Javier Arenas López[1], Rosa Basagoiti Astigarraga[2], Maite Beamurgia Bengoa[1], Jorge Martínez de Alegría Sáenz de Castillo[1]

[1] FAGOR AOTEK S.C. Calle Torrebaso Pasealekua, 4 – 20540 Eskoriatza (Gipuzkoa). Tfno: +34 943 039800, jarenas@aotek.es

[2] Mondragon Goi Eskola Politeknikoa S.Coop. Departamento de Electrónica e Informática. Goiru, 2 – 20500 Arrasate-Mondragón (Gipuzkoa). Tfno: +34 943 712185

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OPTIMIZATION OF CNC PARAMETERS ACCORDING TO PRODUCTIVITY CRITERIA USING A MACHINE MODEL BASED ON NEURAL NETWORKS

ABSTRACT:

Every machine-tool user wants to maximize the productivity of their machines looking for balance between speed, precision and lifetime of mechanical components. Nevertheless, because CNCs have wide-ranging use, their correct parametrization for each case is key to achieving the desired objectives; on the other hand, minimizing the numbers of experimental tests to be performed on the machine is essential to reduce time and costs of the set-up process. In order to solve both difficulties, this paper presents a tool to give final users the necessary information to properly adjust CNC parameters according to productivity criteria. The method makes use of experimental data to obtain a model of the machine based on neural networks. With this model machining time, geometric error and smoothness of any part to be manufactured can be predicted, and, therefore, minimizing test on the real machine and recommending the appropriate values for the CNC.

Keywords: optimization, CNC, neural network, model, machine tool, productivity criteria.

RESUMEN:

Todo usuario de máquina-herramienta desea maximizar la productividad de sus máquinas buscando el compromiso entre rapidez, precisión y durabilidad de los elementos mecánicos. Sin embargo, debido a que los CNCs son generalistas, su correcta parametrización para cada caso resulta clave para lograr los objetivos deseados; por otro lado, minimizar el número de pruebas a realizar sobre la máquina es fundamental para reducir el tiempo y los costes del proceso de puesta en marcha. Para conjugar ambas problemáticas en esta investigación se propone dotar al usuario de una herramienta que proporcione la información necesaria para ajustar correctamente los parámetros del CNC de acuerdo a criterios de productividad. El método utiliza datos extraídos en ensayos empíricos para la obtención de un modelo de la máquina basado en redes neuronales. Este modelo permite predecir el tiempo de mecanizado, el error geométrico y la suavidad del movimiento para cualquier pieza a fabricar, minimizando de esta forma las pruebas sobre la máquina real y recomendando los valores adecuados para el CNC.

Palabras clave: optimización, CNC, red neuronal, modelo, máquina herramienta, criterios de productividad.

1.- INTRODUCTION

During the last few decades, the machine tool industry has had to face a noticeable increase in demand by manufacturers and end users. The industry wants to increase its productivity values in manufacturing processes, improving indicators such as machining time or the geometric precision of parts, without hindering the useful life of mechanical components. All these requirements condition the trajectory generation algorithms of the CNC, implying that their correct parameterization is crucial. Usually, machine tool users start with a CAD file of the part to manufacture and use a CAM system to generate the program-part that will be executed by the CNC. However, depending on the adjustment of the trajectory generation parameters, mainly the ones related to *High Speed Cutting* (HSC) techniques, the final trajectory of the machine may vary significantly starting from the same program-part. The correct settings will depend on the specific needs in each case and the end user of the machine has to make this decision. Given that this adjustment is not trivial, different machining tests are often conducted, which increases commissioning times and material costs.

All these circumstances have motivated this research, aimed at supplying CNC users with a tool that provides a set of HSC parameters suited to their needs in each specific case. This set of parameters will be referred to as *actuator* hereafter. Developing this tool will imply the creation of a machine model that accurately represents the actual behavior of the machine and can be used to conduct offline tests, achieving an optimal actuator with the lowest amount possible of tests with the actual machine.

The following sections describes the state of the art which frames the present research, subsequently followed by the steps taken to obtain a machine model based on neural networks, and an explanation on how to obtain an equivalent model, thus decreasing the necessary amount of data. The last section contains the results of the comparison of the data obtained from the model against the one obtained in the actual machine.

2.- STATE OF THE ART

The first issue when dealing with this research is to determine the productivity criteria are relevant for CNC users. Analyzing the state of the art, one can find multiple references to research projects that propose methodologies to optimize trajectories based on different productivity criteria. Thus, for instance, [1] describes a procedure to obtain an optimal trajectory minimizing the time factor. However, just decreasing machining time does not always yield the desired results, given that there are other important variables to consider. Therefore, [2] attempts to obtain a least-time trajectory, however considering setpoint generation with limited jerk. Jerk is the derivative of acceleration and, as pointed out in [2], jerk values that are too high decrease the useful life of mechanical components. Other research projects such as [3] and [4] discuss trajectory generation taking into account possible restrictions in the axes. As explained in [5], the type of trajectory might have a significant impact on the useful life of the mechanical components of the machine, so introducing smoothness criteria in the adjustment of the control algorithms becomes crucial [6].

On the other hand, there is a wide assortment of literature on minimizing geometrical error both from an offline analysis perspective [7], [8] and with online estimates [9], [10]. Therefore, it becomes clear that these three criteria (time, smoothness and error) are key for adjusting the trajectory generation parameters based on production needs. Once the production criteria have been established, the next step is to achieve a model to analyze them, decreasing the duration of tests on the actual machine as much as possible.

If the search is carried out on the machine tool industry, there are many references that utilize system models to tackle different issues. Thus, for instance, [11] uses empirical models to evaluate power consumption, [8] to determine the geometrical error and [12] to conduct preventive maintenance of the spindle. During the last few years, the development of digital twins has had a significant impact and is currently one of the main research fields [13]. Traditionally, from the point of view of adjustment of control loops, the most commonly used model is one based on a system of two masses connected with a spring-damper component [14]. The problem with these models is that they require an identification of the parameters of the machine, which is not always easy [15]. This inconvenience, along with the increased calculation power of current CNCs, is bringing more advanced models to the forefront of applied research. One such model that stands out in the literature is the use of neural networks.

Neural networks have been used to improve manufacturing with machine tools in different capacities. For instance, to decrease geometrical error [16], [17] or to control the surface roughness of the product [18], [19]. These research papers also point out that both geometrical error and roughness depend on runtimes – the longer it takes to manufacture parts, the lower their geometrical error and roughness, but productivity would be affected [8]. This shows that introducing productivity target implies having to reach compromises between different criteria.

Research paper [20] describes how to use neural networks to adjust cutting parameters dynamically in real time. It explains the current limitations and the importance of cutting parameters. Therefore, they suggest a neural network to determine which cutting parameters are required in each case. Paper [21] also discusses the optimization of CNC cutting parameters in real time, including the radial depth of cut and feed per tooth, using a neural network as a model.

With this approach, this study decides to use neural networks for the optimization of HSC parameters, thus creating a machine model that simulates its behavior. There are many different types of neural networks [22], but after analyzing the state of the art and considering the characteristics of the problem at hand, there are three types of networks which can be considered. On the one hand, NARX (*Nonlinear Autoregressive networks with exogenous inputs*) networks are recurrent dynamic networks with delays*,* which entails that they consider past statuses to determine the next output [18].

LSTM networks (*Long Short-Term Memory*) [23], [24], are recurrent neural networks that can process a variety of data. They are versatile and efficient networks in fields such as image recognition and driverless driving, among others. And the last type to be considered is CNN networks (*Convolutional Neural Networks*) [25]. These networks are very effective for artificial vision tasks, such as the classification and segmenting of images, among others. After analyzing the pros and cons of each network type, NARX is selected as the network to proceed with due to its ability to memorize past input and output values to obtain a more accurate future output.

3.- DEVELOPMENT

The objective, therefore, of this research is to provide a tool that tells the end user which actuator is most suited to their time, geometrical error and smoothness requirements. Figure 1 shows the phases used.

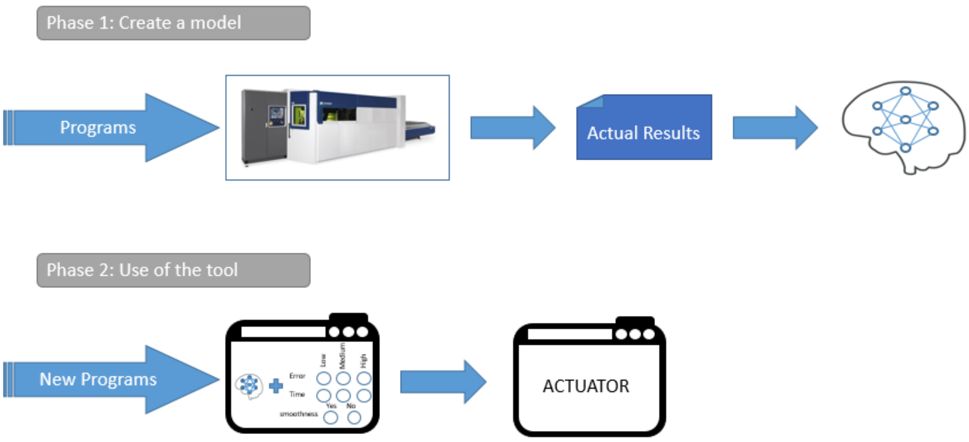

Fig. 1: General diagram of the methodology

The purpose of the first phase is to obtain a machine model based on NARX neural networks. For this purpose, several programs are run on the machine and data is collected, as explained in section 3.1. Afterwards, the neural network is trained with these data -see section 3.2-, thus generating a model of the machine. This phase will only have to be conducted once, as the model is unique for each machine, regardless of the part to manufacture. Only a significant change in the components of the machine would require repeating this phase.

Once phase 1 is complete, the user would be able to use the tool (phase 2). To do this, the user must load the new program-part to manufacture and choose the productivity criteria, which would result in the recommended actuator. Not all options are possible because there is no actuator that is, at the same time, the fastest, most accurate and smoothest; therefore, there are certain limiting factors to the user's requirements. However, once set, the tool will indicate the most suitable actuator.

The end user may test the program in a CNC simulator with the selected actuator, which would let the user know how long it will take to machine the part along with the maximum speed and acceleration values. These indicators can be used to evaluate whether the actuator meets their needs without having to conduct any tests on the machine. The various steps of each phase are explained below.

3.1.- DATA COLLECTION

As mentioned above, the first step is the collection of data from the machine to generate the model. In this research, a three-axis laser machine with linear motors has been used, but the methodology can be exported to any type of machine. The machine has a CNC and linear encoders manufactured by FAGOR to regulate the axes. The CNC has a *datalogger* to store any system variables in sync. For this study, the position, speed and acceleration values of the axes have been captured, all of them provided by the linear encoders installed on the machine. In addition, an accelerometer (manufactured by DIS Sensors, reference number QG40-KAXY-4,0E) has been added to the spindle to provide a better indicator of the smoothness of the movement.

Once the variables to store have been defined, the data must be ensured to be varied enough so that it can be useful when training the neural network. Therefore, a set of tests with a series of programs and actuators has to be defined which can then be run on the machine to obtain the data.

For the selection of the actuators, a previous research project [26] has been taken as a reference, which selects 17 HSC configurations, the most representative of the corresponding productivity criteria. This way one can ensure a range of trajectory generation strategies as extensive as possible that does not extend the data collection process unnecessarily.

As for the programs, 8 actual program-parts from the user of the machine have been taken, with differences between them but with no special characteristics nor common patterns. No specific programs have been decided on to ensure that the methodology can be generalized.

Therefore, for the data collection, 8 programs have been run on the machine, parameterizing the 17 actuators for each of said programs on the CNC, which results in 136 program runs to generate the data set used. The total duration of the data collection process has been of approximately 5 hours. This duration will necessarily depend on the size of the programs selected.

From the collected data, the necessary indicators to evaluate the productivity criteria have been calculated. The procedure for each of them is explained below:

- **Runtime**: A data file is obtained for each run of the program and corresponding actuator. Each file stores the trajectory, point by point, so the runtime is calculated using the total sum of points stored considering that the sampling time is 4 ms.
- **Geometrical error**: It is calculated by comparing the points obtained from the machine with the points of the starting program-part. This way, geometrical error is calculated point by point based on the differences between both logs. Root-mean-square error (RMSE) is used as an indicator.
- **Trajectory smoothness**: This term describes the abruptness or smoothness of the behavior of the machine and thus the vibrations that may affect the quality of the part. A mathematical formula based on the jerk -described in [26]- has been used as a smoothness indicator.

3.2.- NEURAL NETWORK-BASED MODEL

Neural networks are algorithms based on a large set of simple neural units (artificial neurons) in a way that closely resembles the behavior of biological brains. Input data goes through the neural network (where it undergoes different operations) and output values are calculated. Each neuron is connected to the others with certain links, so the output value is that of the previous neuron multiplied by a weight. These weights in the links can increase or decrease the result of the activation of adjacent neurons. By iteration, neural networks alter the weights and biases of the neurons as they approach the solution to the problem. For an overview and/or an in-depth explanation of the basic concepts of neural networks, see [28].

Neural networks are commonly used in classification, recognition, optimization, function fitting and prediction problems. For the problem at hand, a prediction of a temporal non-linear series is required and, therefore, as explained above, NARX architecture is deemed the most suitable approach. It is a supervised training neural network, that is, it starts from a starting set of inputs and a target set of outputs to achieve a trained model. In a series-parallel configuration (open loop), the resulting output value is predicted with the present and past values of the input and the past target output data. In a parallel configuration (closed loop), the prediction is carried out with the present and past input data and the past values of the output prediction itself. For use in real environments, the network must be configured in parallel; however, for training, a series-parallel phase is used at first followed by closed loop training [18].

3.2.1 Training

As usual, a subset from the full data set has been selected for the training. In this case, the data corresponding to 5 of the 8 programs have been used, with all their actuators. During training, the network updates its weights and biases to fit the expected output. The weights modulate the influence of the input on the output and the bias controls the activation of the different neurons.

The training has been conducted in two phases: open loop and closed loop. Initially, the network is trained with the actual output values (open loop); this way, the network starts generating the weights and biases it requires. Afterwards, the closed loop configuration is applied and thus the network is trained with the values generated by it, using actual output values only for verification. This generates a more robust network and optimizes training times [18]. The neural network can be trained in closed loop from the start, but it needs more time to adjust weights and biases as it lacks an initial reference. Once the network is trained, it must be in closed loop to be used.

The resulting neural network has been trained with both the data from axis X and axis Y, to verify its capacity for generalization.

3.2.2 Validation

Once the neural network has been trained, a subset of data comprised of two of the programs not used during training has been used, with their respective actuators. In this manner, neural networks have been trained successively with a different number of layers, neurons and delays. Table 1 shows some of the most relevant results obtained.

RMSE Validation	No. hidden layers	No. neurons	No. delays
9.77E-06	1	20	2
1.75E-05	1	8	3
1.84E-05	2	12 4	6
2.67E-05	1	20	1
2.94E-05	1	12	3
3.45E-05	2	8 3	2

Table 1. Results of neural networks

Therefore, once the validation has been completed, one can conclude that the NARX neural network model which has yielded better results contains a hidden layer with 20 neurons and 2 delays. Figure 2 shows the architecture of the network.

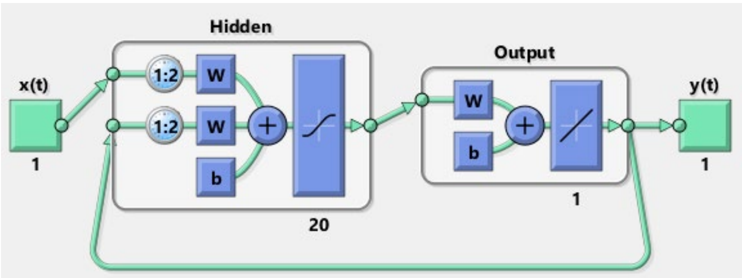

Fig. 2: NARX neural network with 1 hidden layer with 20 neurons and 2 delays

3.2.3 Decrease in training data

An issue that could be argued against the proposed methodology is the need for several machine hours in order to retrieve the data required for the training of the neural network, as explained in section 3.1. This time may be relevant in certain production processes and would go against one of the goals of this research: decreasing the commissioning times of the machines. It is true that this procedure only has to be carried out once during the entire life cycle of the machine, but even so, one should consider the feasibility of achieving a model based on the same typology of neural network -that is, with the same number of layers, neurons and delays obtained in the previous section- but trained with fewer data sets, thus minimizing the machine time required to obtain them.

With this purpose in mind, all 17 actuators originally used have been analyzed. The hypothesis is that, although this set of actuators is significant enough to cover all possible trajectory generations, not all of them are necessarily relevant to obtain the model of the machine.

To verify this, actual input and output, data have been used to conduct a machine identification process, resulting in a Bode diagram. The goal is to determine which actuators provide significant information on the mechanical characteristics of the machine in order to use only that subset for the training of the neural network. Through this analysis, it can be observed that there is a large set of actuators that yield results from which it is very difficult to correctly identify the machine. Figure 3 shows the difference between identification using actuator 1 (top) and actuator 5 (bottom). As can be observed, the Bode plot of actuator 1 shows a resonance at a frequency of 24 Hz that does not appear in the identification of actuator 5. Therefore, it can be concluded that actuator 1 provides more useful information for obtaining the model than actuator 5. This procedure manages to decrease the set of 17 actuators down to just 4.

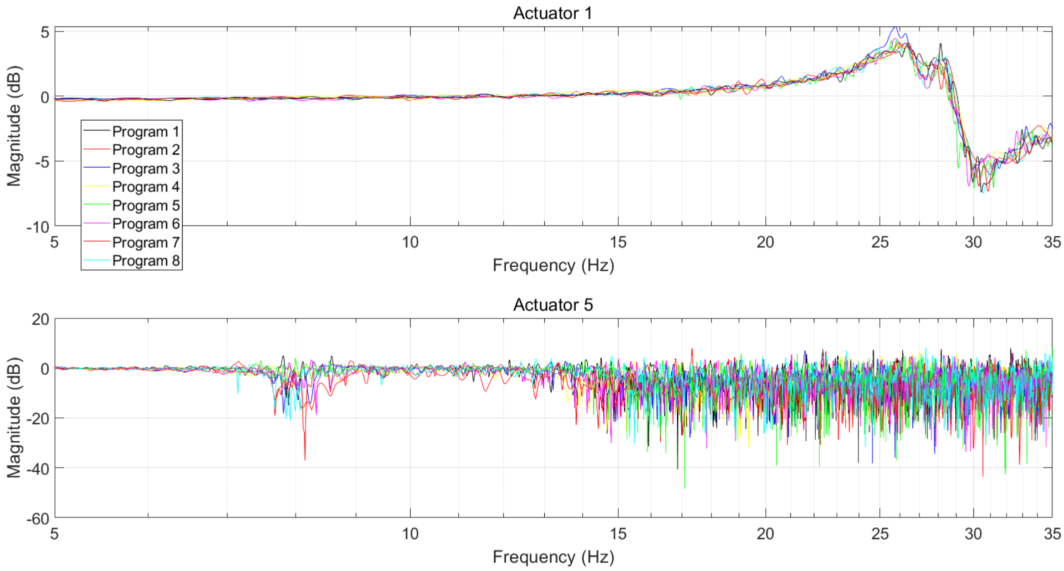

Fig. 3: Bode plot for actuator 1 and actuator 5.

Once the number of data sets has been significantly decreased, a neural network with the same typology as the one in Figure 3 has been trained, following the same procedure explained above.

4.- RESULTS

After obtaining the neural network model and training it with the actual data from the machine, it is time to evaluate whether the model is capable of providing reliable information on the behavior of the machine. For this purpose, the program-part that had not been used either in training or in the validation of the neural network has been selected. To validate these results, the data from this program in the machine has been taken and the indicators of each productivity criterion have been calculated to classify the 17 actuators. This classification is shown graphically on Table 2.

As shown here, the criteria have been distributed in several subsets. Both geometrical error and time in three different categories and smoothness in two. High, medium and low degrees are relative to each machine, which does not imply a specific quantitative level. This way, each actuator is placed on the box that best represents performance for the program and machine used. As shown here, some boxes remain empty, because certain requirements are incompatible; for instance, it is obviously impossible to decrease machining time to a minimum while obtaining the minimum possible error. It is this distribution of the actuators based on performance which is desired to be replicated by using exclusively the data obtained with the neural network model.

		Time		
		high	medium	low
Geometrical Error	high			1* 2* 3* 4*
	medium	16 17	6 10 15 7 11 8 13 9 14	
	low	5 12		

* **Non smooth** Actuator

Table 2: Actual machine data

For this purpose, the trained neural network obtained in section 3.2.1 is simulated, using as input signals the same program and actuators used in the machine to generate Table 2. Table 3 is created with the results obtained from the simulations and with the same indicator calculation and group distribution criteria. By comparing this with Table 2, it is clear that the actuators are distributed in the same groups regarding the geometrical error and time criteria; there are only some small differences in smoothness. This entails that the neural network predicts the performance of the different actuators very reliably and thus is a valid tool for manufacturers to choose the best CNC parameterization based on their machine, the part to manufacture and their production criteria. It must be noted that even if the training process of the neural network takes a significant amount of time, the simulation of the model is fast enough to be performed on-site at the CNC itself, therefore producing the desired actuator.

		Time		
		high	medium	low
Geometrical Error	high			1* 2* 3* 4
	medium	16 17	6 10 15 7 11 8 13 9 14	
	low	5 12		

* **Non smooth** Actuator

Table 3: Neural network data

Table 4 shows the results obtained with the neural network created decreasing the training data, as described in section 3.2.3. On comparing Table 4 to Table 2 and Table 3, it can be appreciated that the distribution of actuators based on geometrical error and time criteria is the same in all cases, the only difference being in the classification of smoothness.

		Time		
		high	medium	low
Geometrical Error	high			1* 2 3 4
	medium	16 17	6 7 8 9 10 11 13 14 15	
	low	5 12		

* Non smooth Actuator

Table 4: Data from neural network trained with reduced data

These results validate the decrease in the amount of data required to train the neural network. The machine time required to obtain the data set is five times lower.

5.- CONCLUSIONS

This research has developed a tool that tells manufacturers the best possible parameterization for the CNC based on the machine, the part and the desired productivity criteria. The method is established on the use of a neural network-based model trained with actual data obtained on the machine. Unlike other publications that deal with the optimization of a single objective, this research contains a comprehensive analysis of the issue and considers three different productivity criteria, looking for a compromise that fulfills the needs of the user based on the machine and the part to manufacture.

The conclusions obtained from the results provided by a neural network-based model have been proven to be equivalent to the ones that would be obtained from actual data. This significantly minimizes the number of tests to conduct on the actual machine and provides criteria for the manufacturer to be able to change the CNC parameterization in a simple manner based on their needs. Moreover, this study describes a method to significantly decrease the amount of data required for training the model.

REFERENCES

1. Chang Y, Tsao T. "Minimum-time contour tracking with model predictive control approach". *Proceedings of the American Control Conference*. p. 1821–1826. 2014. DOI: 10.1109/ACC.2014.6859414.

2. Mattmüller J, Gisler D. "Calculating a near time-optimal jerk-constrained trajectory along a specified smooth path". *International Journal of Advanced Manufacturing Technology*. Vol. 45, no. 9–10, p. 1007–1016. 2009. DOI: 10.1007/s00170-009-2032-9.

3. Bharathi A, Dong J. "A Smooth Trajectory Generation Algorithm for Addressing Higher-Order Dynamic Constraints in Nanopositioning Systems". *Procedia Manufacturing*. Vol. 1, p. 216–225. 2015. DOI: 10.1016/j.promfg.2015.09.006.

4. Zhang Y, Zhao M, Ye P et al. "Optimal curvature-smooth transition and efficient feedrate optimization method with axis kinematic limitations for linear toolpath". *International Journal of Advanced Manufacturing Technology*. Vol. 99, no. 1–4, p. 169–179. 2018. DOI: 10.1007/s00170-018-2496-6.

5. Pawlus W, Hansen MR, Choux M et al. "Mitigation of Fatigue Damage and Vibration Severity of Electric Drivetrains by Systematic Selection of Motion Profiles". *IEEE/ASME Transactions on Mechatronics*. Vol. 21, no. 6, p. 2870–2880. 2016. DOI: 10.1109/TMECH.2016.2573587.

6. Constantinescu D, Croft EA. "Smooth and time-optimal trajectory planning for industrial manipulators along specified paths". *Journal of Robotic Systems*. Vol. 17, no. 5, p. 233–249. 2000. DOI: 10.1002/(SICI)1097-4563(200005)17:5<233::AID-ROB1>3.0.CO;2-Y.

7. Li B, Zhang H, Ye P. "Error constraint optimization for corner smoothing algorithms in high-speed CNC machine tools". *International Journal of Advanced Manufacturing Technology*. Vol. 99, no. –4, p. 635–646. 2018. DOI: 10.1007/s00170-018-2489-5.

8. Lam D, Manzie C, Good M. "Multi-axis model predictive contouring control". *International Journal of Control*. Vol. 86, no. 8, p. 1410–1424. 2013. DOI: 10.1080/00207179.2013.770170.

9. Li X, Zhao H, Zhao X et al. "Interpolation-based contour error estimation and component-based contouring control for five-axis CNC machine tools". *Science China Technological Sciences*. Vol. 61, no. 11, p. 1666–1678. 2018. DOI: 10.1007/s11431-017-9204-y.

10. Pi S, Liu Q, Liu Q. "A novel dynamic contour error estimation and control in high-speed CNC". *International Journal of Advanced Manufacturing Technology*. Vol. 96, no. 1–4, p. 547–560. 2018. DOI: 10.1007/s00170-018-1629-2.

11. Jiang Z, Gao D, Lu Y et al. "Electrical energy consumption of CNC machine tools based on empirical modeling". *International Journal of Advanced Manufacturing Technology*. Vol. 100, no. 9–12, p. 2255–2267. 2019. DOI: 10.1007/s00170-018-2808-x.

12. Moreira LC, Li WD, Lu X et al. "Supervision controller for real-time surface quality assurance in CNC machining using artificial intelligence". *Computers and Industrial Engineering*. Vol. 127, no. December 2018, p. 158–168. 2019. DOI: 10.1016/j.cie.2018.12.016.

13. Luo W, Hu T, Zhang C et al. "Digital twin for CNC machine tool: modeling and using strategy". *Journal of Ambient Intelligence and Humanized Computing* [online]. Vol. 10, no. 3, p. 1129–1140. 2019. DOI: 10.1007/s12652-018-0946-5.

14. Zirn O, Batzies E, Weikert S et al. "State control of servo drives with flexible structural components". *Conference Record - IAS Annual Meeting (IEEE Industry Applications Society)*. Vol. 4, p. 1760–1766. 2006. DOI: 10.1109/IAS.2006.256773.

15. Balmès E. "Frequency domain identification of structural dynamics using the pole/residue parametrization". *IMAC XIV - 14th International Modal Analysis Conference - Noise and Vibration Harshness (NVH)*. 1996.

16. Vinod P, Reddy T, Sajin S et al. "Real-time Positioning Error Compensation for a Turning Machine Using Neural Network". *Procedia Materials Science*. Vol. 5, no. March 2014, p. 2293–2300. 2014. DOI: 10.1016/j.mspro.2014.07.472.

17. Kazem BI, Zangana NFH. "A Neural Network Based Real Time Controller for Turning Process". *Jordan Journal of Mechanical and Industrial Engineering* [online]. Vol. 1, no. 1, p. 43–55. 2007.

18. Huang P. "Neural Networks-Based-In-Process Adaptive Surface Roughness Control (NN-IASRC) System In End-Milling Operations". 2002.

19. Rosdy B, Kollar K, Moser J et al. "Surface Roughness Prediction for CNC Milling Process using Artificial Neural Network". *Epilepsia*. Vol. 57, no. Supplement 2, p. 190. 2016. DOI: http://dx.doi.org/10.1111/epi.13609.

20. Joo J, Yi GR, Cho H et al. "Dynamic planning model for determining cutting parameters using neural networks in feature-based process planning". *Journal of Intelligent Manufacturing*. Vol. 12, no. 1, p. 13–29. 2001. DOI: 10.1023/A:1008995312224.

21. Samek D, Bilek O. "Modeling of CNC Machining Process - Artificial Neural Networks Approach 2 Initial Experiments 3 Data Modeling". p. 168–173.

22. Meireles M, Almeida P, Simões M. "A comprehensive review for industrial applicability of artificial neural networks". *IEEE Transactions on Industrial Electronics*. Vol. 50, no. 3, p. 585–601. 2003. DOI: 10.1109/TIE.2003.812470.

23. Lai G, Chang W, Yang Y et al. "Modeling Long- and Short-Term Temporal Patterns with Deep Neural Networks". [online]. no. July. 2017.

24. Gonzalez J, Yu W. "Non-linear system modeling using LSTM neural networks". *IFAC-PapersOnLine* [online]. Vol. 51, no. 13, p. 485–489. 2018. DOI: 10.1016/j.ifacol.2018.07.326.

25. Wang J, Ma Y, Zhang L et al. "Deep learning for smart manufacturing: Methods and applications". *Journal of Manufacturing Systems*. Vol. 48, no. January, p. 144–156. 2018. DOI: 10.1016/j.jmsy.2018.01.003.

26. Basagoiti RM, Martínez de Alegría J, Beamurgia M et al. “FATIMA : Fabricación avanzada y técnicas de Inteligencia Artificial en las máquinas”. *Acta del XXI Congreso Máquina-Herramienta*. no. October. 2017.

27. Agatonovic-Kustrin S, Beresford R. “Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research”. *Journal of Pharmaceutical and Biomedical Analysis.* Vol. 22, p. 717-727. 2000. DOI: 10.1016/S0731-7085(99)00272-1.