International Journal of Mechanical Engineering and Technology (IJMET)
Volume 14, Issue 06, Nov-Dec 2023, pp. 1-9. Article ID: IJMET_14_06_001
Available online at https://iaeme.com/Home/issue/IJMET?Volume=14&Issue=6
ISSN Print: 0976-6340 and ISSN Online: 0976-6359
DOI: https://doi.org/10.17605/OSF.IO/CJURB

LASER-ASSISTED MACHINING OF NI-BASED SUPER ALLOYS: PREDICTIVE MODELING FOR SURFACE INTEGRITY OPTIMIZATION

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ABSTRACT

The present study investigates the effect of laser power on the machinability of a Nickel-based super alloy using laser assisted machining (LAM). The alloy was machined using a high-power laser, and the machinability was evaluated in terms of surface roughness. The results show that an increase in laser power leads to an improvement in machinability, with a decrease in surface roughness. The study concludes that LAM can be an effective method for machining Nickel- based super alloys and that laser power plays a critical role in determining the machinability of the material. This research provides valuable insights into the use of LAM for machining Nickel- based super alloys and can be used to optimize the machining process for this material. Finally, ANN model was used to optimize the process parameters.

Keywords: LAM, Superalloys, ANN, Surface Roughness.

Cite this Article: Bhukya Rangilal and Nikhil Bharat, Laser-Assisted Machining of NI-Based Super Alloys: Predictive Modeling for Surface Integrity Optimization, International Journal of Mechanical Engineering and Technology (IJMET), 14(6), 2023, pp. 1-9.
https://iaeme.com/Home/issue/IJMET?Volume=14&Issue=6

INTRODUCTION

Due to their high temperature strength retention and low thermal conductivity, super alloys are difficult to machine. Altering the alloy composition or subjecting the metal to heat treatment may have a negative impact on mechanical qualities and has little to no influence on the machinability of the material. Traditional machining techniques have a hard time dealing with the extreme hardness of these metals, resulting in significant tool wear, built-up edge formation, and a subpar surface polish.

Cutting forces, finished surface roughness, and cutting tool wear can all be reduced with laser assisted turning (LAT), a relatively new method for working with difficult-to-cut materials[1–4].

In laser-assisted turning, also known as LAT, the work piece is heated locally with the help of a concentrated laser beam in advance of the major shear zone on the surface of the work piece that has not been cut. This makes LAT an excellent method for the machining of superalloys. This heating enhances the machinability of the workpiece by softening the material of the workpiece and lowering the tool wear, all without causing any damage to the subsurface. If LAT can be shown to be flexible in a variety of various fields of endeavor, only then will it be possible to use it on an industrial scale. It has previously been shown that LAM makes it feasible to process high strength metals such as Ti6Al4V, Inconel718, graphite iron, AISID2 tool steel, and ceramics. Other examples of these materials include metal matrix composites[5, 6].

It is important to note that the bulk of the studies that have been conducted utilizing LAM have relied on a CO_2 laser beam as their primary source of heat.

Yet, because of its low absorption nature, particularly when machining superalloys, high powers may be necessary for effective machining. This is especially true in the case of superalloys.

In addition, CO_2 lasers have a wavelength of ten micrometers, which prevents them from travelling through optical fiber. The Nd: YAG laser facility with a wavelength of 1 μm may offer an excellent source of heat for softening the work material, and it can be utilized very efficiently for chip removal and machining superalloys. Both of these processes are described further below. While there have been some studies on Nd: YAG laser assisted machining, there has not been a full study on pulsed Nd: YAG laser assisted machining of super alloys, and more research is necessary to produce compelling findings for improved machinability of such alloys. When a pulse laser beam is employed, there is the potential for a number of benefits, including improved localized heating, which has less of an influence on the substrate of the material, and better control of the variety. Using a pulse laser beam does, of course, come with a few downsides, the most notable of which being the increased complexity of both the control and processing factors. The impacts of processing variables were taken into consideration in the research that was provided since the experiment was well designed[7].

When producing nickel-based superalloys, it may be quite challenging to attain the requisite qualities while simultaneously reducing production costs by optimizing the process parameters. The use of artificial neural networks (ANN) is becoming more popular in the manufacturing sector as a strong tool for improving process parameters. ANN may be taught to make predictions about the results of different process parameters and to assist in determining which parameters provide the best results for a certain production objective.

ANN has been used in a number of research with the purpose of optimizing the parameters of the production process of nickel-based superalloys. One such work was conducted by Song and Kim et al. (2019), in which ANN was used to improve the processing parameters of Inconel 718. They built an ANN model that could predict, based on the specified material qualities, the ideal process parameters for the manufacturing of Inconel 718. A data set that was produced using a mix of design of experiments and finite element analysis was used throughout the training process of the model. According to the findings, the ANN model was successful in making accurate predictions about the parameters that should be used for the manufacturing of Inconel 718[8–11].

The purpose of this research is to evaluate the impact of Nd:YAG laser factors on the machining properties of a Ni-based superalloy and improve the process parameters using artificial neural network modelling.

MATERIALS AND METHODS

The chemical composition for the Ni-based alloy and their weight% are Ni-63.07%, Mn-1.17%, Cu- 29.88%, C -0.3%, O-2.58%, Si-0.74% and balance Fe. The hardness of the Ni based alloy is 240 Vickers hardness. The EDAX for the Ni based alloy shown in fig 1.

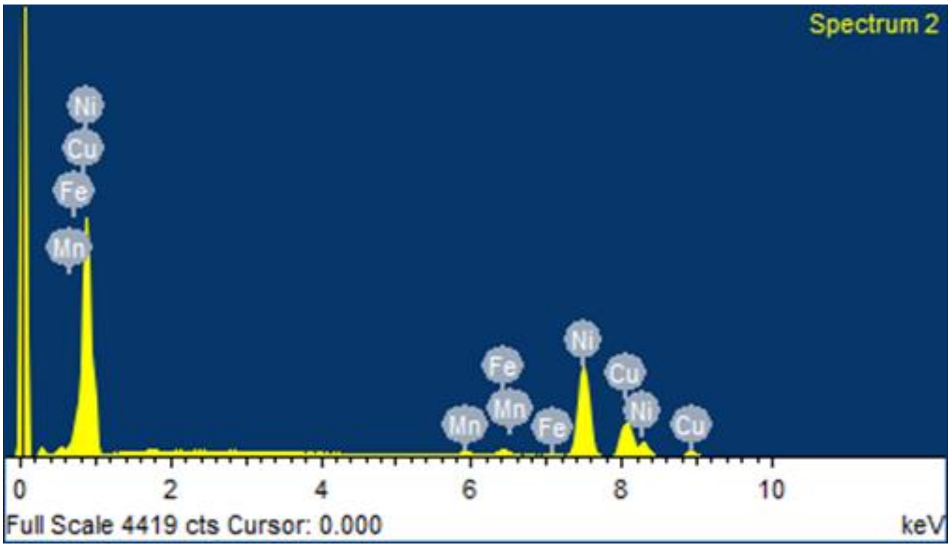

Figure: 1 EDAX for Ni based alloy

In order to conduct testing on laser assisted turning, a pulsed Nd: YAG laser with a maximum average power of 1200W and a wavelength of 1.064 nm was used. After being attached to a fixture that was attached to the support for the lathe, the laser head was positioned on the surface of the workpiece in front of the cutting tool at an angle of ninety degrees circumferentially. With a lens with a spot size of 3.3 millimeters, a fiber optic cable was used to focus and direct the beam. The diameter of the piece of work was 30 millimeters. For each experiment, a length of the material measuring about 50 mm was machined. A coated carbide tool with a model number CNMG120408 and a tool nose radius of 0.8 millimeters was utilized as the cutting insert. A conventional toolholder supported the cutting insert while it was in place. Figure 2 depicts a simplified version of the experimental setup. In all of the trials, the Talysurf instrument was used to measure the surface roughness. We have taken initial values of each process parameters are selected according to tool manufacturing specifications and ASME standards.as shown in Table 1**.**

Figure 2. Laser assisted turning setup with enlarged view.

Table 1. Machining Process parameters and their levels

Parameters	Code	Levels 1	2	3
Cutting velocity (V_C) [m/min]	A	30	42.5	55
Feed rate (f) [mm/rev]	B	0.04	0.06	0.08
Depth of cut(doc) [mm]	C	0.25	0.5	0.75
Laser power (W)	D	200	300	400

RESULTS AND DISCUSSIONS

During laser-assisted turning of Ni-based superalloys, a laser beam is used to preheat the workpiece material before the cutting tool comes in contact with it. The preheating helps to reduce the cutting forces and tool wear, and it can also modify the microstructure of the material. However, the laser beam also introduces additional heat into the cutting zone, which can result in material melting, recrystallization, and deformation, leading to surface roughness.

The laser power is a critical parameter that determines the amount of energy delivered to the workpiece material, and it influences the material removal rate and the heat generated at the cutting zone. A higher laser power results in a higher material removal rate and more significant heat generation, which can lead to higher surface roughness due to the material melting, recrystallization, and deformation. Conversely, a lower laser power may result in insufficient heating and cutting, leading to lower material removal rates and surface roughness.

Therefore, it is essential to find the optimal laser power for a specific Ni-based superalloy during laser-assisted turning to achieve the desired surface finish. The optimal laser power is determined by a trade-off between the material removal rate and the surface roughness, and it depends on factors such as the workpiece material properties, tool geometry, cutting parameters, and the desired surface finish.

ANN Modelling

In recent years, neural network modeling's potential applications have attracted the interest of scientists and engineers across a wide range of disciplines. ANNs are computer systems that are biologically driven and are akin to the activity of the human brain. These systems were developed to represent and learn the input–output data of extremely complex and linear/non-linear issues. In most cases, an ANN model will be organized in three sections, each of which will include a unique set of neurons. This will ensure that the input layer will be connected to the output layer through the required number of hidden layers. A value, known as the link weight, is given to each connection link that exists between any two neurons in a layer. The weight gives an indication of the degree to which the data is going to be boosted by the node connection. The Table 2. Shows the input and output values compared with ANN values.

Table 2. Input and Output response using L_{27} orthogonal array.

Sl. No.	Cutting speed	feed	doc	LP	Ra	ANN output
1	30.0	0.04	0.25	200	1.350	1.274
2	30.0	0.04	0.50	300	1.265	1.235
3	30.0	0.04	0.75	400	1.126	1.094
4	30.0	0.06	0.25	300	1.125	1.036
5	30.0	0.06	0.50	400	1.026	0.924
6	30.0	0.06	0.75	200	1.036	0.891
7	30.0	0.08	0.25	400	1.065	0.816
8	30.0	0.08	0.50	200	1.036	0.799
9	30.0	0.08	0.75	300	1.0126	0.830
10	42.5	0.04	0.25	200	1.0118	0.882
11	42.5	0.04	0.50	300	0.985	1.004
12	42.5	0.04	0.75	400	0.962	0.818
13	42.5	0.06	0.25	300	0.9425	0.912
14	42.5	0.06	0.50	400	0.846	0.895
15	42.5	0.06	0.75	200	0.856	0.947
16	42.5	0.08	0.25	400	0.849	0.874
17	42.5	0.08	0.50	200	0.768	0.873
18	42.5	0.08	0.75	300	0.745	0.874
19	55.0	0.04	0.25	200	0.789	0.866
20	55.0	0.04	0.50	300	0.762	0.748
21	55.0	0.04	0.75	400	0.752	0.749
22	55.0	0.06	0.25	300	0.648	0.666
23	55.0	0.06	0.50	400	0.626	0.593
24	55.0	0.06	0.75	200	0.6036	0.605
25	55.0	0.08	0.25	400	0.5945	0.676
26	55.0	0.08	0.50	200	0.5614	0.662
27	55.0	0.08	0.75	200	0.5489	0.613

Figure 3 depicts the process part of the ANN structure for the cutting parameter. When used to the problem of predicting surface roughness, the ANN design yields (Ra). There are three distinct layers to an ANN network: input, hidden, and output. Nodes represent the input and output layers, while the hidden layer describes the connection between them. It is the problem's ANN architectural geometry that determines how many neurons go into each layer, from input to output. There are four neurons in the input layer and one neuron in the output layer. Nevertheless, there is no hard-and-fast guideline for deciding how many hidden layers to use or how many neurons per layer to use.

In this research, we use a neural network approach based on backpropagation. Surface roughness is employed as the output parameter while the cutting speed, feed rate, depth of cut, and laser power are used as inputs to train the neural network. In order to predict surface roughness, a neural network is trained for 10 iterations, as shown in Fig. 3.

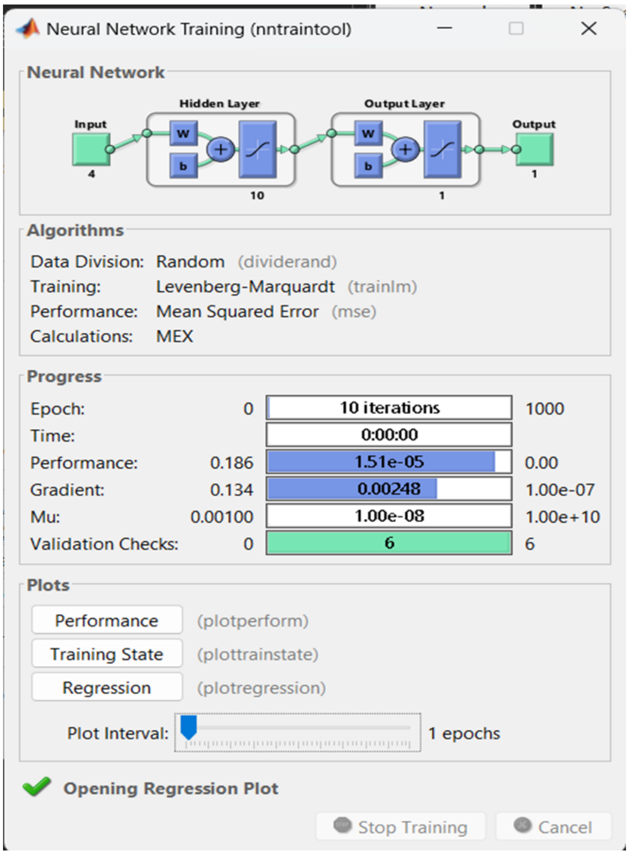

Fig.3 Training of neural network

Figure 4 depicts the Validation Performance after 10 iterations in terms of agreement between experimentation and training, projected value and best result of ANN and error response. The best validation performance is 9.73×10^{-5} at epoch 4.

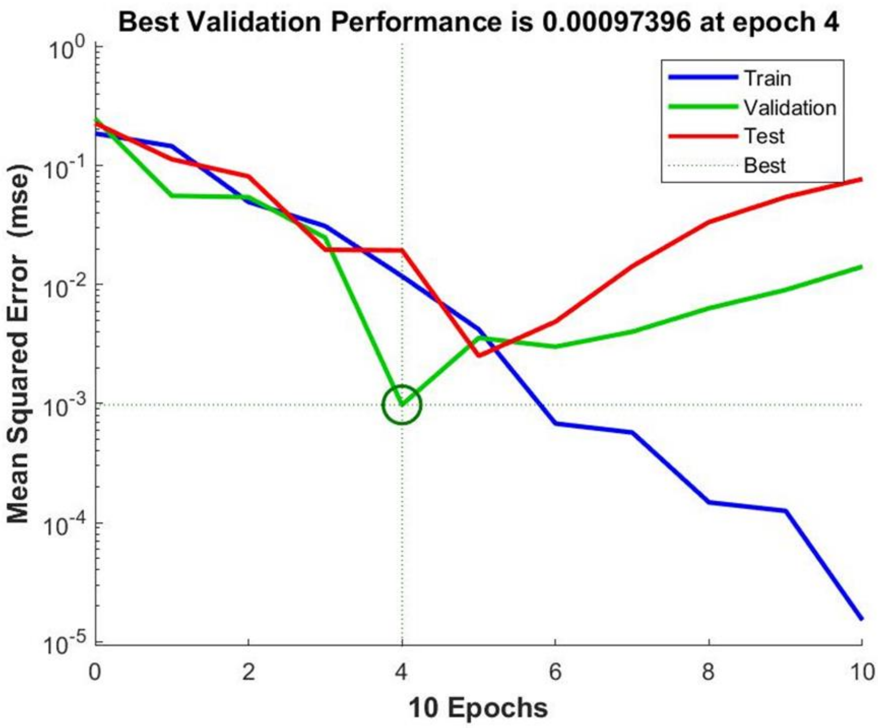

Fig.4 Best validation graph.

The Plot Regression for both the training and validation sets is shown in Fig. 5. Fifteen of the twenty-seven data sets received from the experiment are chosen at random to be used in the training of the ANN model. Twelve datasets are chosen to put the ANN model to the test. From the regression plot graph, it is depicted that the overall R value is 87.7%. It means the training and validation of data's are nearly accurate. Table 2 displays the proportion of inaccuracy between the ANN model's predictions and the experimental data. Table 2 shows that the generated model has been properly trained using ANN and can make accurate predictions. It is determined that the data set has a mean prediction error of 2.1605% and a maximum prediction error of 13.1600%. The experimental data and the ANN's predictions demonstrate excellent agreement.

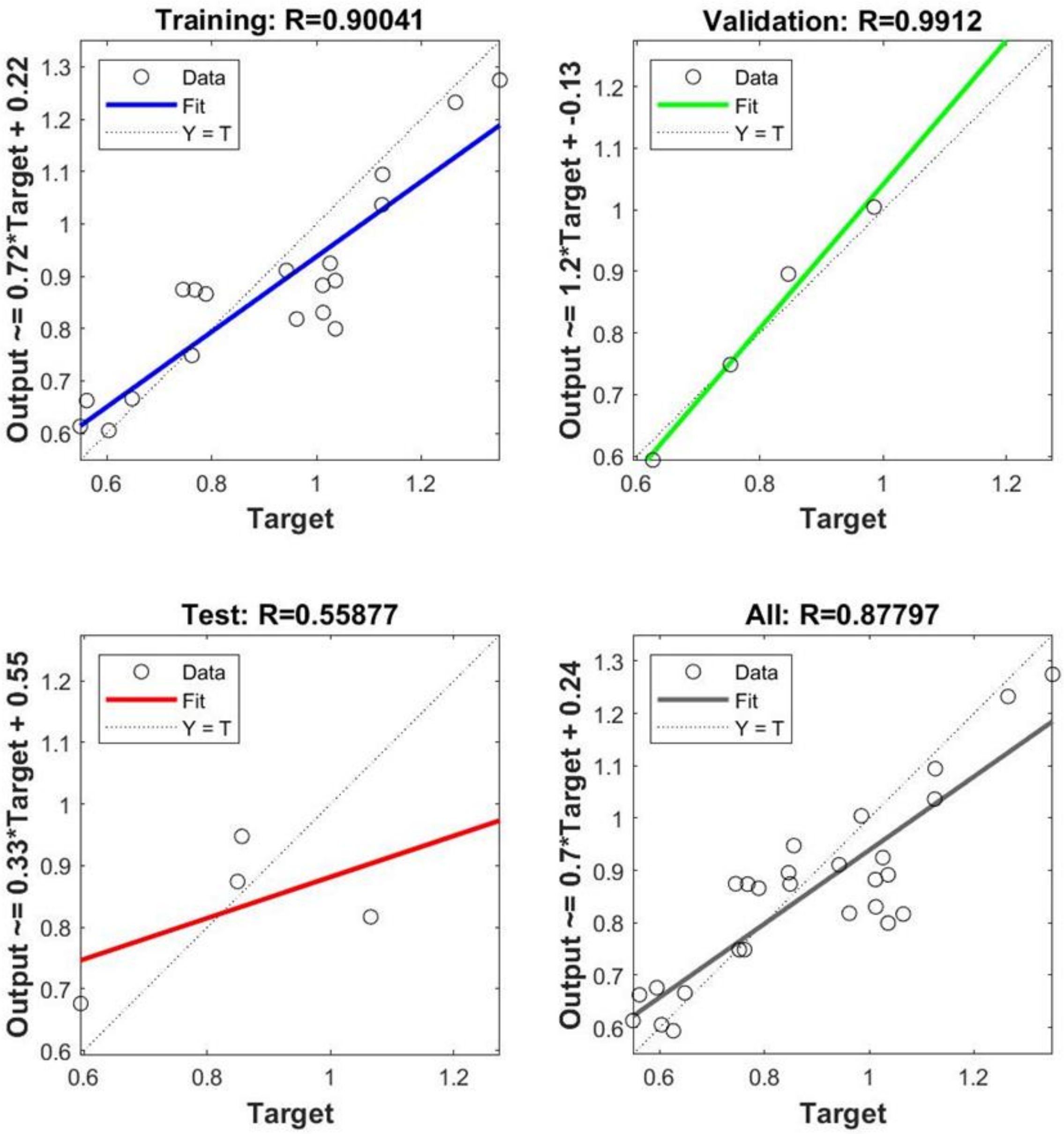

Fig.5 Training, validation and testing graph.

CONCLUSIONS

In this research, we evaluated the surface roughness at the tool work interface for dry condition of Ni based super alloy. The input variables are cutting speed, feed, depth of cut and laser power each had three different levels, all these levels were modified in accordance with the DOE L_{27} Orthogonal array. Feed forward back propagation artificial neural network model is employed as the output parameter that was trained using the Levenberg-Marquardt (LM) method produced high regression values. The model has a 4-10-1 architecture. The greatest possible result was accomplished by using 9 numbers of neurons and achieving an R-Value of 87.79%. The best validation performance is 9.73×10^{-5} at epoch 4. The ANN Model could be applied very effectively to more accurately anticipate and quantify surface roughness. This was possible because to the model's flexibility. Optimal conditions of Surface roughness (Ra) is 0.593µm , Cutting speed 55m/min, feed 0.06mm/rev, depth of cut 0.5 mm, and laser power 400 watts. Hence, The ANN predicted and experimentally obtained results were closely related. The study proves that artificial neural network will be most beneficial approach for anticipating different attributes during CNC Laser assisted machining process. Future research work will be conduct towards inclusion of more process parameters such as tool wear, spot diameter of laser , cutting force and MRR etc.

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Citation: Bhukya Rangilal and Nikhil Bharat, Laser-Assisted Machining of NI-Based Super Alloys: Predictive Modeling for Surface Integrity Optimization, International Journal of Mechanical Engineering and Technology (IJMET), 14(6), 2023, pp. 1-9.

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