Journal of Manufacturing Engineering, September 2022, Vol. 17, Issue. 3, pp 091-097

A COMPARATIVE STUDY ON PREDICTION OF CUTTING FORCE USING ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM DURING MACHINING OF Ti-6Al-4V

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ABSTRACT

The purpose of this comparative study is to improve the predictive accuracy of the cutting force during the turning of Ti-6Al-4V on a lathe machine. By optimizing the machining process parameters such as cutting speed, feed rate, and depth of cut, the cutting force in the machining process can be improved significantly. Cutting force is one of the crucial characteristics that must be monitored during the cutting process in order to enhance tool life and the surface finish of the workpiece. This paper is based on the experimental dataset of cutting forces collected during the turning of titanium alloy under the Minimum Quantity Lubrication (MQL) condition. To predict the cutting forces, two machine learning techniques are explored. Firstly, a black-box model called an Artificial Neural Network (ANN) is proposed to predict cutting force. Using the Levenberg-Marquardt algorithm, a two-layered feedforward neural network is built in MATLAB to predict cutting force. The second model to be implemented was the Genetic Algorithm (GA), a white-box model. GA is an optimization technique which is based on Darwinian theories. It is a probabilistic method of searching, unlike most other search algorithms, which require definite inputs. Using symbolic regression in HeuristicLab, a GA model is developed to estimate cutting force. The anticipated values of cutting forces for both models were compared. Since the ANN model had fewer errors, it was ascertained that the particular model is preferable for machining process optimization.

Keywords: *Genetic programming, Minimum quantity lubrication, Neural network, Symbolic regression and Titanium alloy.*

1. Introduction

The cutting of titanium and its alloys was previously regarded as a challenging task until the past few decades. Cutting these alloys and deploying them in an ever-expanding range of industrial engineering applications became increasingly appealing with the improvement of modern manufacturing processes and techniques [1]. Ti-6Al-4V has exceptional qualities, notably its superior strength-to-weight ratio, powerful resistance to corrosion, and ability to maintain high strength at high temperatures. Because of this, titanium alloys have witnessed an increase in their consumption in the aerospace, bio-medical and armour industries [2]. The chemical industry is the largest user of titanium due to its high strength and corrosion resistance. The aerospace industry is the second largest user of titanium due its elevated temperature capabilities.

However, titanium and its alloys are categorized as hard-to-machine materials due to its low heat conductivity, high chemical reactivity, and low elastic modulus. These distinct attributes result in high cutting temperatures, limited tool life, and high amount of tool vibration [3]. The machining process is influenced by various parameters. For instance, it has been identified that both cutting edge radius and cutting speed have an impact on the coefficient of friction on the tool-workpiece interface [4]. The basis for evaluating, simulating, and further modifying the parameters for achieving greater precision at output is provided by cutting force analysis. There are a variety of variables that have a substantial impact on the amount and distribution of the cutting forces [5]. Significant research efforts have been made to develop a high precision cutting force model in order to ensure that the predictions are accurate.

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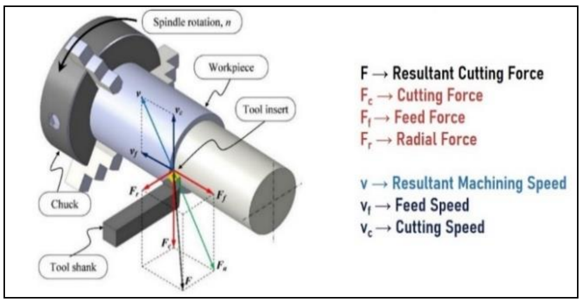

Fig. 1 Components of Force in Machining

The magnitude and range of the cutting force determine the machining quality, tool wear, and power consumption during the turning process. Cutting force is one of the significant physical parameters in the research of the machining process of titanium alloys [6]. Cutting forces vary depending on the tool material, tool angles, and machining techniques. Typically, cutting forces are produced in three axes as the material removal occurs during machining [7]. A machine-tool dynamometer is used to measure the forces applied by the cutting tool edge on the workpiece during the machining process. In order to precisely assess the cutting forces and optimize the machining process, machine-tool dynamometers are being adopted more frequently in industries [8]. By measuring the forces in each of the three spatial dimensions, the dynamometer determines the cutting force.

Since it requires more effort and adds up to expenses, it becomes tedious to conduct continuous experimentation. Machine learning approaches have recently been used to solve various engineering problems. Machine learning focuses on learning from data and enhances its accuracy over time without a lot of coding. Algorithms are "trained" to search vast amounts of data for patterns and characteristics to make decisions and predictions based on the input data [9]. The accuracy of the decisions and predictions increases with the algorithm's performance. Researchers have been exploring optimization techniques, which include tools like expert systems, fuzzy logic, genetic algorithms, neural networks, customized computer software and mathematical programming [10]. These techniques can perhaps analyze data, establish correlations between variables, and learn on their own, speeding up the process and relieving people of laborious job.

2. Literature Survey

There is a plethora of innovative strategies that various researchers have developed and examined. The techniques that have been created, which the biological evolution process and the human brain have sought, are far more effective at recommending and exploring superior solutions. As stated in [11], Artificial intelligence-based modelling approaches are favoured and are deemed to be compelling, consistent, and effective in real-time applications when compared to analytical modelling. For the purpose of minimizing cutting force, a hybrid model based on Neural Network (NN) and Genetic Algorithm (GA) approach is suggested. Depending on how complicated the problem is, different optimization techniques may necessitate a significant computational expense [12]. When used in addition to traditional analysis and optimization techniques, Artificial Neural Network (ANN) is one of the vital methods for reducing computational work without compromising the quality of the final result.

According to [13], the main disadvantage of implementing physical models is the requirement for a huge, reliable collection of data that is arduous to obtain. The weights and parameters of neural networks were optimized using a modelled genetic algorithm, and the programme was developed in C++. The predicted values were found to be pretty close to the observed values, which implies that the model has a higher likelihood of capturing the nonlinearity which already exists in the data. In the study conducted in [14], models for an experimental dataset involving nano-fluids in machining through minimum quantity lubrication (MQL) were developed using both the regression approach and the ANN technique. The responses predicted by ANN were optimized using GA. In comparison to the regression model, the combination of the ANN and GA model was more accurate in predicting the response and was also able to obtain the optimized cutting force.

As mentioned in [15], theoretical cutting force calculations were unable to provide accurate results because of the complex cutting tool scenario of metal cutting processes as well as some unknown characteristics. Variations in the cutting speed, feed rate and depth of cut were taken into account while planning the experiment. The NN-based models have demonstrated good agreement between predicted results and cutting force that was experimentally verified. The cutting forces were modelled in ANN as a function of cutting conditions, viz., cutting speed, feed and depth of cut in [16]. The cutting force was predicted and found to be increasing with an increase in the depth of cut and feed rate. In [17], using inputs such as cutting speed, feed, depth of cut and workpiece hardness, the ANN model is employed to anticipate cutting forces. In machining, the resultant cutting force consists of three components: cutting force, feed force, and radial force. The developed model found perfect agreement with the experimental data.

GA was used to determine the ideal values of crucial machining parameters like metal removal rate (MRR) and cutting forces [18]. Using analysis of variance (ANOVA), the significant parameters and the proportion of their contribution were identified. GA was used to determine the optimal machining configuration, and Response Surface Methodology (RSM) was used to construct highly accurate quadratic regression equations for the MRR and cutting forces. By using GA [19], machining parameters, including feed rate, cutting speed and depth of cut, are enhanced. The tool path length was optimized using the turning operation in the machining process. Five separate runs are used to investigate the value of the machining parameters, with an average forecast error of 5%. In ball-end milling, the effects of cutting speed, feed per tooth, axial depth of cut, and radial depth of cut are investigated in [20]. Experimental data of the tangential and radial forces were collected, and these were fitted into a quadratic model. GA was used to identify the optimal solution, and experimentation was carried out to verify it.

3. Research Methodology

While turning Ti6Al4V, three parameters, i.e., cutting speed, feed rate and depth of cut, were taken into account for modelling and process optimization. Models were created for an experimental dataset using both the GA and ANN approaches.

3.1 Machining Setup

The Ti6Al4V bar that was used had 250 mm in length and 30 mm in diameter. Due to its ability to turn hard materials, cubic boron nitride (CBN) was chosen as the cutting tool. It is the second-hardest substance found on the planet, following diamond. A variety of different input parameters were used in the experiment to assess the cutting forces. A major objective in the manufacturing sector has been to optimize the machining process, and the design of experiments (DOE) method has been practised for its powerful advantages. The experimentation was executed using a full factorial design of Taguchi's L27 orthogonal array.

Table 1. Machining Parameter Factors and Levels

Factors	Level 1	Level 2	Level 2
Cutting Speed (m/min)	45	73	101
Feed Rate (mm/rev)	0.11	0.18	0.25
Depth of Cut (mm)	0.25	0.5	0.75

A PSG conventional lathe model A141 is used for the turning operation. The MQL method was utilized to lubricate the tool-workpiece interface. A cutting fluid is sprayed as a fine mist in MQL by combining it with highly pressurized air. MQL reduces the amount of cutting fluid consumed, saves additional expenses and safeguards against the adverse effects of lubricants on the climate and labour. Unlike other lubrication methods, MQL reduces the amount of lubricant used per hour as it sprays a mixture of environment-friendly oil and compressed air at the tool-workpiece interface.

Fig. 2 Machining Setup

Coconut oil was dispersed on the tool-workpiece interface using the jet nozzle. The Kistler 9257BA Dynamometer was used to capture the cutting force data. A laptop was used to constantly store the data supplied by the Kistler amplifier.

3.2 Artificial Neural Network

An Artificial Neural Network (ANN) is a deep learning technique inspired by the structure of the human brain [21]. The brain's neuron transmits the signals required for carrying out the activities. In NN, artificial neurons interconnect together to perform versatile functions. A biological neuron can have excited or non-excited sets of outputs, depending on the attenuation in the synapses, which are the pathways that interconnect the neurons [22]. NN is intended to predict the values of estimated multivariable functions and model input-output interactions in a training process. The network acquires knowledge by evaluating several datasets and adjusting the weights and biases. Weight refers to the numerical values that link the neurons together. The weight distinguishes NN's potential for learning between neurons. ANN is one of the most effective machine-learning techniques at the moment. An ANN is comprised of three types of layers: an input layer that takes three input variables viz. cutting speed, feed rate, and depth of cut into consideration.

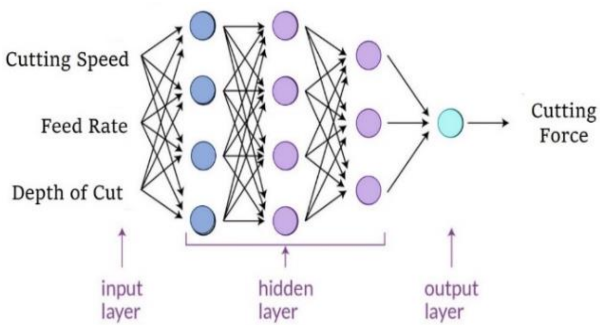

Fig. 3 Neural Network Architecture

Several neurons constitute the hidden layers, and the output layer is composed of one layer related to the cutting force. While the output layer uses a linear function to conduct regression, the hidden layers are made up of a certain number of neurons that perform a particular nonlinear function, such as sigmoid [23]. In order to find responses that are closer to the desired outcome, the weights in the network are recalculated as the output results of the network are compared to the experimental values. The main benefit of using ANN is the ability to learn from the process and eventually present the desired output [24].

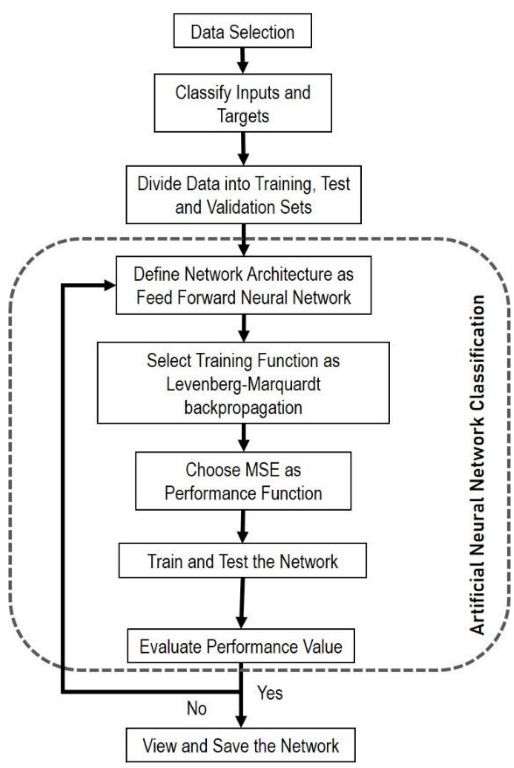

Fig. 4 Flowchart of Neural Network

3.3 Genetic Algorithm

GA is a rapidly growing branch of artificial intelligence and is a subfield of evolutionary algorithms (EA) that was inspired by the process of natural evolution [25]. Darwin's Theory contributed to the evolution mechanism referred to as natural selection. Fitter organisms in the environment will have a higher chance of surviving and propagating the genes that helped them succeed.

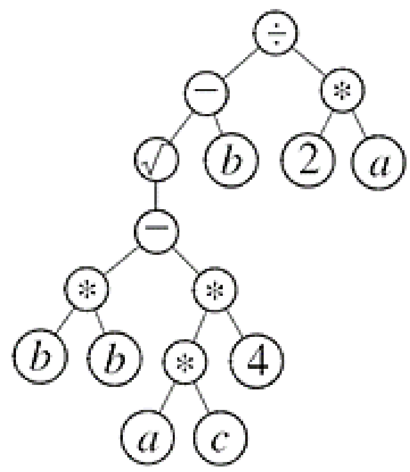

Fig. 5 Example of Genetic Algorithm for Roots of Polynomial Equation

The concepts of "survival of the fittest" and "natural selection" are also the principles of GA. It is inherently parallel and has implicit parallelism, which means that instead of analyzing and improving a single solution, it simultaneously analyses and adjusts several solutions [26]. Because of their efficient and reliable performance, GA has undergone intense studies and has been extensively applied in varied applications.

At the beginning of 1990, Koza developed genetic programming (GP) to expand the GA based on EA [27]. GP is based on simplifying concepts of genetic recombination and natural selection. Beginning with an initial population, the GP algorithm's underlying cycle evolves over time by identifying the fittest individuals depending on their performance. GP is based on an approach for finding the best solution by maximizing or minimizing the function. Symbolic Regression (SR) is an application of GP. In SR, the objective is to find an equation in the system of symbols that better suits the values of the dependent variables and their corresponding desired values of the independent variables. The symbolic expression tree grammar describes the mathematical operators and functions that would be utilized to represent the outcome. In addition, subtraction, multiplication, division, exponential and logarithmic functions, and constants as terminals were the selected symbols in SR.

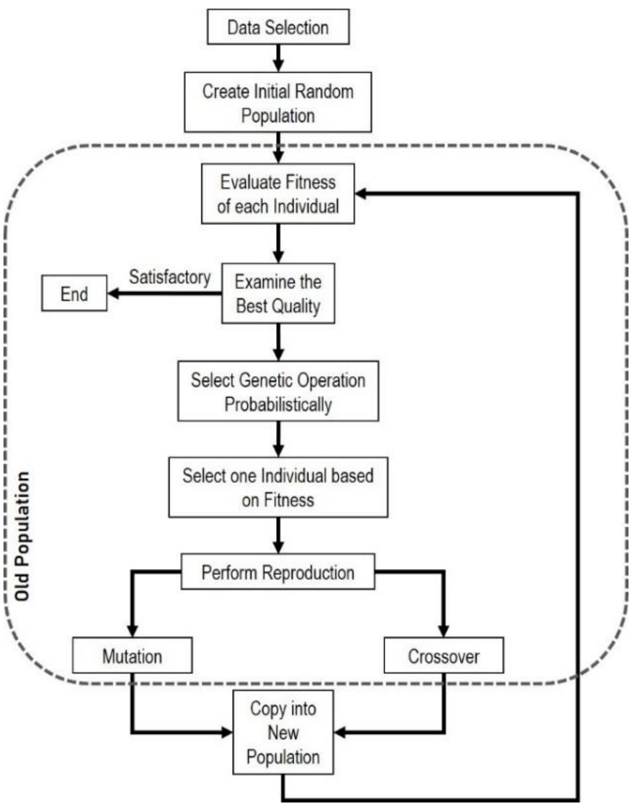

Fig. 6 Flowchart of Genetic Algorithm

4. Comparative Results

Both models were developed successfully to predict cutting forces in Ti6Al4V turning. While the ANN model was developed in MATLAB R2021a, the GA model was created on HeuristicLab, an optimizer for evolutionary and heuristic algorithms. The NN model was computed minimally, while it took approximately twelve seconds to develop the SR model. Since ANN interconnects the data, the operation of the data is not visible to the user. In GA, a parse tree and a mathematical equation are displayed. As a standard metric to evaluate both models, mean squared error (MSE) was selected as the performance function. The value of the MSE is computed using the squares of the absolute error, and their average is taken together. It measures how closely a regression line resembles the set of data points. The lower the MSE, the more data is closely aligned with the fit. The MSE of the ANN model is 0.27907, while the MSE of the GA model is 5.89951. It shows that the ANN model is a better fit for the data when compared to GA.

Table 2 Results of ANN and GA model for Cutting Force Prediction

Sr. No.	Experimental Cutting Force (N)	ANN Model		GA Model	
		Cutting Force (N)	Percentage Error	Cutting Force (N)	Percentage Error
1	160.083	160.0756	-0.00462	159.012	-0.66906
2	164.123	164.0871	-0.02187	162.276	-1.12562
3	168.635	168.5531	-0.04857	166.585	-1.21623
4	152.321	154.5688	1.4757	153.329	0.65214
5	157.539	157.5332	-0.00368	158.011	0.29962
6	160.121	160.039	-0.05121	162.443	1.4509
7	165.964	165.8874	-0.04615	161.295	-2.81456
8	166.121	166.0253	-0.05761	166.517	0.23852
9	169.567	169.4307	-0.08038	172.111	1.5015
10	142.234	142.2765	0.02988	145.726	2.45438
11	144.387	144.387	0	147.996	2.49953
12	147.126	147.0649	-0.04153	150.325	2.17523
13	145.124	144.5494	-0.39594	146.27	0.79281
14	149.293	149.9431	0.43545	147.536	-1.17178
15	152.326	152.3181	-0.00519	149.603	-1.78771
16	145.178	145.3195	0.09747	146.805	1.1196
17	149.655	150.4151	0.5079	149.787	0.08776
18	153.123	152.1814	-0.61493	152.975	-0.09725
19	139.298	139.3326	0.02484	140.24	0.67608
20	144.654	144.701	0.03249	141.886	-1.91291
21	147.872	147.9478	0.05126	143.564	-2.91184
22	141.221	141.2818	0.04305	141.285	0.0453
23	144.651	144.6672	0.0112	142.261	-1.65207
24	146.656	146.6263	-0.02025	143.668	-2.03783
25	142.567	142.1463	-0.29509	140.73	-1.29233
26	145.221	145.2289	0.00544	142.781	-1.68011
27	148.765	148.7645	-0.00034	144.966	-2.5537

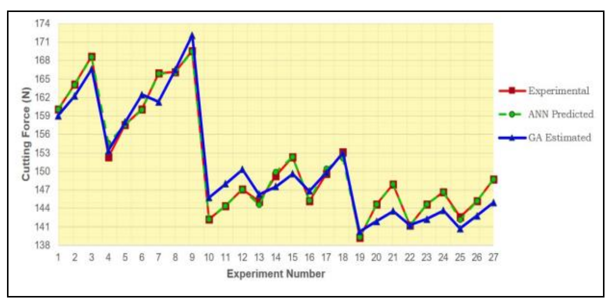

Fig. 7 Comparison of Experimental, ANN and GA Models

The accuracy of each model can be used to judge the reliability of the model for optimizing the machining process. The accuracy of the developed model can be determined using the following formula:

$$\text{Accuracy} = 100*\left\{1 - \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \overline{y_i}}{y_i}\right|\right\} \quad (1)$$

here,

n stands for the number of rows
y represents the experimental outcome
$\overline{y_i}$ represents the predicted value by the model.

The accuracy of ANN model stands at 99.83%, while that of the GA model is 97.08%. It is suggested that the ANN model is more reliable than the GA model. The plot of the experimental data, ANN and GA model depicts that the ANN model almost predicts the values closer to experimental ones than GA. The significant difference between both is that ANN uses adaptive learning to train the model; meanwhile, the GA model solves the problem by evaluating numerous solutions to find the best one. GA has a considerable number of errors, and the model can yield larger differences when estimating unknowns. ANN model has a minimum percentage error of 0, suggesting a perfect fit at that point, while the maximum error is 1.4757%. The GA model's minimum percentage error is 0.04532%, and the maximum percentage error observed is -2.91333%.

Since the maximum and minimum errors are minimal in ANN compared to the GA model, the ANN model is more suitable for finding optimal parameters in turning operations.

5. Conclusion

ANN and GA based models were created to predict the cutting force during titanium alloy machining. Both models could be used to determine the optimal machining parameters. The results of the study can be summarised as follows:

i. ANN model is better suited for predicting cutting forces during MQL machining of Ti6Al4V.
ii. Given the extent of spotted errors, the GA model developed for estimating cutting forces appears to be a lesser reliable model.
iii. The GA model can be beneficial for analytical calculations, wherein using high-end computational systems is not feasible.

References

1. *D. A. Coroni and S. M. Croitoru, "Prediction of Cutting Forces at 2D Titanium Machining", 24th DAAAM International Symposium on Intelligent Manufacturing and Automation, Vol. 69, pp. 81-89, 2014.*

2. *Yun Chen et al., "Analytical modelling of cutting forces in near-orthogonal cutting of titanium alloy Ti6Al4V", Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, Vol. 229, Issue 6, pp.1122-1133, 2015.*

3. *S. Sun et al., "Characteristics of cutting forces and chip formation in machining of titanium alloys", International Journal of Machine Tools and Manufacture, Vol. 49, Issues 7–8, pp. 561-568, 2009.*

4. *C. F. Wyen and K. Wegener, "Influence of cutting edge radius on cutting forces in machining titanium", CIRP Annals, Vol. 59, Issue 1, pp. 93-96, 2010.*

5. *Bin Li and Hong Wang, "Numerical simulation and prediction of cutting force in turning of titanium alloy", Advanced Materials Research, Vol. 580, pp. 63-66, 2012.*

6. *Yahui Hu et al., "Simulation and Experimental Research on Cutting Force of Turning Titanium Alloy", 7th International Conference on Mechanical and Electronics Engineering (ICMEE 2015), MATEC Web of Conferences, Vol, 31, No. 03013, 2015.*

7. *Dhamodharan N et al., "A Review of Cutting Force and Optimization In Metal Cutting Process", International Journal of Applied Engineering Research (IJAER), Vol. 10, Issue 6, pp. 15207-15224, 2015.*

8. *Bharat Sharma, "Effect Of Parameters Like Spindle Speed, Depth Of Cut And Feed Rate On The Cutting Force Of A Single Point Cutting Tool", International Journal of Engineering Applied Sciences and Technology, Vol. 4, Issue 12, pp. 525-530, 2020.*

9. *Utkaarsh Bhaskarwar et al., "Machine Learning Approach to Predict the Trends of the COVID-19 Pandemic: A survey", International Research Journal of Engineering and Technology (IRJET), Vol. 08, Issue 06, 2021.*

10. *Zoran Jurkovic et al., "A comparison of machine learning methods for cutting parameters prediction in high speed turning process", Journal of Intelligent Manufacturing, Vol. 29, pp. 1683–1693, 2018.*

11. *K. Leo Dev Wins et al., "Artificial Neural Network and Genetic Algorithm-Based Models for Predicting Cutting Force in Turning of Hardened H13 Steel", Trends in Manufacturing and Engineering Management, Part of Lecture Notes in Mechanical Engineering, Springer, 2020.*

12. *Sergio D. Cardozo et al., "Optimization of laminated composite plates and shells using genetic algorithms, neural networks and finite elements", Latin American Journal of Solids and Structures, Vol. 8, pp. 413 – 427, 2011.*

13. *C. C. Gowda and S. G. Mayya, "Comparison of Back Propagation Neural Network and Genetic Algorithm Neural Network for Stream Flow Prediction", Journal of Computational Environmental Sciences, Vol. 2014, No. 290127, 2014.*

14. *U. Mukkamala and S. R. Gunji, "Comparison of Regression Model with Multi-layer Perceptron Model While Optimizing Cutting Force Using Genetic Algorithm", Mathematical Modelling of Engineering Problems Vol. 7, No. 2, pp. 265-272, 2020.*

15. *Issam Hanafi et al., "Artificial neural networks back propagation algorithm for cutting force components predictions", Mechanics & Industry, Vol. 14, No. 6, pp. 431 – 439, 2013.*

16. *Sanjib Banerjee et al., "Artificial Neural Network Modeling of the Effect of Cutting Conditions on Cutting Force Components during Orthogonal Turning", International Journal of Current Engineering and Technology, Special Isssue-2, pp. 127-130, 2014.*

17. *Marwa Qasim Ibraheem, "Prediction of Cutting Force in Turning Process by Using Artificial Neural Network", Al-Khwarizmi Engineering Journal, Vol. 16, No. 2, pp. 34- 46, 2020.*

18. *A. V. Pradeep et al., "Optimization for Machining Parameters in Turning of AISI 52100 Steel for Manufacturing Services-Genetic Algorithm Method", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol. 9, Issue 3, 2020.*

19. *Besart Berisha et al., "Optimization of Turning Process and Cutting Force Using Multiobjective Genetic Algorithm", Universal Journal of Mechanical Engineering, Vol. 7, No. 2, pp. 64-70, 2019.*

20. *Amit Jyoti Banerjee et al., "Analysis of Cutting Forces and Optimization of Cutting Parameters in High Speed Ball-end Milling Using Response Surface Methodology and Genetic Algorithm", International Conference on Advances in Manufacturing and Materials Engineering (ICAMME), Vol. 5, pp. 1623-1632, 2014.*

21. *M. Bagińska and P. E. Srokosz, "The Optimal ANN Model for Predicting Bearing Capacity of Shallow Foundations Trained on Scarce Data", KSCE Journal of Civil Engineering, Vol. 23, pp. 130–137, 2019.*

22. *Abhishek K et al., "Ann Modeling For Prediction Of Cutting Force Component During Orthogonal Turning", International Research Journal of Engineering and Technology (IRJET), Vol. 05, Issue 06, 2018.*

23. *Vishal S. Sharma et al., "Estimation of cutting forces and surface roughness for hard turning using neural networks", Journal of Intelligent Manufacturing, Vol. 19, pp. 473–483, 2008.*

24. *N Efkolidis et al., "Prediction of cutting forces in drilling AL6082-T6 by using artificial neural networks", IOP Conference Series: Materials Science and Engineering, Vol. 916, No. 012036, 2020.*

25. *A. Ansari and A. A. Bakar, "A Comparative Study of Three Artificial Intelligence Techniques: Genetic Algorithm, Neural Network, and Fuzzy Logic, on Scheduling Problem", 2014 4th International Conference on Artificial Intelligence with Applications in Engineering and Technology, pp. 31-36, 2014.*

26. *Ling Wang, "A hybrid genetic algorithm–neural network strategy for simulation optimization", Applied Mathematics and Computation, Vol. 170, Issue 2, pp. 1329-1343, 2005.*

27. *Cristian DINU et al., "Genetic Programming Technique Applied For Flash-Flood Modelling Using Radar Rainfall Estimates", Modelling in Civil Environmental Engineering, Vol.13, No.4, pp.27-38, 2017.*

