Article

Not peer-reviewed version

Training an Artificial Neural Network Based on Results of the Experiment on Machining of Aluminum Alloys 2196, 2043 and 2099 Used in the Aeronautical Industry

Nicolae Ioan Pasca , Mihai Banica * , Vasile Nasui

Posted Date: 16 March 2026

doi: 10.20944/preprints202603.1100.v1

Keywords: alloy; aluminum; artificial; diamond; machining; network

Preprints.org is a free multidisciplinary platform providing preprint service that is dedicated to making early versions of research outputs permanently available and citable. Preprints posted at Preprints.org appear in Web of Science, Crossref, Google Scholar, Scilit, Europe PMC.

Copyright: This open access article is published under a Creative Commons CC BY 4.0 license, which permit the free download, distribution, and reuse, provided that the author and preprint are cited in any reuse.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

Disclaimer/Publisher's Note: The statements, opinions, and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions, or products referred to in the content.

Article

Training an Artificial Neural Network Based on Results of the Experiment on Machining of Aluminum Alloys 2196, 2043 and 2099 Used in the Aeronautical Industry

Nicolae Ioan Pasca, Mihai Banica* and Vasile Nasui

Technical University of Cluj-Napoca
* Correspondence: Mihai.Banica@imtech.utcluj.ro

Abstract

The paper presents the cutting tool-life of uncoated and DLC-coated inserts used for machining of aluminum-lithium components used in the structure of Airbus A350 aircraft. Based on the collected data, a feed-forward artificial neural network with two hidden layers was created, trained using the Bayesian Regularization (trainbr) algorithm in MATLAB. The obtained results indicate a high performance of the model, with a low mean square error (MSE) and a correlation coefficient $R > 0.98$, which reflects an excellent generalization capacity and a close correlation between the actual and estimated values. The regression plot and error analysis confirmed the accuracy of the predictions made by the network. The internal parameters of the algorithm, such as the gradient and μ, provided additional information regarding the optimization process.

Keywords: alloy; aluminum; artificial; diamond; machining; network

---

1. Introduction

In the context of increasingly stringent requirements regarding the characteristics of materials used in the aeronautical industry, aluminum alloys from the 2xxx series, such as 2196, 2043 and 2099, are gaining particular importance due to their superior mechanical properties and low weight. Machining these alloys by cutting requires careful monitoring and optimization of technological parameters to ensure surface quality and process efficiency.

Modeling the complex phenomena involved in the machining of these materials is essential for understanding the influence of process parameters on the final characteristics of the parts. Due to their ability to learn complex nonlinear relationships between variables, artificial neural networks (ANNs) represent a modern and efficient tool for analyzing and predicting the quality of machined parts and the behavior of cutting tools used in machining processes.

The paper presents the results obtained from training an artificial neural network based on experimental data obtained from the processing of aluminum alloys 2196, 2043 and 2099, with the aim of predicting the tool-life of milling cutters with uncoated inserts code XDHT150440R-U10-HU612 and DLC coated inserts code XDHT150440R-U11-V0105-P. Knowing the tool-life is important because it helps to remove the cutting tools from use before they are destroyed due to excessive exploitation. This approach can significantly contribute to reducing the rate of non-conformities and to reducing manufacturing costs.

Research objectives:

- Implementation of the experimental plan to establish the tool-life of the two types of cutting inserts;
- Statistical analysis of the data obtained during the experiment;
- Training of the artificial neural network;

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

- Validation and evaluation of the network performance;
- Formulation of conclusions regarding the tool-life and machining costs.

2. Experimental Methodology

In the following, the types of materials for which the experiment is performed, the equipment and cutting tools used, and the experimental methodology will be presented. To carry out the experiment we need equipment such as a numerically controlled machine, milling cutters, cutting inserts, cutting tool measuring and balancing machines, roughness tester, microscope and measuring and control devices.

Aluminum-based alloys containing lithium (Al-Li) represent an advanced class of materials used extensively in the aeronautical field, due to their exceptional properties. The introduction of lithium as an alloying element determines a series of technological and mechanical advantages essential for the construction of modern aerostructures.

Reducing weight is one of the most valuable assets of these alloys. Lithium is the lightest metal known, and its incorporation into the aluminum matrix contributes to the decrease in the total density of the material. Reducing the structural weight of the components allows for improved fuel efficiency and increased aircraft autonomy. The high mechanical strength, in relation to the low density, makes Al-Li alloys have a higher specific strength than conventional aluminum alloys. This allows the design of thinner components, but strong enough to withstand the intense mechanical stresses in flight. Increased corrosion resistance is another important advantage, providing greater durability in severe weather conditions and aggressive environments, such as those found at high altitudes or in coastal areas.

Also, modern manufacturing technologies, necessary for the uniform processing of Al-Li alloys, have led to the development of innovative casting, rolling and machining methods, contributing to the overall advancement of aerospace technology.

2.1. Aluminum Alloy 2196-T8511

Alloy 2196-T8511 is an aluminum-lithium-based extruded material designed for aerospace applications that require an optimal combination of low density, high mechanical strength, and durability in corrosive environments. The T8511 heat treatment helps stabilize the structure and achieve improved mechanical properties. Compared to traditional alloys used in the aerospace industry, such as 7075 and 2024, alloy 2196 offers superior performance in both specific strength and corrosion behavior. It also stands out for its good machinability, which is essential for the manufacture of complex components. Currently, 2196-T8511 is used to make fuselage rails, seat rails, and other structural components where a balance between low weight and mechanical performance is required [1].

2.2. Aluminum Alloy 2043-T83

Alloy 2043-T83 is an advanced 2xxx series copper-lithium alloy developed for aerospace structural applications where a combination of high strength, crack toughness and damage tolerance is required. The T83 heat treatment involves a cold working process after thermal solution and artificial precipitation, resulting in a stable microstructure with excellent performance. Compared to conventional alloys 2024-T3 or 2124-T851, alloy 2043 offers superior mechanical strength and improved crack propagation characteristics, making it suitable for critical aircraft components such as fuselage panels, structural plates and interior components subjected to cyclic loads. This alloy also exhibits satisfactory machinability and good fatigue behavior, compatible with today's requirements for lightweight and durable aerospace structures [2].

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

2.3. Aluminum Alloy 2099-T83

The 2099-T83 Al-Li alloy is one of the most advanced metallurgical solutions developed for aerospace applications, characterized by low density, high mechanical strength and excellent structural stability in demanding environments. Its optimized chemical composition, based on the addition of lithium, copper and manganese, provides a significantly higher strength-to-weight ratio compared to conventional aluminum alloys. The addition of lithium directly contributes to reducing density by up to 3%, which causes a significant decrease in the mass of aero structural components. At the same time, an increase in rigidity is achieved, an essential aspect for maintaining structural integrity during flight.

Key characteristics include:

- Superior specific strength and rigidity, maintained even under variable thermal conditions;
- Excellent fatigue and damage tolerance, allowing the material to be used in components subjected to repetitive stress cycles;
- High corrosion resistance, especially stress corrosion cracking, making it suitable for chemically and atmospherically aggressive environments;
- Thermal stability over a wide temperature range, making it suitable for both civil and military or space applications.

Typical applications of alloy 2099 include:

- Fuselage panels and bulkheads;
- Wing structural components;
- Spacecraft load-bearing structures;
- Cryogenic fuel tanks;
- Helicopter structural components [3].

2.4. The Cutting Tools Used for Machining Experiment

The Mapal ICM901-032-086-A063-Z3R-XD15 is a high-precision milling cutter designed for advanced machining applications. This type of tool is equipped with an HSK-A63 clamping system, known for its superior rigidity and dimensional stability in dynamic working conditions, especially at high speeds. The constructive configuration of the milling cutter allows the installation of three removable inserts. The inserts are fixed using dedicated screws, code M4×7.8-TX15-IP, designed to ensure firm clamping, high stability and good repeatability in the event of successive replacements.

This constructive configuration offers several operational advantages, such as reducing vibrations and increasing the stability of the machining process, improving the quality of the surfaces obtained, increasing the durability of the tool-insert assembly and high efficiency in front and side milling operations. Also, the design of the milling body includes internal channels for optimal flow of the coolant, facilitating thermal dissipation and extending the life of the inserts [4].

Figure 1 illustrates the tool geometry, the positioning of the insert and the configuration of the HSK-A63 clamping system, providing a clear representation of the relevant constructive elements.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

Figure 1. The body of the tested milling cutter [4].

Dynamic balancing is important because it reduces vibrations that occur at very high speeds, thus protecting the spindle, bearings and the cutting tools. An unbalanced tool holder can cause rapid wear, poor surface quality and dimensional deviations. By balancing, accuracy, cutting tool durability and operational safety are increased, and the machine can work at the speeds for which it was designed. Holes in the tool holder allow the mass distribution to be adjusted to achieve the necessary balance above 25000 rpm.

The uncoated cutting inserts with the Mapal code XDHT150440R-U10-HU612 [4] shown on the left side of Figure 2 and the DLC-coated cutting inserts with the Mapal code XDHT150440R-U11-V0105-P shown on the right side of Figure 2 are metal carbide inserts. The only difference between the two types of inserts is that one has a DLC coating. DLC (Diamond-Like Carbon) is a thin amorphous carbon coating with diamond-like properties, applied to cutting tools by methods such as PVD (Physical Vapor Deposition) or PACVD (Plasma Assisted Chemical Vapor Deposition). It contains a combination of sp^3 (like diamond) and sp^2 (like graphite) bonds, providing high hardness and low friction. Advantages of DLC coatings: high hardness, low friction, corrosion resistance, machining performance [5].

Figure 2. Cutting inserts XDHT150440R-U10-HU612 and XDHT150440R-U11-V0105-P.

2.5. The equipment`s Used

The CNC machine used for machining was Bavius PBZ HD 600 and is shown in Figure 3. It has the following important characteristics:

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

- Maximum dimensions of the machined part: 12000 x 800 x 575 mm;
- Maximum travel of the spindle on the Y axis: 1000 mm;
- Maximum axis movement speed: X = 70 m/min, Y = 40 m/min, Z = 40 m/min;
- Spindle technical maximum data: Power: 80 kW/h, Speed: 30000 rpm, Torque: 36 N/m.

Figure 3. Bavius HD 600 [6].

The EZset 600 presetter is an advanced tool measuring, setting and checking system for CNC machining. It offers an extended measuring range with a maximum tool length of 600 mm and a diameter of 400 mm, allowing for efficient preparation of large tools before inserting them into the machine. It is equipped with SK-40, HSK E50, HSK-A63, HSK-A100 adapters. The advanced optical system, based on a CCD camera with a telecentric lens, allows for measurements with an accuracy of 1 µm, as well as visual inspection of edges at magnifications of up to 20×. The dedicated software integrates automatic functions for determining the tool contour and identifying the edge shape, facilitating quality control and minimizing setting errors. By external tool presetting, the EZset 600 helps to reduce the downtime of the CNC machine and increase the productivity of the technological process [7]. The EZset 600 measuring machine was used for measuring the characteristics of the tool. The machine is shown in Figure 4.

Figure 4. EZset 600 [7].

2.6. The Process Parameters

To carry out the machining experiment, a series of representative technological parameters for the milling process were established. The choice of these parameter values was made based on the recommendations provided by tool manufacturers and the specialized literature, aiming to obtain a varied range of cutting conditions that would allow the efficient training of the neural network. Since MATLAB only works with numerical values, each parameter was assigned an integer. Table 1 presents the process parameters, the index assigned for MATLAB according to each type of process parameter.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

Table 1. Process parameters.

Name of the process parameter	Index for MATLAB	The type of the process parameter
Alloy	1	2196
	2	2043
	3	2099
Machining Phase	1	Phase 1
	2	Phase 2
Feed per tooth	0.167	0.167 [mm/tooth]
	0.226	0.226 [mm/tooth]
	0.200	0.200 [mm/tooth]
The type of cutting insert	1	Uncoated insert
	2	DLC insert
The face of the cutting insert	1	Face 1
	2	Face 2

2.7. The Measurements Performed and Experimental Data Tables

Microsoft Excel was used for collecting all the data. The data are structured in four columns. The first column represents the type of alloy to be machined. The second column represents the machining phase. The third column represents the adopted feed per tooth, and the fourth column represents the type of cutting insert. The values after calculations are presented in Figure 5.

IQR (Interquartile Range) is a statistical measure of the dispersion of data, representing the difference between the upper quartile (Q3) and the lower quartile (Q1). In applied research, the IQR is valued for its robustness and for reflecting the variability of real data better than outlier-sensitive measures. Therefore, it is frequently used in experimental data quality analysis, industrial data processing, robust statistics, reporting results in engineering, social, and biomedical sciences [8,9].

Steps to identify outliners using IQR:

- Calculate percentiles: Q1 – 25% percentile and Q3 – 75% percentile;
- Calculate IQR:

$$IQR = Q_3 - Q_1 \tag{1}$$

- Calculate confidence intervals with the formulas:

for the left limit:

$$I_{min} = Q_1 - 1.5 \times IQR \tag{2}$$

for the right limit:

$$I_{max} = Q_3 + 1.5 \times IQR \tag{3}$$

- Calculate relative amplitude with the formula:

$$R_a = \frac{\max - min}{Med} \tag{4}$$

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Alloy	Machining_Phase	fz	Insert_type	Tool-life	Q1	Q3	IQR	(-	+)	Relative amplitude
1	1	0.167	1	106	112.5	124.25	11.75	94.875	141.875	22.73%
1	1	0.167	2	402	416.25	428	11.75	398.625	445.625	17.38%
1	1	0.200	1	130	138	149.75	11.75	120.375	167.375	19.46%
1	1	0.200	2	470	486	507.75	21.75	453.375	540.375	29.30%
1	1	0.226	1	93	103.25	109	5.75	94.625	117.625	16.98%
1	1	0.226	2	301	309	327	18	282	354	29.71%
1	2	0.167	1	101	106	124	18	79	151	22.57%
1	2	0.167	2	402	409.25	420.75	11.5	392	438	20.61%
1	2	0.200	1	118	129	146.75	17.75	102.375	173.375	24.02%
1	2	0.200	2	446	451	471.75	20.75	419.875	502.875	21.55%
1	2	0.226	1	92	96	104	8	84	116	28.38%
1	2	0.226	2	302	308	320	12	290	338	27.97%
2	1	0.167	1	96	101.25	110.75	9.5	87	125	23.51%
2	1	0.167	2	340	350.25	367.5	17.25	324.375	393.375	19.14%
2	1	0.200	1	99	108	117	9	94.5	130.5	21.47%
2	1	0.200	2	423	430.25	447	16.75	405.125	472.125	25.39%
2	1	0.226	1	82	88	96	8	76	108	20.30%
2	1	0.226	2	238	244.75	266	21.25	212.875	297.875	22.59%
2	2	0.167	1	101	106	115.75	9.75	91.375	130.375	8.09%
2	2	0.167	2	345	361	381	20	331	411	11.62%
2	2	0.200	1	102	108.25	120	11.75	90.625	137.625	10.86%
2	2	0.200	2	397	408.25	424.75	16.5	383.5	449.5	6.26%
2	2	0.226	1	86	93	104	11	76.5	120.5	7.01%
2	2	0.226	2	240	250.25	268.5	18.25	222.875	295.875	9.07%
3	1	0.167	1	101	109	120	11	92.5	136.5	11.41%
3	1	0.167	2	376	389	405.75	16.75	363.875	430.875	16.75%
3	1	0.200	1	109	114	126.75	12.75	94.875	145.875	7.30%
3	1	0.200	2	426	436	444.75	8.75	422.875	457.875	12.43%
3	1	0.226	1	82	86	92	6	77	101	15.35%
3	1	0.226	2	266	274.25	288.75	14.5	252.5	310.5	9.37%
3	2	0.167	1	100	108.25	121	12.75	89.125	140.125	9.07%
3	2	0.167	2	391	399.25	415	15.75	375.625	438.625	11.39%
3	2	0.200	1	106	113.5	126	12.5	94.75	144.75	5.23%
3	2	0.200	2	432	442.5	457.75	15.25	419.625	480.625	9.33%
3	2	0.226	1	88	96	102	6	87	111	10.71%
3	2	0.226	2	275	281.25	296	14.75	259.125	318.125	7.98%

Figure 5. The results obtained.

Following data processing, from the initial total of 1440 recorded values, the procedure for identifying and eliminating outliers indicated the need to exclude 6 of them. Thus, the final data set used in the analysis was reduced to 1434 valid values, considered representative of the real behavior of the system. For a general picture of the structure of the analyzed data, Figure 6 shows a fragment of the "Input_data" file, a file that was subsequently imported and processed in MATLAB.

Input_data ×

1434×4 double

	1	2	3	4
1	1.0000	1.0000	0.1670	1.0000
2	1.0000	1.0000	0.1670	1.0000
3	1.0000	1.0000	0.1670	1.0000
4	1.0000	1.0000	0.1670	1.0000
5	1.0000	1.0000	0.1670	1.0000
6	1.0000	1.0000	0.1670	1.0000
7	1.0000	1.0000	0.1670	1.0000
8	1.0000	1.0000	0.1670	1.0000
9	1.0000	1.0000	0.1670	1.0000
10	1.0000	1.0000	0.1670	1.0000
11	1.0000	1.0000	0.1670	1.0000
12	1.0000	1.0000	0.1670	1.0000
13	1.0000	1.0000	0.1670	1.0000
14	1.0000	1.0000	0.1670	1.0000
15	1.0000	1.0000	0.1670	1.0000
16	1.0000	1.0000	0.1670	1.0000
17	1.0000	1.0000	0.1670	1.0000
18	1.0000	1.0000	0.1670	1.0000
19	1.0000	1.0000	0.1670	1.0000
20	1.0000	1.0000	0.1670	1.0000
21	1.0000	1.0000	0.1670	1.0000

Figure 6. Input data.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

3. Artificial Neural Network

3.1. The Type of Neural Network Used and the Program Used

Artificial Neural Networks (ANN) are mathematical models inspired by the functioning of biological neural networks. They are used to solve complex problems, such as pattern recognition, classification, regression or modeling of nonlinear processes. The neural network used was a "Multilayer Perceptron". MLP is one of the most widely used ANN architectures. It includes one or more hidden layers between the input and output layers. The neurons are fully connected between the layers, and the network is usually trained with the Backpropagation algorithm. MLP can model complex nonlinear relationships and is suitable for regression, classification and modeling problems of industrial processes, including materials processing [10–12].

The program used for ANN modeling was Matlab. MATLAB is a computing environment and high-level programming language developed by MathWorks. MATLAB provides specialized tools for: development and training of neural networks. A major advantage is the dedicated toolboxes, such as, which allow rapid implementation of machine learning and artificial intelligence algorithms [13]. The use of artificial neural networks (ANN) in the analysis of technological processes in the field of advanced materials processing represents a modern and efficient method for modeling the complex relationships between process parameters and the output characteristics of the obtained parts.

The advantages of the use of a multi-layer perceptron (MLP) neural network with feedforward propagation, due to the following considerations:

- Nonlinear modeling capability: Al-Li alloy machining processes involve complex nonlinear relationships between technological parameters (alloy, feed per tooth, machining phase etc.) and resulting characteristics. The MLP network can learn these relationships without requiring an explicit mathematical formulation [14];
- Generalization capability: after training, the network can provide accurate predictions for new, unfamiliar data, making it ideal for industrial applications where machining conditions may vary [15];
- Flexibility and scalability: the network structure can be adjusted (number of neurons, hidden layers, activation functions), providing adaptability depending on the complexity of the data set and the desired accuracy;
- Robustness in the presence of noise: ANNs can identify relevant patterns even in the presence of experimental data with natural variations or noise, which is common in real processing conditions [16];
- Proven applicability in industry: MLP-type ANNs have already been successfully used in the modeling of milling, turning, grinding and heat treatment processes, especially for materials used in the aerospace field (including aluminum, titanium and composites.

3.2. ANN Structure

To model the relationship between the technological parameters of the aluminum alloy machining process (2196, 2043 and 2099) and the obtained exploitation times, a multi-layer perceptron (MLP) artificial neural network with feed-forward propagation, trained by the Backpropagation algorithm, was used.

The structure of the network was chosen to balance the learning capacity with avoiding the overfitting phenomenon. It is composed of the following components and is schematically presented in Figure 7:

- Input layer contains 4 neurons corresponding to the variables;
- Hidden layers: two hidden layers with 15 neurons each were used. These layers use a non-linear activation function of the sigmoid type or ReLU, to capture the non-linear relationships between the data;

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

- Output layer contains a neuron that provides the predicted value of the feature of interest: exploitation time. In the case of continuous output, a linear activation function was used;

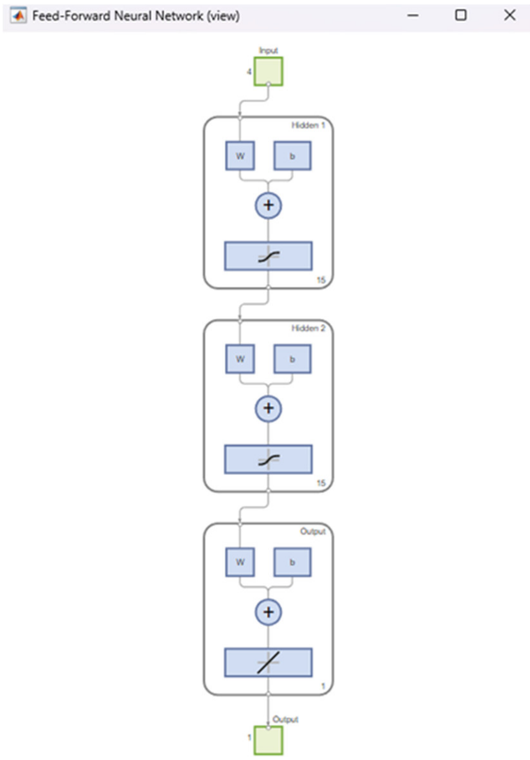

Figure 7. ANN structure.

- Training algorithm: the network was trained using the "Bayesian Regularization" method due to its fast convergence speed and good accuracy for moderate data sets;
- Data set: the experimental data collected from alloy machining were divided into two subsets: training (90%), validation (10%), to ensure objective evaluation of the model performance. It has integrated validation. The testing will be done with different data than the input;
- Epochs: for this study, the maximum number of epochs was set to 2000. In the process of training the artificial neural network, an essential parameter that influences both the accuracy of the model and the training time is the number of epochs. An epoch represents a complete traversal of the entire training data set [17–21].

4. Results Obtained

4.1. The Histogram of Errors

The histogram of the errors obtained is shown in Figure 8. The histogram contains 20 columns, and the minimum error occurs at epoch 1730 out of the 2000 epochs.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

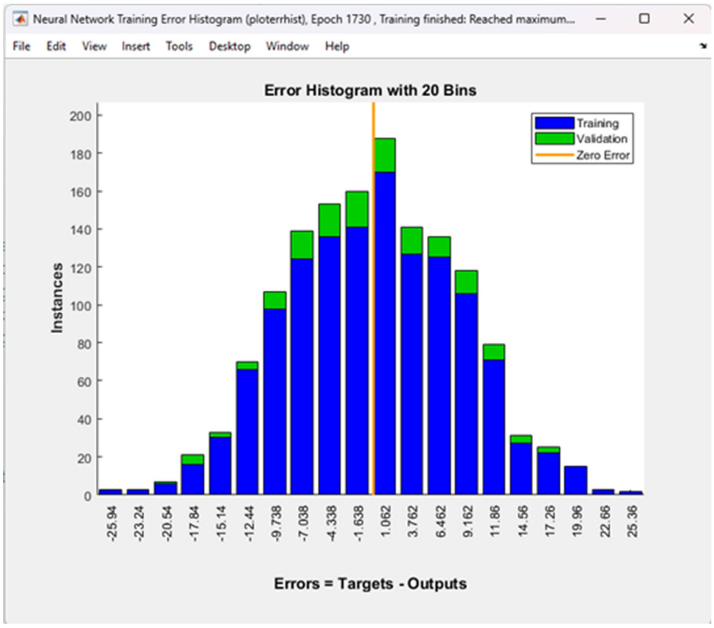

Figure 8. The errors histogram.

Error histogram analysis (20 bins) indicates that the residuals, defined as e = T - O are symmetrically distributed around zero, with the highest frequency concentrated in the vicinity of the zero-error line. This behavior suggests the absence of systematic bias and confirms that the trained MLP model provides an unbiased estimation of the target variable. The approximately Gaussian shape of the distribution further indicates that the remaining prediction errors can be attributed primarily to stochastic variability rather than structural model inadequacy. Moreover, the substantial overlap between training and validation error distributions demonstrates good generalization capability and the absence of significant overfitting. Such a residual pattern is consistent with the statistical assumptions of nonlinear regression theory and is widely considered a reliability indicator in neural network-based process modeling.

In the error relationship, e = T - O, the quantity e represents the prediction error or residual of the model, defined as the difference between the experimental value and the value estimated by the neural network. The term **T**, Target denotes the actual experimentally measured value of the output variable – in the context of machining process modeling, this corresponds to the measured milling tool service life. The term **O**, Output represents the value predicted by the MLP model for the same set of input parameters.

The sign of the error provides additional insight into model behavior: a positive value of e indicates underestimation of the real value, whereas a negative value indicates overestimation. Error values close to zero reflect good approximation capability of the model [15,22–24].

4.2. Mean Squared Error

Mean Squared Error measures the average of the squares of the differences between the actual values and those estimated by the model. The smaller the MSE, the more accurate the model. It is sensitive to extreme values (outliers), because the errors are squared [15].

It is one of the most common performance measures in regression:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - y_i)^2 \quad (5)$$

where: n is the number of observations; x_i – the actual value; y_i – the estimated value.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

4.3. Correlation Coefficent

The correlation coefficient, denoted by "R", measures the proportion of the variation in the actual data that and is explained by the predictive model:

$$R = 1 - \frac{SS_{res}}{SS_{tot}} \quad (6)$$

where: $SS_{res} = \sum(x_i - y_i)^2$

$SS_{tot} = \sum(x_i - y)^2$

Interpretation:

R = 1: perfect prediction;

R = 0: the model explains that there is no correlation between the training and testing data at all;

R < 0: the model is weaker than a simple average.

The result which was obtained (0.9803) is very close to 1, which means that the prediction is very close to a perfect prediction.

4.4. Prediction Versus Actual Values Graph

Figure 9 shows the correlation between the actual values and those estimated by the neural network on the test set. A good alignment of the points around the xy line is observed, which confirms the accuracy of the model, consistent with the MSE and R values.

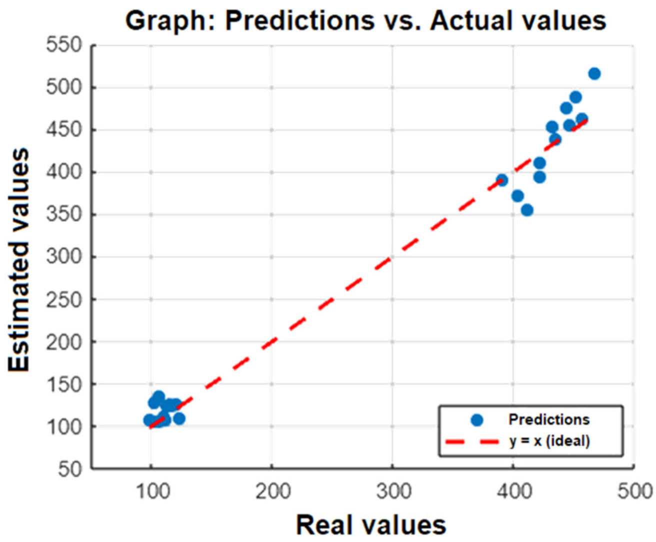

Figure 9. Prediction versus actual values graph.

Figure 10 shows the test completion report. The interpretation of the parameters:

- Gradient: measures the slope (derivative) of the error function with respect to the network parameters. It is used to decide whether the training algorithm has stopped "because it has nothing more to learn". A very small gradient indicates that the network is at a local minimum, so training can be stopped [19];
- Mu: Levenberg-Marquardt adaptation coefficient. It is an adaptive tuning parameter between two optimization methods: the Gauss-Newton method (fast) and gradient descent (safe). If Mu is small, it means that the network has learned well and uses fast optimization. If Mu is large, the network has difficulties and tries to learn with small and safe steps [25,26];
- Num Parameters: total number of parameters trained in the network (weights + biases). It is proportional to the complexity of the network. It depends on the number of neurons in the hidden layers and the number of inputs and outputs. The value indicates a low network in terms of complexity;

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

- Sum squared of parameters (operam): the sum of the squares of the values of all trained parameters (weights and biases). It is used in regularization. The trainbr algorithm tries to minimize not only the error, but also the complexity of the network by controlling this sum (keep the weights low, then the network results in a more "regular" network). The values indicate moderate parameters, the network is not overloaded;
- Validation check: the number of consecutive epochs in which the error on the validation set has not decreased. It is used for early stopping – if the model no longer improves on the validation set, training is stopped to avoid overfitting [19,27].

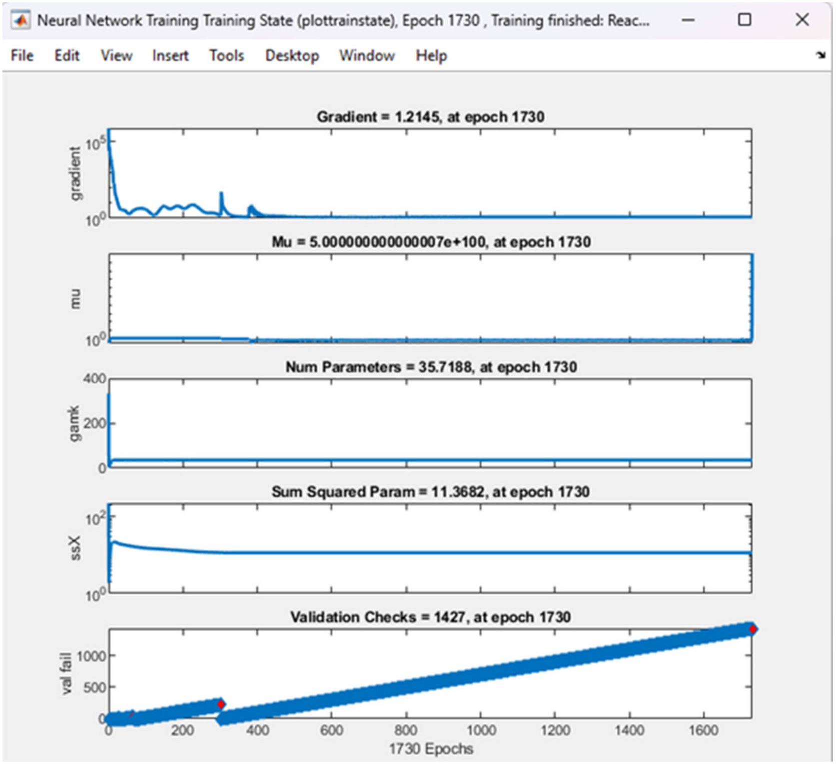

Figure 10. The completion report.

4.5. Regression Graph

The performance of the neural network was evaluated by the regression plot between the experimental and predicted values, determining the correlation coefficient R, like the approach used by Zain et al. [19]. Figure 11 shows the linear regressions of the artificial neural network. The values R=1 mean that the neural network is perfect. The value obtained for training is R=0.99824 and for validation is R=0.9983. The value obtained for verification and testing of the neural network is R=0.99825. These values close to 1 mean that the neural network has the capability to learn and estimate values close to the initial ones. Also, testing the neural network confirms that the estimated values are close to the real initial ones.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

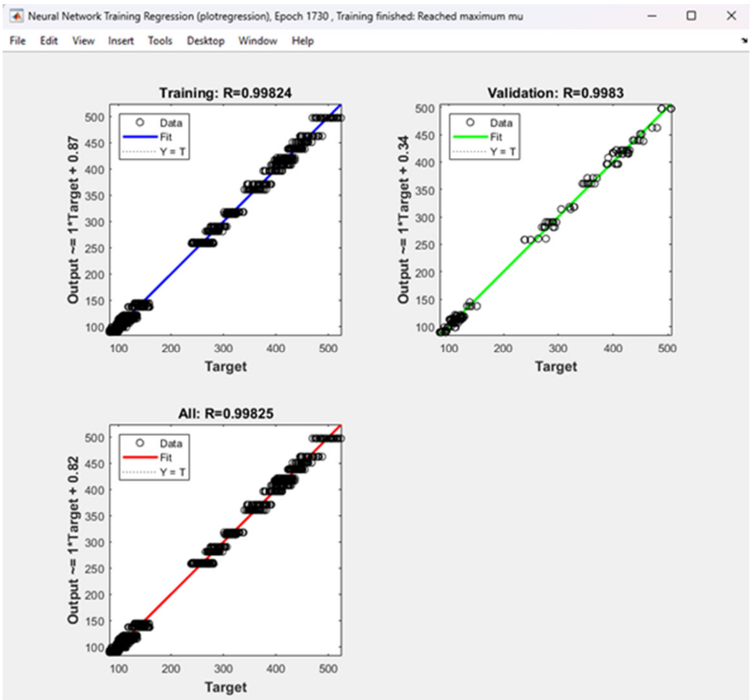

Figure 11. The linear regression.

5. Conclusions

- The artificial neural network trained in this study showed: good numerical performance, stable behavior on unknown data and a clear ability to accurately estimate output values depending on the input data;
- This makes it suitable for modeling the aluminum alloy machining process and can be integrated into an optimization or intelligent control system in industrial environments;
- The artificial neural network (ANN) was trained to model the relationship between the input process parameters and the output result in the machining of aluminum alloys in the aeronautical industry;
- Average relative errors below 10%, which reflects an acceptable prediction for industrial purposes;
- $R \approx 0.98$ – suggesting a high generalization capacity of the network;
- The regression and actual vs. estimated value plots confirmed that most of the predictions align well with the actual values, thus demonstrating that the ANN learned a consistent relationship between the input and output data;
- The number of parameters (35) and the sum of the squares of the parameters (11.36) indicate a network of medium complexity, without overload, which is favorable.

Abbreviations

The following abbreviations are used in this manuscript:

ANN	Artificial Neural Network
DLC	Diamond-Like Coating
IQR	Interquartile Range
MLP	Multilayer Perceptron
MSE	Mean Square Error
PACVD	Plasma Assisted Chemical Vapor Deposition
PVD	Physical Vapor Deposition

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

References

1. Constellium. Company Presentation. *Available online:* https://www.constellium.com/ (accessed on 13 February 2026)
2. ASM Handbook Committee. ASM Handbook, Volume 2: Properties and Selection: Nonferrous Alloys and Special-Purpose Materials; ASM International: Materials Park, OH, USA, 1990
3. Davis, J.R., Ed. *Aluminum and Aluminum Alloys*; ASM Specialty Handbook; ASM International: Materials Park, OH, USA, 1993
4. MAPAL. NeoMill-Alu-QBig: High-Volume Milling of Aluminium Materials; Press Release, 17 May 2024. *Available online:* https://mapal.com/en-int/a/neomill-alu-qbig-high-volume-milling-aluminium (accessed on 13 February 2026)
5. Oerlikon Balzers. World-class DLC Coatings: Extreme Hardness, Low Friction. *Available online:* https://www.oerlikon.com/balzers/us/en/portfolio/balzers-surface-solutions/pvd-and-pacvd-based-coating-solutions/balinit/dlc-coatings-and-other-carbon-based-coatings/ (accessed on 13 February 2026**)**
6. Bavius technologie gmbh. Company Presentation. *Available online:* https://www.bavius-technologie.com/en/ (accessed on 13 February 2026)
7. EZset. Product Presentation. *Available online:* https://www.ezset.info/home/ (accessed on 20 January 2026
8. Singh, H.P.; Martínez Puertas, S.; Singh, S. Estimation of Interquartile Range of the Study Variable Using the Known Interquartile Range of Auxiliary Variable. *Int. J. Appl. Math. Stat.* **2006**, *6*, 33–47
9. Habibzadeh, F. Statistical Data Editing in Scientific Articles. *J. Korean Med. Sci.* **2017**, *32*, 1072–1076
10. El-Mounayri, H.; Briceno, J.F.; Gadallah, M. A New Artificial Neural Network Approach to Modeling Ball-End Milling. *Int. J. Adv. Manuf. Technol.* **2010**, *47*, 527–534
11. Davim, J.P., Ed. *Machining: Fundamentals and Recent Advances*; Springer: London, UK, 2008. https://doi.org/10.1007/978-1-84800-213-8
12. Balonji, S.; Tartibu, L.K.; Okokpujie, I.P. Surface Roughness Prediction in CNC Milling of Al6061 Using Soft Computing Techniques. *Appl. Sci.* **2023**, *13*, 4147. https://doi.org/10.3390/app13074147
13. MathWorks. MATLAB—Product Overview. *Available online:* https://www.mathworks.com/ (accessed on 20 January 2026)
14. Fischer, M.M. Neural Networks: A General Framework for Non-Linear Function Approximation. *Trans. GIS* **2006**, *10*, 521–533
15. Haykin, S. *Neural Networks and Learning Machines*, 3rd ed.; Pearson: Upper Saddle River, NJ, USA, 2009
16. Freiesleben, T.; Grote, T. Beyond Generalization: A Theory of Robustness in Machine Learning. *Synthese* **2023**, *202*, 109–134
17. Fang, N.; Srinivasa Pai, P.; Edwards, N. Neural Network Modeling and Prediction of Surface Roughness in Machining Aluminum Alloys. *J. Comput. Commun.* **2016**, *4*, 1–9. https://doi.org/10.4236/jcc.2016.45001
18. Repiso-López, I.; Martín-Béjar, S.; Trujillo-Vilches, F.J.; Sevilla-Hurtado, L. Optimization of ANN Used to Predict the Surface Roughness in Dry Turning of UNS A97075 Aeronautical Aluminum Alloy. *Acta Tech. Napocensis* **2023**, *66* (Special II), 317–326
19. Zain, A.M.; Haron, H.; Sharif, S. Prediction of Surface Roughness in the End Milling Machining Using Artificial Neural Network. *Expert Syst. Appl.* **2010**, *37*, 1755–1768. https://doi.org/10.1016/j.eswa.2009.07.033
20. Vardhan, M.V.; Sankaraiah, G.; Yohan, M. Prediction of Surface Roughness and Material Removal Rate for Machining of P20 Steel in CNC Milling Using Artificial Neural Networks. *Mater. Today Proc.* **2018**, *5*, 18376–18382. https://doi.org/10.1016/j.matpr.2018.06.177
21. Muhammad, W.; Kang, J.; Ibragimova, O.; Inal, K. Experimental Investigation and Development of a Deep Learning Framework to Predict Process-Induced Surface Roughness in Additively Manufactured Aluminum Alloys. *Weld. World* **2023**, *67*, 897–921. https://doi.org/10.1007/s40194-022-01445-8
22. Bishop, C.M. *Neural Networks for Pattern Recognition*; Oxford University Press: Oxford, UK, 1995
23. Benardos, P.G.; Vosniakos, G.C. Predicting Surface Roughness in Machining: A Review. *Int. J. Mach. Tools Manuf.* **2003**, *43*, 833–844. https://doi.org/10.1016/S0890-6955(03)00059-2
24. Montgomery, D.C.; Peck, E.A.; Vining, G.G. *Introduction to Linear Regression Analysis*, 5th ed.; Wiley: Hoboken, NJ, USA, 2012

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1100.v1

25. Hagan, M.T.; Demuth, H.B.; Beale, M.H.; De Jesús, O. *Neural Network Design*, 2nd ed.; Martin Hagan: Stillwater, OK, USA, 2014
26. Siddiqi, F.U.R.; *et al.* Artificial Neural Network-Based Data-Driven Parameter Optimization Using Levenberg–Marquardt Algorithm. *Mathematics* **2024**, *12*, 3407. https://doi.org/10.3390/math12213407
27. Beale, M.H.; Hagan, M.T.; Demuth, H.B. *Neural Network Toolbox™ User's Guide*; The MathWorks, Inc.: Natick, MA, USA, 2017. (R2017a–R2018a)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.

© 2026 by the author(s). Distributed under a Creative Commons CC BY license.