast iron columns by reliably forecasting correction parameters for both the guide and side profiles. This leads to improved production efficiency and resource utilisation. The research yields precise results through a thorough technique that encompasses data gathering, correlation analysis, model creation, and validation. The validation step, which includes 14 more samples, further confirms the effectiveness of the suggested technique, since most cases show a decrease in material removal compared to earlier methods. This not only emphasises the precision of the ANN forecasts but also emphasises the possibility of concrete enhancements in industrial processes. Implementing the proposed method in the production environment has the potential to significantly reduce the need for re-machining and improve overall manufacturing efficiency. Continued surveillance and data gathering will allow for additional improvement and tailoring of the ANN models to match the changing requirements of the firm. This research enhances the progress in AI-driven optimisation in the manufacturing field. It provides valuable insights and methodologies for using neural networks to make production processes more efficient and stay competitive in the ever-changing industrial context.

Acknowledgement

We are very grateful for the support of the European Union's Horizon Europe research and innovation programme, under grant agreement No. 101057294, AIDEAS (AI-Driven industrial Equipment) project.

References

[1] Z. Müller-Zhang, T. Kuhn, and P. O. Antonino, "Towards live decision-making for service-based production: Integrated process planning and scheduling with Digital Twins and Deep-Q-Learning," *Comput Ind*, vol. 149, p. 103933, Aug. 2023, doi: 10.1016/J.COMPIND.2023.103933.

[2] S. Antomarioni, M. Bevilacqua, F. E. Ciarapica, I. De Sanctis, and J. Ordieres-Meré, "Lean projects' evaluation: the perceived level of success and barriers," Total Quality Management and Business Excellence, vol. 32, no. 13–14, pp. 1441–1465, 2021, doi: 10.1080/14783363.2020.1731301.

[3] M. A. Farahani et al., "Time-series pattern recognition in Smart Manufacturing Systems: A literature review and ontology," J Manuf Syst, vol. 69, pp. 208–241, Aug. 2023, doi: 10.1016/j.jmsy.2023.05.025.

[4] O. Pisacane, D. Potena, S. Antomarioni, M. Bevilacqua, F. Emanuele Ciarapica, and C. Diamantini, "Data-driven predictive maintenance policy based on multi-objective optimization approaches for the component repairing problem," Engineering Optimization, vol. 53, no. 10, pp. 1752–1771, 2021, doi: 10.1080/0305215X.2020.1823381.

[5] A.-I. Carmen, Salvador Izquierdo, and Gabriel Baquedano, Data-driven modeling of semi-batch manufacturing: a rubber compounding test case, Proceedings, 2019. Aalto University, Helsinki-Espoo, Finland,: IEEE 17th International Conference on Industrial Informatics (INDIN), 2019.

[6] V. Fani, S. Antomarioni, R. Bandinelli, and M. Bevilacqua, "Data-driven decision support tool for production planning: a framework combining association rules and simulation," Comput Ind, vol. 144, Jan. 2023, doi: 10.1016/j.compind.2022.103800.

[7] M. Elbasheer, F. Longo, L. Nicoletti, A. Padovano, V. Solina, and M. Vetrano, "Applications of ML/AI for 468 Decision-Intensive Tasks in Production Planning and Control," in Procedia Computer Science, Elsevier B.V., 2022, 469 pp. 1903–1912. doi: 10.1016/j.procs.2022.01.391.

[8] I. Pietrangeli, G. Mazzuto, F. E. Ciarapica, and M. Bevilacqua, "Artificial Neural Networks approach for Digital Twin modelling of an ejector," in European Modeling and Simulation Symposium, EMSS, Cal-Tek srl, 2023. doi: 10.46354/i3m.2023.emss.007.

[9] E. Dimla, "Development of an innovative tool wear monitoring system for zero-defect manufacturing," International Journal of Mechanical Engineering and Robotics Research, vol. 7, no. 3, pp. 305–312, May 2018, doi: 10.18178/ijmerr.7.3.305-312.

[10] J. P. Siew, H. C. Low, and P. C. Teoh, "An interactive mobile learning application using machine learning framework in a flexible manufacturing environment," International Journal of Mobile Learning and Organisation, vol. 10, no. 1–2, pp. 1–24, 2016, doi: 10.1504/IJMLO.2016.076187.

[11] R. Teti, "Advanced IT methods of signal processing and decision making for zero defect manufacturing in machining," in Procedia CIRP, Elsevier B.V., 2015, pp. 3–15. doi: 10.1016/j.procir.2015.04.003.

[12] S. Wang, X. Lu, X. X. Li, and W. D. Li, "A systematic approach of process planning and scheduling optimization for sustainable machining," J Clean Prod, vol. 87, no. 1, pp. 914–929, 2015, doi: 10.1016/J.JCLEPRO.2014.10.008.

[13] Azab, E.; Nafea, M.; Shihata, L.A.; Mashaly, M. A Machine-Learning-Assisted Simulation Approach for Incorporating Predictive Maintenance in Dynamic Flow-Shop Scheduling. Appl. Sci. 2021, 11, 11725.

[14] Simeunovic, N.; Kamenko, I.; Bugarski, V.; Jovanovic, M.; Lalic, B. Improving workforce scheduling using artificial neural networks model. Adv. Prod. Eng. Manag. 2017, 12, 337–352.

[15] "sklearn.neural_network.MLPRegressor — scikit-learn 1.4.1 documentation." Accessed: Feb. 19, 2024. [Online]. Available: https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPRegressor.html