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MLP and ANFIS Applied to the Prediction of Hole Diameters in the Drilling Process

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Additional information is available at the end of the chapter

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1. Introduction

The control of industrial machining manufacturing processes is of great economic importance due to the ongoing search to reduce raw materials and labor wastage. Indirect manufacturing operations such as dimensional quality control generate indirect costs that can be avoided or reduced through the use of control systems [1]. The use of intelligent manufacturing systems (IMS), which is the next step in the monitoring of manufacturing processes, has been researched through the application of artificial neural networks (ANN) since the 1980s [2].

The machining drilling process ranks among the most widely used manufacturing processes in industry in general [3, 4]. In the quest for higher quality in drilling operations, ANNs have been employed to monitor drill wear using sensors. Among the types of signals employed is that of machining loads measured with a dynamometer [5, 6], electric current measured by applying Hall Effect sensors on electric motors [7], vibrations [8], as well as a combination of the above with other devices such as accelerometers and acoustic emission sensors [9].

This article contributes to the use of MLP [10-12] and ANFIS type [13-16] artificial intelligence systems programmed in MATLAB to estimate the diameter of drilled holes. The two types of network use the backpropagation method, which is the most popular model for manufacturing applications [2]. In the experiment, which consisted of drilling single-layer test specimens of 2024-T3 alloy and of Ti6Al4V alloy, an acoustic emission sensor, a three-dimensional dynamometer, an accelerometer, and a Hall Effect sensor were used to collect

information about noise frequency and intensity, table vibrations, loads on the x, y and z axes, and electric current in the motor, respectively.

2. Drilling Process

The three drilling processes most frequently employed in industry today are turning, milling and boring [3], and the latter is the least studied process. However, it is estimated that today, boring with helical drill bits accounts for 20% to 25% of all machining processes.

The quality of a hole depends on geometric and dimensional errors, as well as burrs and surface integrity. Moreover, the type of drilling process, the tool, cutting parameters and machine stiffness also affect the precision of the hole [19].

It is very difficult to generate a reliable analytical model to predict and control hole diameters, since these holes are usually affected by several parameters. Figure 1 illustrates the loads involved in the drilling process, the most representative of which is the feed force F_z , since it affects chip formation and surface roughness.

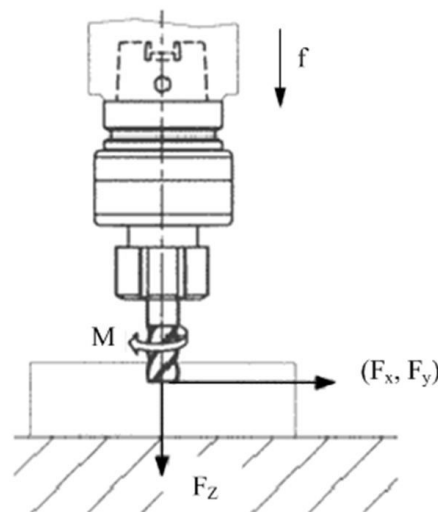


Figure 1. Loads involved in drilling processes.

3. Artificial Intelligent Systems

3.1. Artificial multilayer perceptron (MLP) neural network

Artificial neural networks are gaining ground as a new information processing paradigm for intelligent systems, which can learn from examples and, based on training, generalize to process a new set of information [14].

Artificial neurons have synaptic connections that receive information from sensors and have an attributed weight. The sum of the values of the inputs adjusted by the weight of each

synapse is processed and an output is generated. The training error is calculated in each iteration, based on the calculated output and desired output, and is used to adjust the synaptic weights according to the generalized delta rule:

$$w_{ij}^{(l)}(n+1) = w_{ij}^{(l)}(n) + \alpha [w_{ij}^{(l)}(n-1)] + \eta \delta_j^{(l)}(n) y_i^{(l-1)}(n) \quad (1)$$

where η is the learning rate and α is the moment, which are parameters that influence the learning rate and its stability, respectively; $w_{ij}^{(l)}$ is the weight of each connection; and $\delta_j^{(l)}$ is the local gradient calculated from the error signal.

A neural network artificial (ANN) learns by continuously adjusting the synaptic weights at the connections between layers of neurons until a satisfactory response is produced [9].

In the present work, the MLP network was applied to estimate drilled hole diameters based on an analysis of the data captured by the sensors. The weight readjustment method employed was backpropagation, which consists of propagating the mean squared error generated in the diameter estimation by each layer of neurons, readjusting the weights of the connections so as to reduce the error in the next iteration.

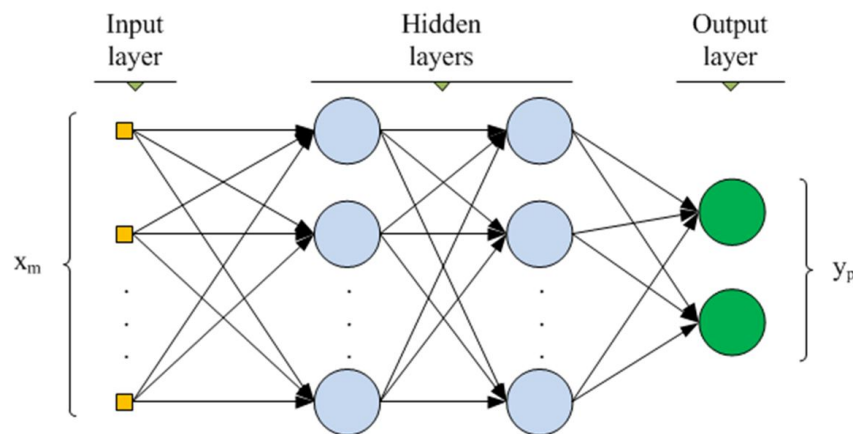


Figure 2. Typical architecture of an MLP with two hidden layers.

Figure 2 shows a typical MLP ANN, with m inputs and p outputs, with each circle representing a neuron. The outputs of a neuron are used as inputs for a neuron in the next layer.

3.2. Adaptive neuro-fuzzy inference system (ANFIS)

The ANFIS system is based on functional equivalence, under certain constraints, between RBF (radial basis function) neural networks and TSK-type fuzzy systems [15]. A single existing output is calculated directly by weighting the inputs according to fuzzy rules. These rules, which are the knowledge base, are determined by a computational algorithm based on neural networks. Figure 3 exemplifies the ANFIS model with two input variables (x and y) and two rules [11].

Obtaining an ANFIS model that performs well requires taking into consideration the initial number of parameters and the number of inputs and rules of the system [16]. These parameters are determined empirically, and an initial model is usually created with equally spaced pertinence functions.

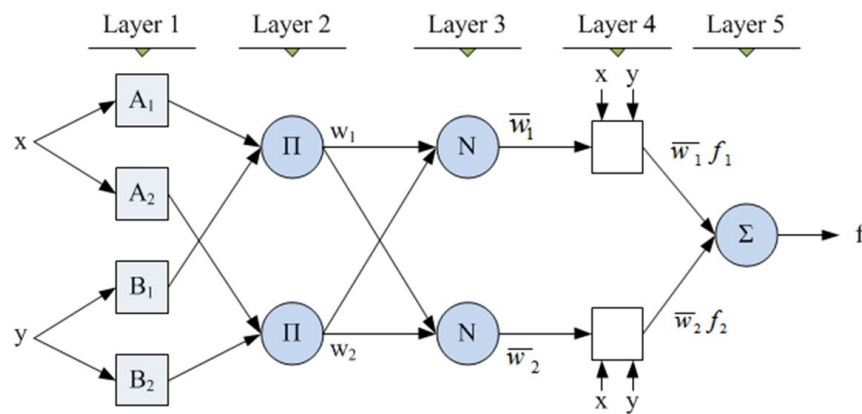


Figure 3. ANFIS architecture for two inputs and two rules based on the first-order Sugeno model.

However, this method is not always efficient because it does not show how many relevant input groups there are. To this end, there are algorithms that help determine the number of pertinence functions, thus enabling one to calculate the maximum number of fuzzy rules.

The subtractive clustering algorithm is used to identify data distribution centers [17], in which are centered the pertinence curves with pertinence values equal to 1. The number of clusters, the radius of influence of each cluster center, and the number of training iterations to be employed should be defined as parameters for the configuration of the inference system. At each pass, the algorithm seeks a point that minimizes the sum of the potential and the neighboring points. The potential is calculated by equation (2):

$$P_i = \sum_{j=i}^n \exp\left(-\frac{4}{r_a^2} \|x_i - x_j\|^2\right) \quad (2)$$

where P_i is the potential of the possible cluster, x_i is the possible cluster center, x_j is each point in the neighborhood of the cluster that will be grouped in it, and n is the number of points in the neighborhood.

ANFIS is a fuzzy inference system introduced in the work structure of an adaptive neural network. Using a hybrid learning scheme, the ANFIS system is able to map inputs and outputs based on human knowledge and on input and output data pairs [18]. The ANFIS method is superior to other modeling methods such as autoregressive models, cascade correlation neural networks, backpropagation algorithm neural networks, sixth-order polynomials, and linear prediction methods [10].

4. Methodology

4.1. Signal collection and drilling process

The tests were performed on test specimens composed of a package of sheets of Ti6Al4V titanium alloy and 2024-T3 aluminum alloy, which were arranged in this order to mimic their use in the aerospace industry. The tool employed here was a helical drill made of hard metal.

A total of nine test specimens were prepared, and 162 holes were drilled in each one. Thus, a considerable number of data were made available to train the artificial intelligence systems. The data set consisted of the signals collected during drilling and the diameters measured at the end of the process.

The drilling process was monitored using an acoustic emission sensor, a three-dimensional dynamometer, an accelerometer, and a Hall Effect sensor, which were arranged as illustrated in Figure 4.

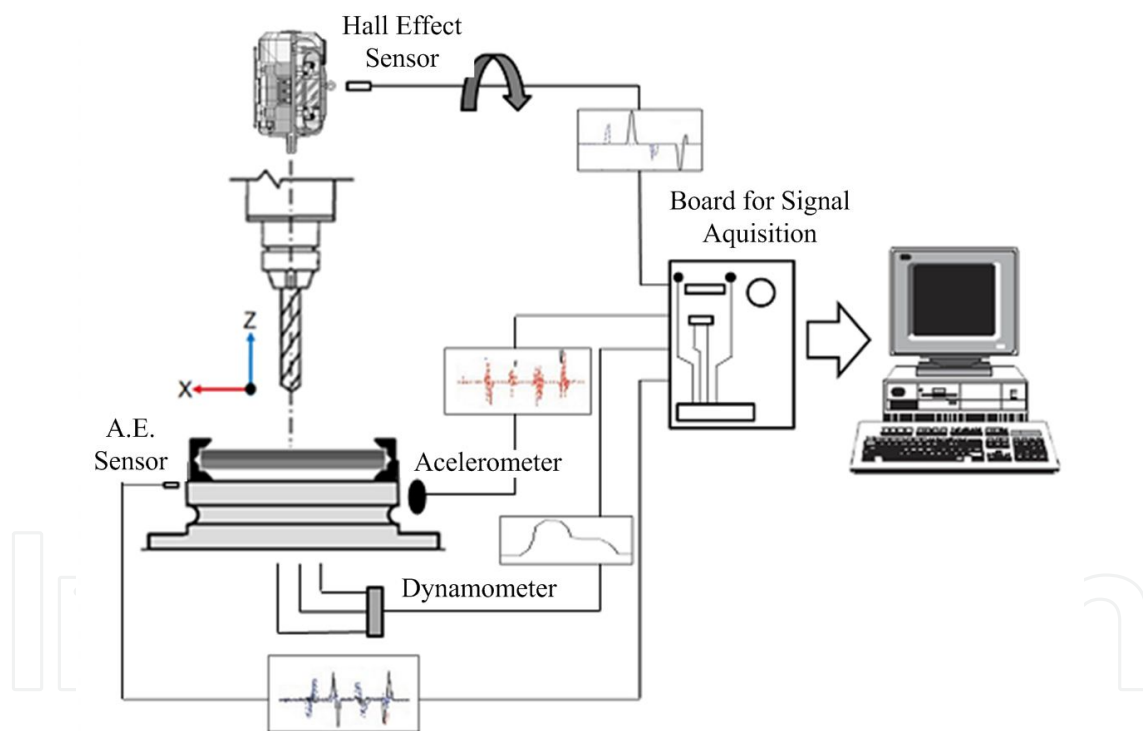


Figure 4. Sensor assembly scheme for testing.

The acoustic emission signal was collected using a Sensis model DM-42 sensor. The electric power was measured by applying a transducer to monitor the electric current and voltage in the terminals of the electric motor that activates the tool holder. The six signals were sent to a National Instruments PCI-6035E data acquisition board installed in a computer. LabView software was used to acquire the signals and store them in binary format for subsequent analysis and processing.

To simulate diverse machining conditions, different cutting parameters were selected for each machined test specimen. This method is useful to evaluate the performance of artificial intelligence systems in response to changes in the process. Each test specimen was dubbed as listed in Table 1.

Condition	ID	Spindle [rpm]	Feed Speed [mm/min]
1	1A	1000	90.0
2	1B	1000	22.4
3	1C	1000	250.0
4	2A	500	90.0
5	2B	500	22.4
6	2C	500	250.0
7	3A	2000	90.0
8	3B	2000	22.4
9	3C	2000	250.0

Table 1. Machining conditions used in the tests.

Each pass consisted of a single drilling movement along the workpiece in a given condition. The signals of acoustic emission, loads, cutting power and acceleration shown in Figure 5 were measured in real time at a rate of 2000 samples per second.

4.2. Diameter measurements

Because the roundness of machined holes is not perfect, two measurements were taken of each hole, one of the maximum and the other of the minimum diameter. Moreover, the diameter of the hole in each machined material will also be different due to the material's particular characteristics.

A MAHR MarCator 1087 B comparator gauge with a precision of $\pm 0.005\text{mm}$ was used to record the measured dimensions and the dimensional control results were employed to train the artificial intelligence systems.

4.3. Definition of the architecture of the artificial intelligence systems

The architecture of the systems was defined using all the collected signals, i.e., those of acoustic emission; loads in the x , y and z directions; electrical power and acceleration. An MLP network and an ANFIS system were created for each test specimen material, due to the differences in the behavior of the signals (see Figure 5) and in the ranges of values found in the measurement of the diameters.

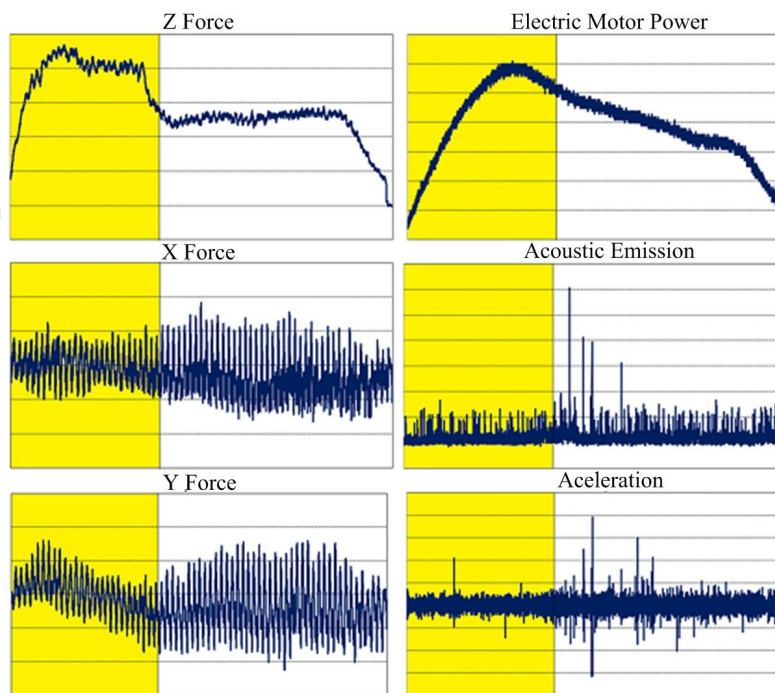


Figure 5. Signals collected during the drilling process of Ti6Al4V alloy (left) and 2024-T3 alloy (right).

4.3.1. Multilayer Perceptron

In this study, the signals from the sensors, together with the maximum and minimum measured diameters, were organized into two matrices, one for each test specimen material. These data were utilized to train the neural network. The entire data set of the tests resulted in 1337 samples, considering tool breakage during testing under condition 2C.

Parameters	Ti6Al4V	2024-T3
Neurons in each layer	[5 20 15]	[20 10 5]
Learning rate	0.15	0.3
Moment	0.2	0.8
Transfer function	tansig	poslin

Table 2. Architecture of the MLP networks.

The MLP network architecture is defined by establishing the number of hidden layers to be used, the number of neurons contained in each layer, the learning rate and the moment. An algorithm was created to test combinations of these parameters. The final choice was the combination that appeared among the five smallest errors in the estimate of the maximum and minimum diameters. Parameters such as the number of training iterations and the desired error are used as criteria to complete the training and were established at 200 training iterations and 1×10^{-7} mm, respectively. This procedure was performed for each material,

generating two MLP networks whose configuration is described in Table 2. The remaining parameters were kept according to the MATLAB default.

4.3.2. ANFIS

The same data matrix employed to train the MLP neural network was used to train the ANFIS system. This system consists of a fuzzy inference system (FIS) that collects the available data, converts them into If-Then type rules by means of pertinence functions, and processes them to generate the desired output. The FIS is influenced by the organization of the training data set, whose task is performed with the help of MATLAB's Fuzzy toolbox. The subtractive clustering algorithm (subclust) is used to search for similar data clusters in the training set, optimizing the FIS through the definition of points with the highest potential for the cluster center. Parameters such as the radius of influence, inclusion rate and rejection rate help define the number of clusters, and hence, the number of rules of the FIS. Table 3 lists the parameters used in the ANFIS systems. The desired error was set at 1×10^{-7} mm. The training method consists of a hybrid algorithm with the method of backpropagation and least-squares estimate.

Parameters	Ti6Al4V	2024-T3
Radius of influence	1.25	1.25
Inclusion rate	0.6	0.6
Rejection rate	0.4	0.1

Table 3. ANFIS parameters.

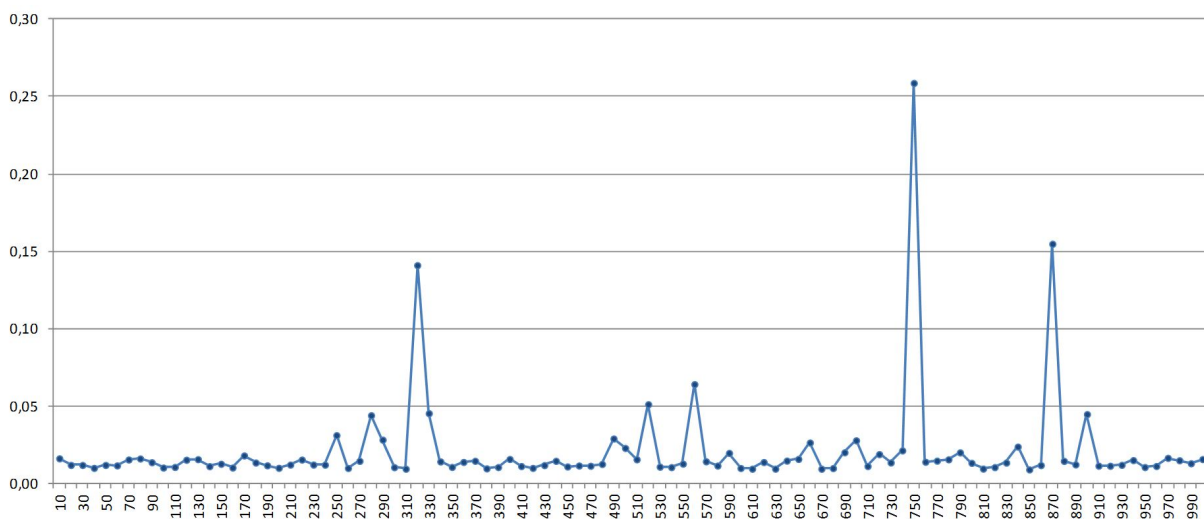


Figure 6. Mean error of hole diameters estimated by the ANFIS system for several training iterations.

Because training in the ANFIS system is performed in batch mode, with the entire training set presented at once, the appropriate number of training iterations was investigated. Thus,

an algorithm was created to test several numbers of training iterations ranging from 10 up to 1000. Figure 6 illustrates the result of this test.

The larger the number of training iterations, the greater the computational effort. Thus, avoiding the peaks (Figure 6), the number de training iterations was set at 75, which requires low computational capacity.

5. Influence of inputs on the performance of diameter estimation

5.1. Use of all the collected signals

Initially, the systems were trained using all the collected signals. Given the data set of the sensors and the desired outputs, which Consist of the measured diameters, the performance of the neural network is evaluated based on the error between the estimated diameter and the measured diameter, which are shown on graphs.

5.1.1. MLP

For the Ti6Al4V titanium alloy, the estimate of the minimum diameter resulted in a mean error of 0.0067mm, with a maximum error of 0.0676mm.

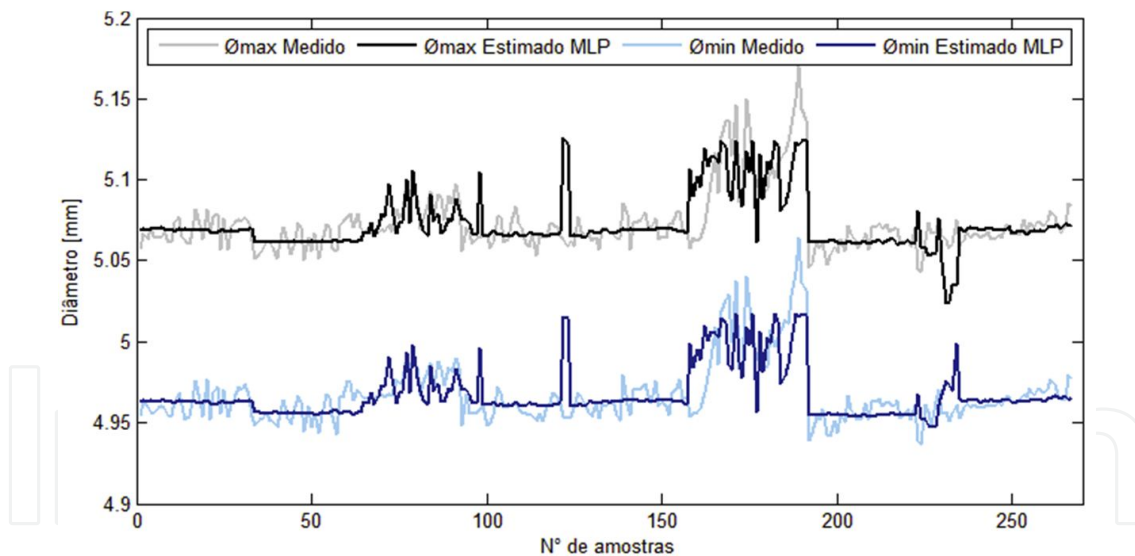


Figure 7. Minimum and maximum diameters (actual vs. estimated by the MLP) for the Ti6Al4V alloy.

For the maximum diameter, the resulting mean error was 0.0066mm, with a maximum error of 0.0668mm. Figure 7 depicts the results of these estimates.

Figure 8 shows the result of the estimation of the hole diameters machined in the 2024-T3 aluminum alloy. The mean error for the minimum diameter was 0.0080mm, with a maximum error of 0.0649mm. For the maximum diameter, the mean error was 0.0086mm, with a maximum error of 0.0655mm.

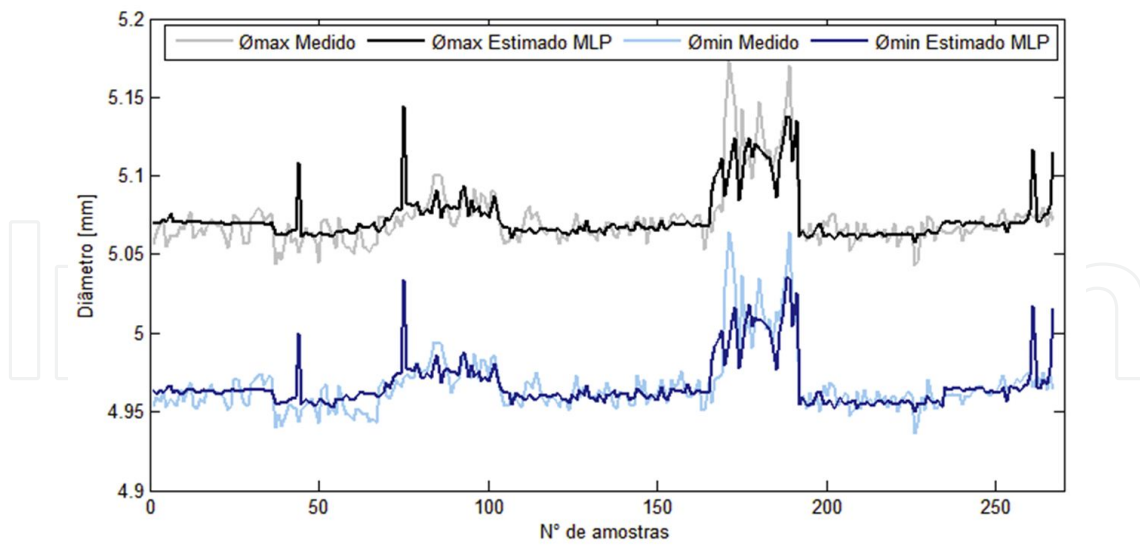


Figure 8. Minimum and maximum diameters (actual vs. estimated by the MLP) for the 2024-T3 alloy.

5.1.2. ANFIS

Figure 9 shows the diameters estimated by ANFIS. The mean error in the estimate of the minimum diameter was 0.01102mm, with a maximum error of 0.0704mm. For the maximum diameter, the resulting mean error was 0.01188mm, and the highest error was 0.0718mm.

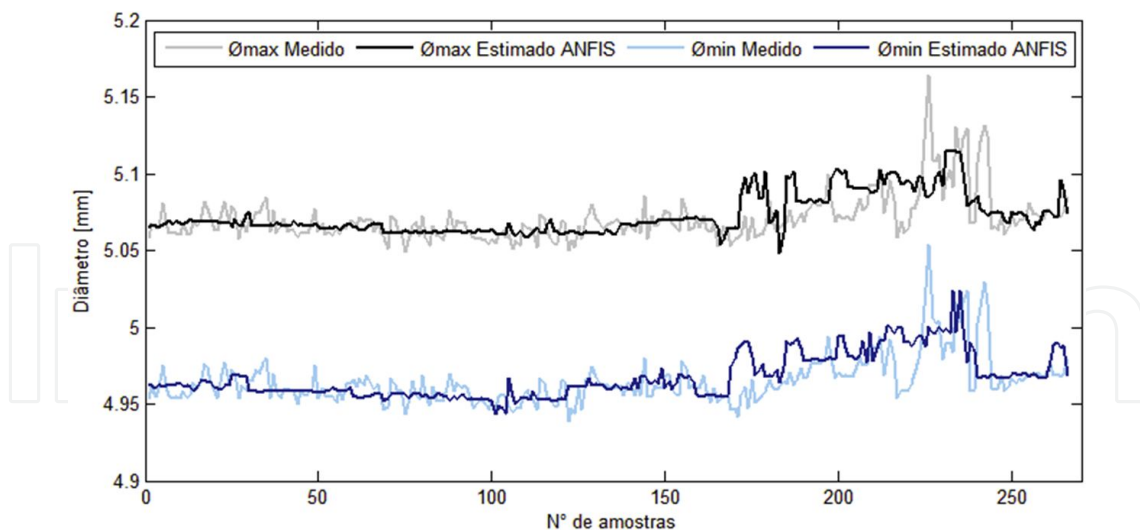


Figure 9. Minimum and maximum diameters (actual vs. estimated by ANFIS) for the Ti6Al4V alloy.

Figure 10 illustrates the result of the machined hole diameter estimated for the 2024-T3 alloy, using the same network configuration. The mean error for the minimum diameter was 0.0980mm, with a maximum error of 0.0739mm. The maximum diameter presented a mean error of 0.00990mm, and a maximum error of 0.0791mm.

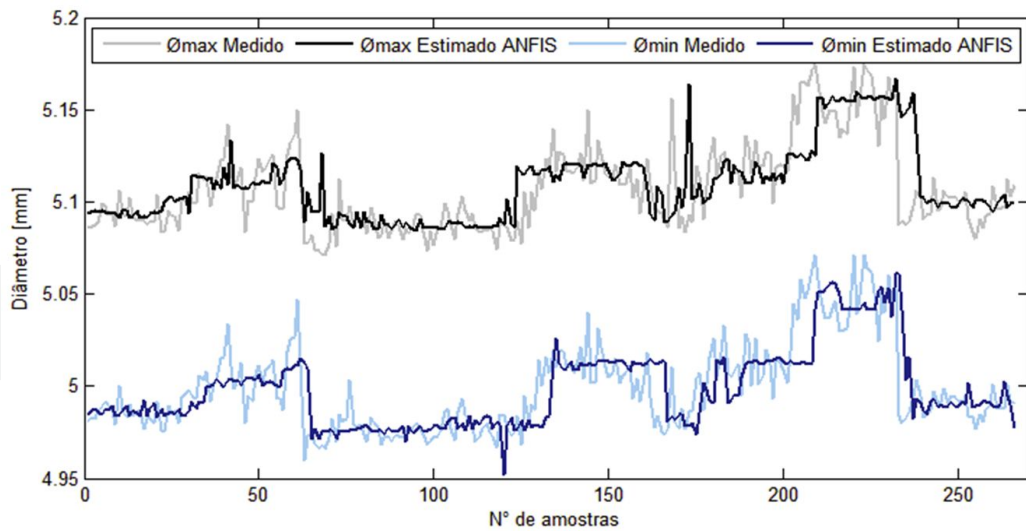


Figure 10. Minimum and maximum diameters (actual vs. estimated by the MLP) for the 2024-T3 alloy.

5.2. Isolated and combined use of signals

To optimize the computational effort, an algorithm was created to test the performance of each type of system in response to each of the signals separately or to a combination of two or more signals. This procedure was adopted in order to identify a less invasive estimation method.

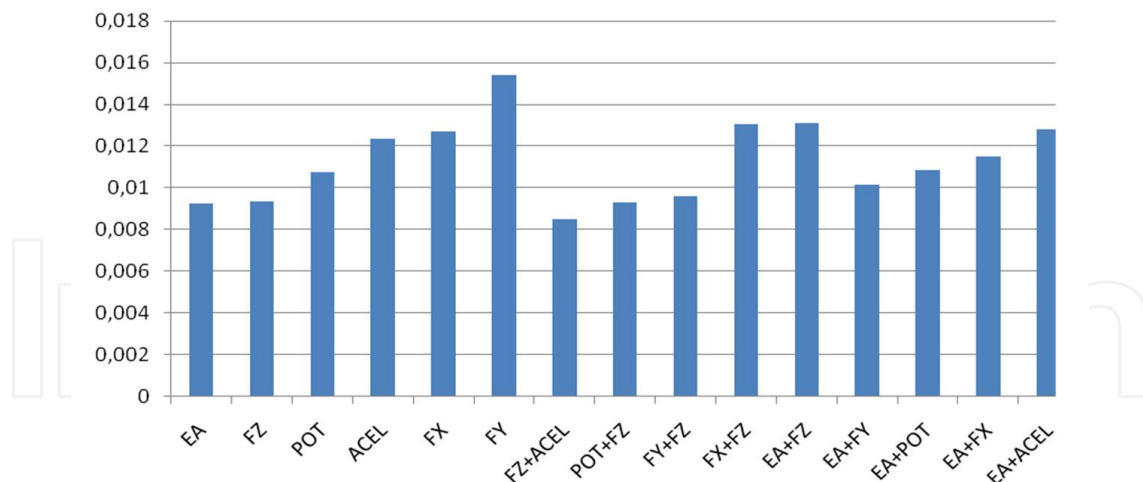


Figure 11. Performance of individual and combined signals in the estimation of hole diameters in Ti6Al4V alloy by the MLP network

Individual signals and a combination of two distinct signals were tested for the MLP network. The best individual inputs for the Ti6Al4V alloy were the acoustic emission and Z force signals. Combined, the Z force and acceleration signals presented the lowest error. The classified signals are illustrated in Figure 11.

For the 2024-T3 alloy, the best individual input was the Z force. When combined, the Z force and acceleration signals presented the lowest error. Figure 11 depicts the classified signals.

In the ANFIS system, the Z force provided the best individual signal for the estimate of the drilled hole diameter in Ti6Al4V alloy. The acoustic emission signal combined with the Z force presented the best result with two combinations, as indicated in Figure 12.

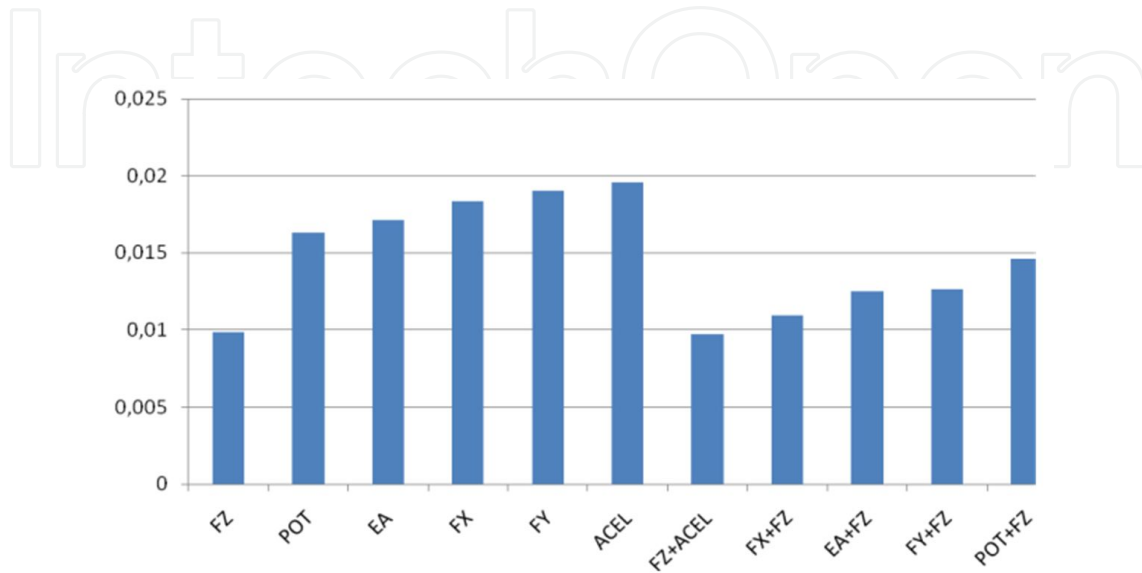


Figure 12. Performance of individual and combined signals in the estimation of hole diameters in 2024-T3 alloy by the MLP system.

For the aluminum alloy, the ANFIS system presented the best performance with the individual Z force signal and with a combination of the Z force and acoustic emission signals, as indicated in Figure 14.

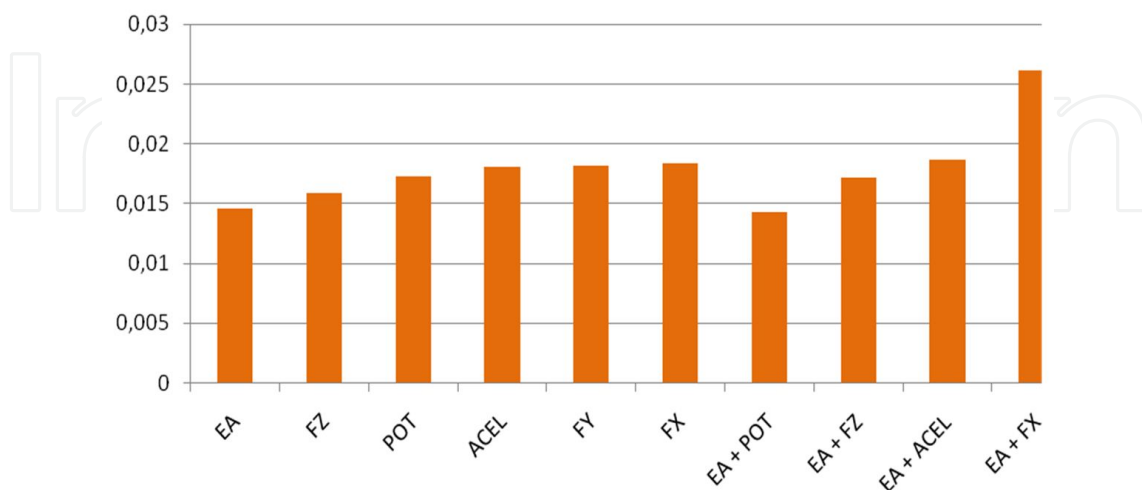


Figure 13. Performance of individual and combined signals in the estimation of hole diameters in Ti6Al4V alloy by the ANFIS system.

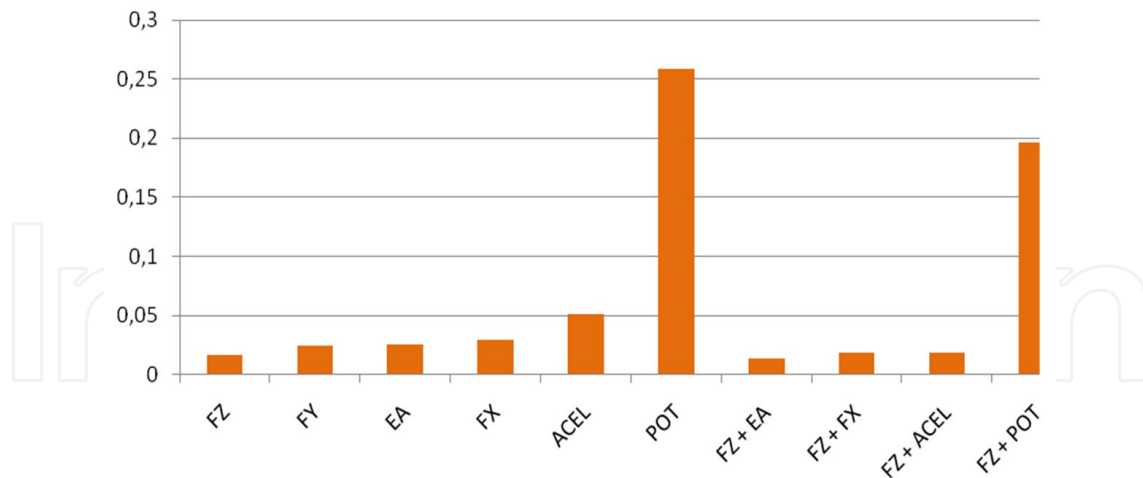


Figure 14. Performance of individual and combined signals in the estimation of hole diameters in 2024-T3 alloy by the ANFIS system.

6. Performance using the Z force

Because the performance of the artificial intelligence systems in the tests was the highest when using the Z force signal, new tests were carried out with only this signal. The errors were divided into four classes, according to the following criteria: precision of the instrument ($\leq 5\mu\text{m}$), tolerance required for precision drilling processes ($\leq 12\mu\text{m}$), tolerance normally employed in industrial settings ($\leq 25\mu\text{m}$), and the errors that would lead to a non-conformity ($> 25\mu\text{m}$). The configurations used in the previous tests were maintained in this test.

6.1. MLP

The multilayer perceptron ANN was trained with the information of the Z force and the minimum and maximum measured diameters.

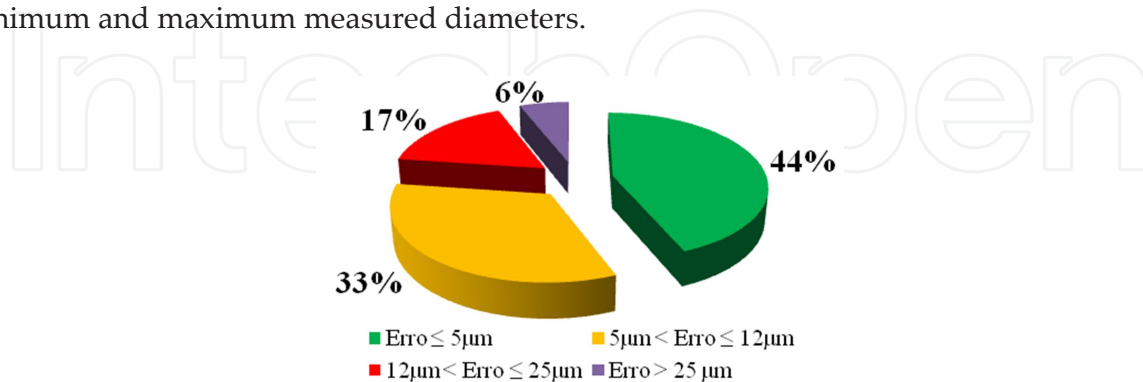


Figure 15. Classification of estimation errors for the 2024-T3 alloy obtained by the MLP network.

The simulation of the MLP network for the aluminum alloy presented lower precision errors than the measurement instrument used in 44% of the attempts. Thirty-three percent of the

estimates presented errors within the range stipulated for precision holes and 17% for the tolerances normally applied in industry in general. Only 6% of the estimates performed by the artificial neural network would result in a product conformity rejection.

The simulation of the MLP network for the titanium alloy presented lower precision errors than the measurement instrument used in 45% of the attempts. Thirty-seven percent of the estimates presented errors within the range stipulated for precision holes and 15% for the tolerances normally applied in industry in general. Only 3% of the estimates performed by the artificial neural network would result in a product conformity rejection.

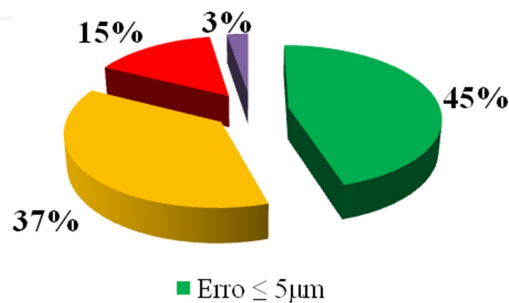


Figure 16. Classification of estimation errors for the Ti6Al4V alloy obtained by the MLP network.

6.2. ANFIS

The ANFIS system was simulated in the same way as was done with the MLP network, but this time using only one input, the Z force. This procedure resulted in changes in the FIS structure due to the use of only one input.

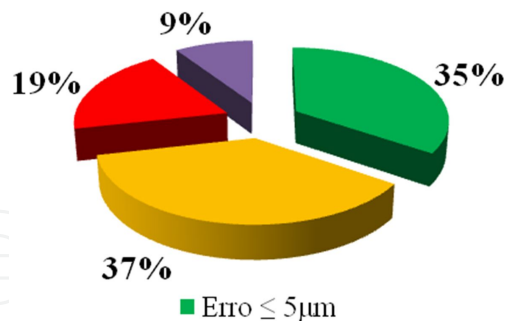


Figure 17. Classification of estimation errors for the 2024-T3 alloy obtained by the ANFIS system.

For the aluminum alloy, ANFIS presented lower precision errors than the measurement instrument employed in 35% of the attempts. Thirty-seven percent of the estimates presented errors within the range stipulated for precision holes and 19% for the tolerances normally used in industry in general. Only 9% of the estimates performed by the artificial neural network would result in a product conformity rejection, as indicated in Figure 17.

For the titanium alloy, ANFIS presented lower precision errors than the measurement instrument employed in 40% of the attempts. Thirty-four percent of the estimates presented

errors within the range stipulated for precision holes and 15% for the tolerances normally used in industry. Only 11% of the estimates performed by the artificial neural network would lead to a product conformity rejection, as indicated in Figure 18.

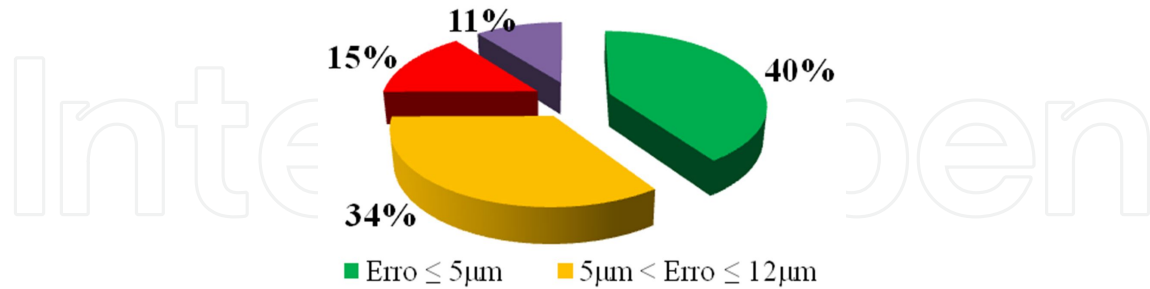


Figure 18. Classification of estimation errors for the Ti6Al4V alloy obtained by the ANFIS system.

7. Conclusions

Artificial intelligence systems today are employed in mechanical manufacturing processes to monitor tool wear and control cutting parameters. This article presented a study of the application of two systems used in the dimensional control of a precision drilling process.

The first system used here consisted of a multiple layer perceptron (MLP) artificial neural network. Its performance was marked by the large number of signals used in its training and for its estimation precision, which produced 52% of correct responses (errors below 5 μm) for the titanium alloy and 42% for the aluminum alloy. As for its unacceptable error rates, the MLP system generated only 4% and 8% for the titanium and aluminum alloys, respectively.

The second approach, which involved the application of an adaptive neuro-fuzzy inference system (ANFIS), generated a large number of correct responses using the six available signals, i.e., 45% for the titanium alloy and 33% for the aluminum alloy. A total of 11% of errors for the titanium alloy and 20% for the aluminum alloy were classified above the admissible tolerances ($> 25\mu\text{m}$).

The results described herein demonstrate the applicability of the two systems in industrial contexts. However, to evaluate the economic feasibility of their application, another method was employed using the signal from only one sensor, whose simulations generated the lowest error among the available signals. Two signals stood out: the Z force and acoustic emission signals, with the former presenting a better result for the two alloys of the test specimen and the latter presenting good results only in the hole diameter estimation for the titanium alloy. Therefore, the Z force was selected for the continuation of the tests.

The results obtained here are very encouraging in that fewer estimates fell within the range considered inadmissible, i.e., only 6% for the aluminum alloy and 3% for the titanium alloy, using the MLP network.

The results produced by the ANFIS system also demonstrated a drop in the number of errors outside the expected range, i.e., 9% for the aluminum alloy and 11% for the titanium alloy.

Based on the approaches used in this work, it can be stated that the use of artificial intelligence systems in industry, particularly multilayer perceptron neural networks and the adaptive neuro-fuzzy inference systems, is feasible. These systems showed high accuracy and low computational effort, as well as a low implementation cost with the use of only one sensor, which implies few physical changes in the equipment to be monitored.

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