Process Design for Milling Operation of Titanium Alloy (Ti6Al4V) Using Artificial Neural Network

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***Abstract*—Titanium alloy is characterized with excellent mechanical properties such as lightweight, and good corrosion resistance ability, hence, it finds application in many industrial and engineering applications. This study considers the process design of the milling operation of titanium alloy using artificial intelligence. The numerical experimentation involves the use of the Artificial Neural Network (ANN) back propagation and Levenberg-Marquardt algorithm for the correlation of the process parameters while the physical experiments were investigated using a DMU80monoBLOCK Deckel Maho 5-axis CNC milling machine and carbide-cutting inserts of 12 and 14 mm (RCKT1204MO-PM S40T) under the cooling and dry machining conditions. The developed network was used to obtain a regression analysis which is suitable for the prediction of the feasible range of the process parameters. The results obtained from the physical experiments indicate significant reduction in the rate of tool wear under the cooling conditions as opposed to the dry machining. The findings of this work will find suitable application as a decision making tool in the manufacturing industries most especially the manufacturing industries, which employs titanium alloy for component part development.**

***Index Terms*—ANN, milling operation, process design, process parameters, titanium alloy**

I. Introduction

The use of high strength and low weight materials is gaining increased attention in the quest for manufacturing sustainability. Titanium alloy is characterized with excellent mechanical properties such as lightweight, high strength and corrosion resistance ability, hence, it finds application in many industrial and engineering applications [1-3]. However, its low thermal conductivity often makes it difficult to machine most especially in high temperature and high speed cutting operations. This is because its low thermal conductivity allows the material to absorb and retain heat rather than quick dissipation to the conducting chips and other part of the material. The effect of high heat retention at the tool-work piece interface results in the build-up of temperature which promotes the development of residual stress and subsequently surface roughness and dimensional inaccuracies. The higher the surface roughness and dimensional inaccuracies of the final product, the lower the probability that the product will meet its functional and service requirements. This implies that the quality of a product is partly a function of its surface finish and dimensional accuracies.

Nomenclature

T_d	Inscribed circle diameter (mm)
d_c	Depth of cut (mm)
α	Nose Radius (mm)
t	Insert thickness (mm)
φ	Lead angle (deg.)
d_i	Diameter of insert (mm)
h_n	Number of the neurons in the hidden layer
w	Weight of the input parameters,
i	Number of input parameters
b	Bias

With increasing temperature, the hardness of cutting tool will reduce thereby resulting in low rates of material removal, and poor surface finish. Continuous cutting under this condition may also lead to the development of built up edges and subsequent failure of the cutting tool edge. Furthermore, titanium has the tendency to work harden most especially under uncontrolled cooling condition causing the shear zone to become harder than the

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rest of the work piece. This work hardening phenomenon also has the tendency to promote surface roughness. Another issues is that titanium is also very tough and does not shear easily, hence, sufficient force is required to bring about an effective cutting action and the production of chips. When long chips are produced, provision must be made for quick evacuation in order to prevent the development of built edges which can cause poor surface finish and catastrophic failure of the cutting tool. Adequate process design involving the selection of cutting tool with the appropriate geometry will pave way for quick chip removal before edges are built up around the cutting tool [4-6]. Hence, the geometry of the cutting tool is another factor that has been identified which influences the rate of machinability and heat generation via friction during the machining operation [7-9]. The angle at which the cutting tool approaches the work piece for material removal influences certain factors such as the magnitude of the cutting force, rate of chip removals, material removal rate etc.

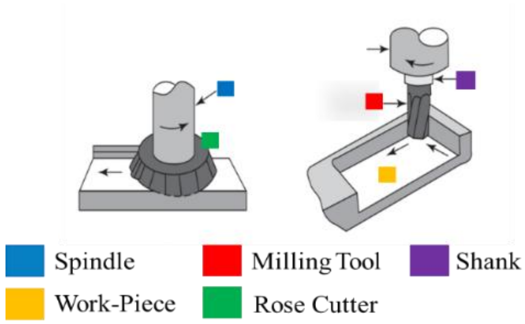

Figure 1. The schematic representation of the milling process

Fig. 1 illustrates the engagement of the cutting tool and work piece during milling operation leaving sufficient space for chip removal. Effective chips removal will bring about significant reduction in the cutting temperature, reduction in the tendency for built up edges and increased chances for good surface finish. In order to mitigate these challenges associated with titanium alloy during machining operations, many researchers have proposed some approaches such as the development of special high performance cutting tool, computer aided modelling and simulation of the cutting process, the optimization of the process parameters, the use of coolants and incorporation of smart devices for temperature measurement and monitoring in real time [10-12]. Many analytical, numerical and physical experimentation approaches have been carried out to improve the machinability of titanium alloy during milling operation [13]. Courbon *et al.* [14] carried out the tribological assessment of Ti6Al4V and Inconel 718 in order to determine their behaviour under dry and cryogenic conditions while Dhananchezian and Kumar [15] studied the cryogenic turning of the Ti–6Al–4V alloy with some modification on the cutting tool inserts. The findings of the studies indicate that the cryogenic cooling technology is suitable for enhancing the machinability of titanium alloy under controlled conditions. Elshwain *et al.* [16] carried out the assessment of degree of machinability of nickel and titanium alloys under gas based coolant-lubricants. The findings established that the use of the gas-based coolant-lubricants is clean and environmentally friendly but requires adequate process design for optimum performance. Rotella *et al.* [17] studied the effects of the cooling conditions on surface integrity in the machining of Ti6Al4V alloy. It can be inferred from the studies that the surface integrity and machinability of titanium alloy increases under certain cooling conditions as compared to dry machining. Furthermore, Strano *et al.* [18] carried out the comparative analysis of Ti6Al4V machining forces and tool life for cryogenic and conventional cooling while Park *et al.* [19] investigated the effect of cryogenic cooling and minimum quantity lubrication during the end milling operation of titanium alloy (Ti-6Al-4V). The findings of the works indicate that the machining forces decrease with an increase in the tool life under the cryogenic cooling condition as compared to the conventional cooling methods. In addition, Shan *et al.* [20] developed an improved analytical model for cutting temperature in an orthogonal cutting of Ti6Al4V while Daniyan *et al.* [21] performed the mathematical modelling and optimization of the cutting forces during Ti6Al4V milling process using the Response Surface Methodology. The works provide an analytical and predictive models for the prediction and optimization of the cutting temperature and forces during the machining operations of Ti6Al4V.

The use of ANN for process design, modelling and optimisation during machining operations have been reported [22-24].

The ANN has been proven to be a modelling technique which is suitable for investigating the relationship between the input and output variables so as to make reliable predictions. The ANN technique can be employed for performing modelling and optimization of simple or complex linear as well as non-linear systems with multi-dimensional relationships [25-29].

The aim of this work is to employ the Artificial Neural Network (ANN) for the prediction of the process conditions and parameters such as the temperature, cutting force, cutting frequency and depth of cut. The work also seek to investigate the rate of tool wear for different cutting inserts under the same cutting conditions and parameters for comparative analysis. The process design and the prediction of process parameters via the artificial neural network have not been sufficiently highlighted by the existing literature. Hence, this work will assist manufacturers who employs titanium alloy for product development in the quest for the development of an efficient process for high performance cutting.

The succeeding sections present details of the materials and method employed, results and discussion as well as the conclusion and recommendations.

II. Materials & Methods

The chemical composition as well as the mechanical and electrical properties of the titanium alloy (Ti-6Al-4V) used as the work piece are presented in Tables 1 and 2 respectively.

TABLE I. CHEMICAL COMPOSITION OF TITANIUM ALLOY (TI-6AL-4V) [30].

Element	Al	Fe	O	Ti	V
Percent weight (wt.%)	6	0.25	0.2	90	4

TABLE II. MECHANICAL AND THERMAL PROPERTIES OF TITANIUM ALLOY (TI-6AL-4V) [30].

S/N	Properties	Value
	Mechanical	
1.	Density (kg/m^3)	45000
2.	Brinell's hardness	334
3.	Yield strength (MPa)	880
4.	Ultimate tensile strength (MPa)	950
5.	Bulk modulus (GPa)	150
6.	Modulus of elasticity (GPa)	113.8
7.	Poison's ratio	0.342
8.	Shear modulus (GPa)	44
9.	Shear strength (MPa)	550
	Thermal	
11.	Specific heat capacity (J/g℃)	0.5263
12.	Thermal conductivity (W/m.K)	6.7
13.	Melting point (℃)	1660
14.	Coefficient of thermal expansion (K^{-1})	8.70

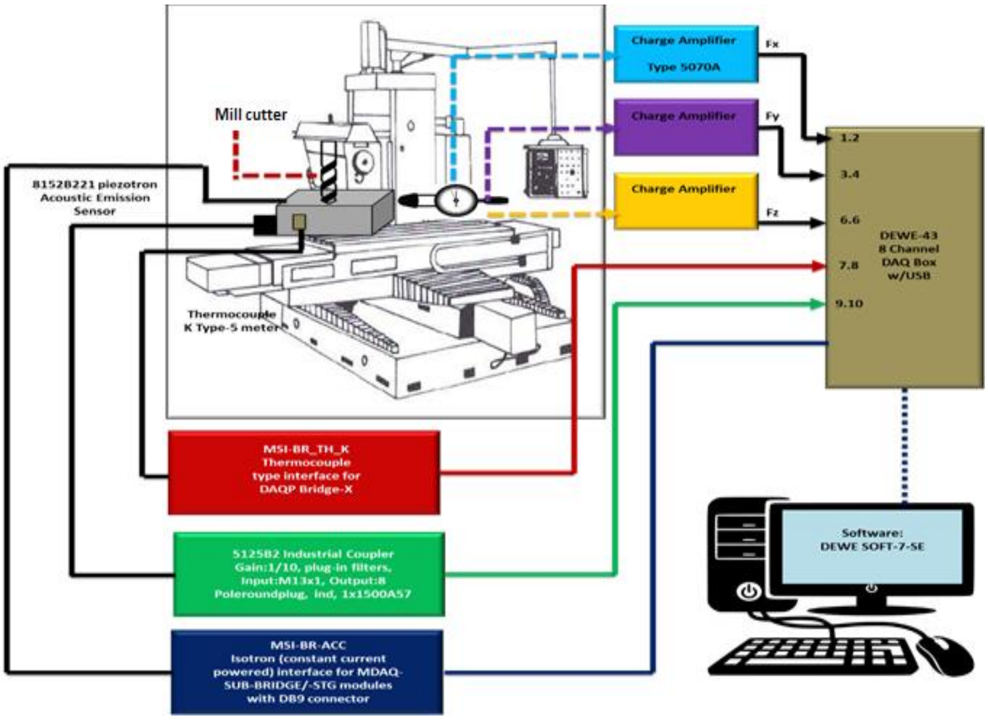

Figure 2. The schematic of the experimental set up and the DAQ.

The physical experiments were performed using a DMU80monoBLOCK Deckel Maho 5-axis CNC milling machine with a maximum spindle speed of 18000 rpm. Two carbide cutting inserts of 12 and 14 mm (RCKT1204MO-PM S40T) were used for the machining operation for comparison purpose. The physical experimentations employ the predicted process parameters by ANN for the determination of the rate of the tool wear and temperature profiles during titanium milling operation using the cutting inserts of diameters 12 mm and 14 mm. The cryogenic cooling involving the injection of liquid nitrogen (LN_2) at the interface of the cutting tool and work piece was employed as the cooling medium. In order to prevent hardening due to its extreme low temperature, the amount of the cooling agent introduced through an external spray was regulated in relation to the temperature measured in real time. The temperature of the cutting operation was also measured and monitored using a professional infrared video thermometer with LCD display and camera function (MT 696) with infrared temperature range of -50-1000℃. The instrument is highly sensitive to temperature variation and highly suitable for temperature measurement and monitoring. The stationary dynamometer (KISTLER 9257A 8-Channel Summation of Type 5001A Multichannel Amplifier) with the Data Acquisition System (DAQ) were employed for the cutting force measurement in real time. The schematics of the process design is shown in Fig. 2. The tool wear was measured with the aid of the toolmaker's microscope (type LS 3003). The Figure illustrates the integration of the software and data acquisition system with the CNC milling machining and the temperature monitoring system. This enables the collection of data and storage of the data relating to the machining operations in real time.he specifications of the cutting tool is presented in Table III.

TABLE III. THE CUTTING TOOL GEOMETRY.

Symbol	Parameter	Value
T_d	Inscribed circle diameter (mm)	3.987
d_c	Depth of cut (mm)	1.760
α	Nose Radius (mm)	6.000
t	Insert thickness (mm)	4.750
φ	Lead angle (deg.)	0º
d_i	Diameter of insert (mm)	12 & 14

The Artificial Neural Network (ANN) which comprises of a network iteratively trained by the Levenberg-Marquardt backpropagation algorithm was developed. The choice of the Levenberg-Marquardt backpropagation algorithm was informed by its high ability to study and correlate simple and complex relationships between the data sets. Furthermore, the algorithm is highly efficient for training, correlative and predictive purposes within a little time [25].

Figure 3. The physical experimental set-up.

For the physical experimentations, the feed per tooth, feed rate, maximum chip thickness and the cutting speed were used as the input parameters while the temperature, cutting force, cutting frequency and the depth of cut serve as the measured output. The physical experimentation produced 15 experimental trials. The set-up of the physical experimentation process is shown in Fig. 3. The input and output (target) parameters employed for the training are as follow:

Input= [0.20 0.20 0.20 0.20 0.20 0.25 0.25 0.25 0.25 0.25 0.30 0.30 0.30 0.30 0.3; 0.20 0.20 0.20 0.20 0.20 0.25 0.25 0.25 0.25 0.25 0.30 0.30 0.30 0.30 0.30; 0.10 0.10 0.10 0.10 0.10 0.20 0.20 0.20 0.20 0.20 0.30 0.30 0.30 0.30 0.30; 250000.00 25000.00 250000.00 250000.00 250000.00 260000.00 260000.00 260000.00 260000.00 260000.00 270000.00 270000.00 270000.00 270000.00 270000.00];

Target= [300.00 300.00 300.00 300.00 300.00 400.00 400.00 400.00 400.00 400.00 500.00 500.00 500.00 500.00 500.00;250.00 250.00 250.00 250.00 250.00 350.00 350.00 350.00 350.00 350.00 500.00 500.00 500.00 500.00 500.00;200.00 200.00 200.00 200.00 200.00 500.00 500.00 500.00 500.00 500.00 1000.00 1000.00 1000.00 1000.00 1000.00; 0.10 0.10 0.10 0.10 0.10 0.20 0.20 0.20 0.20 0.20 0.30 0.30 0.30 0.30 0.30];

The architecture of the developed neural network which comprises of four inputs and outputs as well as ten hidden and four output layers is presented in Fig. 4.

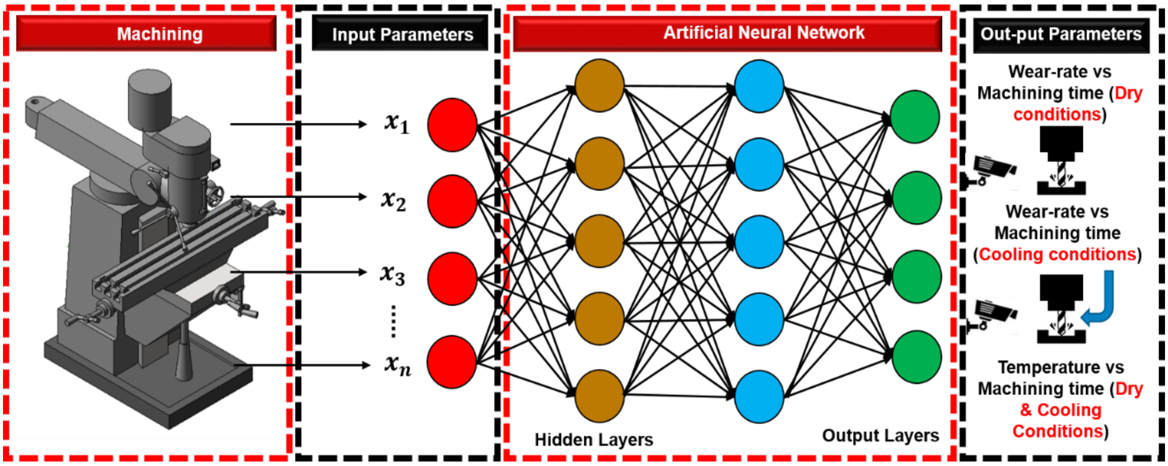

Figure 4. The architecture of the neural network.

The number of neurons in the input and output layers equals the number of input and output variables in the data being processed which in this case is four. The hidden layer is the neuron layer in between the input and output layers. The artificial neurons receives a set of weighted inputs and produce a corresponding output based on the input received.

The number of the neurons in the hidden layer (h_n) equals the weighted sum of inputs and bias expressed as expressed by (1).

$$h_n = \sum(wi) + b \qquad (1)$$

Where w is the weight of the input parameters, i *is the number of input parameters* and b is the bias.

For the four input data parameters fed into the ANN, the number of the neurons in the hidden layer was obtained as ten while the corresponding number of output layer was four.

Using the Levenberg Marquardt algorithm, the network was iteratively trained until a network with good predictive and correlative abilities was developed. The training plots of the developed network is shown in Fig. 5. Fig. 5 indicates that that it takes maximum of five iterations (5 epochs) for a good network with high predictive capability to be developed and that the best training performance was gotten at the second iterations. Also, the negligible value of the Mean Square Error (MSE) indicates that the network was adequately trained.

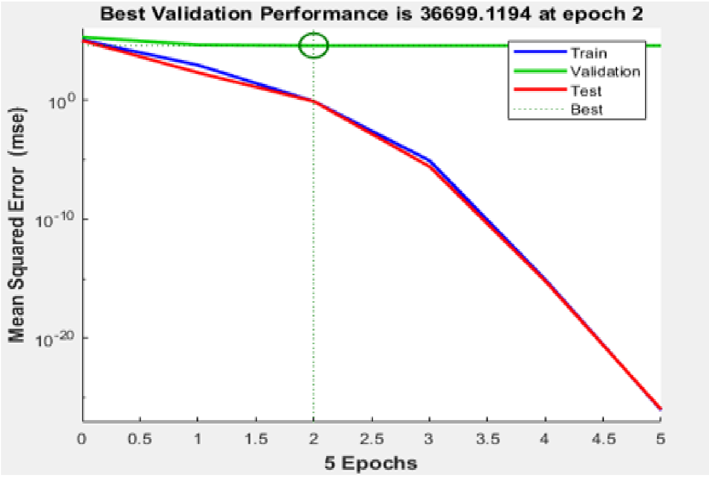

Figure 5. The performance training plot.

III. Results and Discussion

Fig. 6 is a plot of the gradient, training gain Mu and validation check after the network has been adequately trained. The gradient was 7.6552×10^{-11} while the training gain Mu was 1.00×10^{-8} after 5 iterations. The negligible values of the gradient and the training gain indicate that the difference between the network output and target is negligible. This is an indication that the developed network is suitable for correlative and predictive purposes.

Fig. 7 shows the regression plots for the training, validation, test and overall correlation, which has the correlation coefficients as 1, 0.72447, 1 and 0.97787 respectively. The closer the correlation coefficient to 1, the more efficient the network is and vice versa. The correlation coefficient can be made closer to 1 by increasing the size of the data set and iteratively training the data set until there is a significant performance training plot. The model equations from the ANN models for the training, test, validation and overall process are expressed as (2-5) respectively.

$$Output\ Y, Linear\ Fit: Y = (1)T + (9.8 \times 10^{-12}) \quad (2)$$

$$Output\ Y, Linear\ Fit: Y = (1)T + (-2.0 \times 10^{-11}) \quad (3)$$

$$Output\ Y, Linear\ Fit: Y = (0.91)T + (88.0) \quad (4)$$

$$Output\ Y, Linear\ Fit: Y = (0.99)T + (13.0) \quad (5)$$

Where: T is the target variable.

The fact that the correlation coefficients were close to 1 indicate that the network is capable of performing the corrective and predictive functions accurately with minimal deviations from the target. Only the correlation coefficient for the validation process (0.72447) was not very close to 1 as compared to others. However, others which were close to 1 justified the efficiency of the developed neural network for predictive purpose. The fact that the value of the correlation coefficient of the validation process was lightly farther from 1 may be due to the limited data samples used in training the network. Larger data samples may produce a better correlation coefficient. In addition, the process is iterative, and the network parameters can be further adjusted until a better coefficient is obtained.

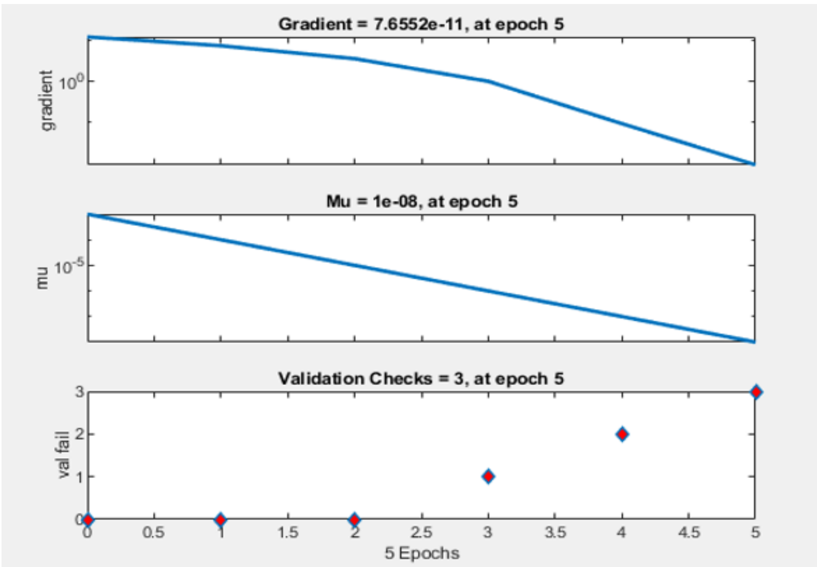

Figure 6. The plot of the gradient, training gain Mu and validation.

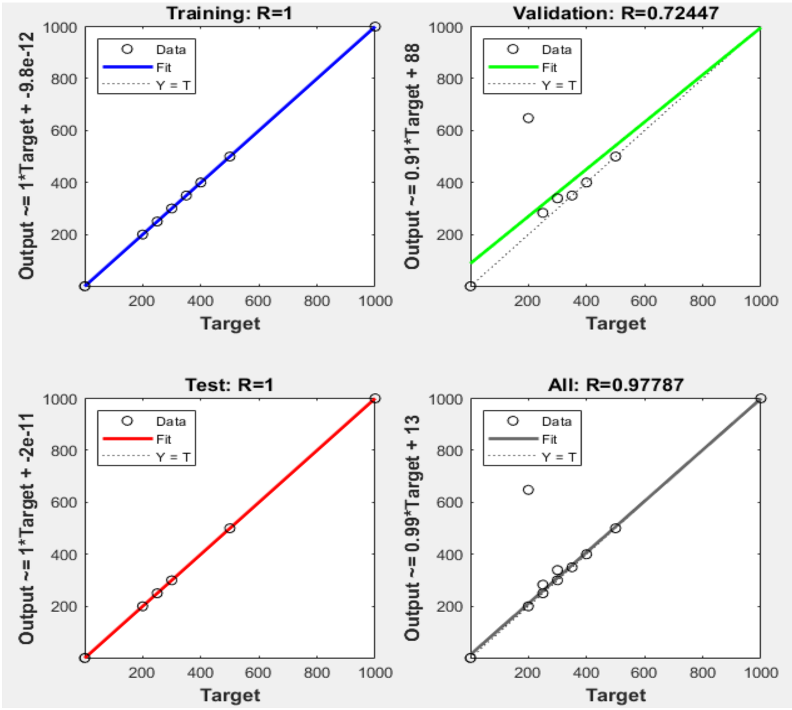

Figure 7. The regression plots.

From the plot, it is obvious that the degree of agreement between the output of the network and the experimental targets were in good agreement. The validation of the developed network was carried out using random values selected from the physical experimentations and the results obtained were found to be within the range of the physical experimental values as presented in Table IV.

The results obtained indicated that that the predicted output of the network namely the temperature, cutting force, cutting frequency and depth of cut were within the range of the physical experimentation values by interpolation. This indicates that the developed network is a suitable tool for the prediction of the machining process parameters. The corresponding predictive mathematical modelling equations are also shown in the Figure.

The physical experiments were carried out based on the use of the ANN for the process parameters selection and prediction for the milling operation of titanium alloy. Using the feasible combination of process parameters predicted from the ANN, the milling operations were performed using two different cutting inserts namely 12 and 14 mm under different cooling conditions namely; liquid nitrogen coolant and under dry conditions (no cooling). The corresponding tool wear as a function of the cutting force were determined in both cases (Fig. 8 and 9). Fig. 8 and 9 indicate that an insert of 12 mm produced lower tool wear as opposed to the 14 mm cutting inserts.

This might be connected to the fact that frictional activities which promote tool wear increases with an increase in the diameter of the cutting tool inserts and vice versa. The results also indicate a higher rate of tool wear under dry machining as opposed to the machining under the cooling condition of liquid nitrogen. The reduction in the magnitude of tool wear was because the temperature at the work piece, tool and chip interface reduce considerably with the application of coolants with significant reduction in the cutting force requirements than under the dry machining conditions. The developed chips was also observed to break away easily from the work piece surface without developing edges around the tool or work piece under cooling conditions. This prevents the development of "built up edges" with significant reduction in the rate of tool wear.

In Fig. 8 and 9, the tool wear was also observed to increase with an increase in the magnitude of the cutting force. This may be due to the fact that the stress developed in the cutting tool coupled with increasing frictional activities due to insufficient cooling. The formation of chips of longer lengths were observed under the dry machining conditions as opposed to the cutting under the cooling conditions. This is due to the absence of lubrication.

This can promote an increase in the cutting temperature due to frictional activities between the interface of the cutting tool and the work piece thereby increasing the rate of tool wear. It can also bring about the development of built up edges, a phenomenon whereby the chips generated sticks on to the surface of the cutting tool or work piece. This phenomenon can promote sudden fracture of the tool and can as well increase the profile irregularities of the work piece surface. It was observed that the thickness of the chips generated increases with an increase in the cutter diameter [31-33]. The temperature profiles of the milling operation of titanium alloy under the cooling and dry conditions for the 12 mm insert is presented in Fig. 10. The temperature profiles of the work piece and cutting tool is important because it influences the rate of energy consumption of the machining operation, tool life, work piece strength and surface finish. The temperature profile has to be consistently monitored and kept within the optimum range through the use of effective process monitoring and control devices in order to promote the overall sustainability of the cutting process [34-36].

Comparing the cutting operation under cooling and no cooling conditions as shown in Fig. 10, there is a significant reduction in the temperature distribution across the work piece, and tool interface. This achieved with the use of the liquid nitrogen coolant. This will reduce the development of residual stress with improved surface finish of the work piece due to the reduction in the frictional activities at the interfaces of the cutting tool, work piece and the chips formed. Furthermore, the reduction in temperature with the use of coolants will also cause the chips formed to break away easily thereby preventing the formation of built up edges.

Fig. 11 presents the relationship between the cutting force and the cutting temperature under cooling and no cooling conditions using the 12 mm cutting insert. The results obtained indicate that the magnitude of the cutting temperature increases with an increase in the magnitude of the cutting force.

The increase in cutting temperature becomes more pronounced in the absence of cooling conditions (under no cooling condition). This may be due to an increase in frictional activities in the interface of the cutting tool and work piece. An increase in the cutting temperature beyond the optimum may increase the energy requirement of the cutting process thereby making the process less sustainable in terms of energy consumption, cost-effectiveness and environmental friendliness. It may also provoke surface roughness and dimensional inaccuracies in the work piece.

High temperature between the cutting tool and work piece interface may also reduce the hardness of the cutting tool, thereby increasing the machining time. As the hardness of the cutting tool decreases, there are chances that the rate at which the cutting tool will penetrate the work piece for material removal will reduce. The rate of distortion may also increase thereby promoting profile irregularities in the work piece. This further underscores the importance of temperature monitoring and control. This result is in line with the findings of some existing work which emphasis effective process design that will ensure quick heat dissipating, efficient temperature monitoring and control, quick chip removal, application of effective cooling strategy, as well as optimisation of process parameters in order to achieve significant reduction in the magnitude of cutting temperature at the shear zone. This will promote the rate of machinability, degree of surface finish, process economics and sustainability [37-38]. Since the cutting force has been observed to influence the rate of tool wear and cutting temperature which are detrimental to the tool life and the surface finish of the work piece, the optimisation of the cutting force will be helpful in the determination of the optimum range of the cutting force. Once the optimum range is determine, the acquisition of the cutting force data and monitoring in real time will assist in keeping the magnitude of the cutting force within the optimum range. It is also worth mentioning that the determination of right orientation and geometry of the cutting tool in relation to the nature of the work piece to be machined and the degree of surface finish required are important decisions that can influence the magnitude of the cutting force.

TABLE IV. THE PROCESS PARAMETER FOR TITANIUM ALLOY MILLING.

Trials	Feed per tooth	Feed rate (mm/min)	Maximum chip thickness (mm)	Cutting speed (mm/sec)	Temperature (ºC)	Cutting force (N)	Cutting frequency (Hz)	Depth of cut (mm)
1	0.18	0.19	0.09	255000	298.984	25.3334	20.1007	0.11
2	0.18	0.18	0.08	256000	302.198	25.5665	20.0675	0.10
3	0.19	0.21	0.10	250000	301.223	24.8439	20.0985	0.10
4	0.20	0.22	0.11	255000	300.993	25.0995	20.2007	0.19
5	0.21	0.22	0.11	255000	298.468	25.4678	20.1085	0.10
6	0.22	0.24	0.22	265000	405.346	35.7885	50.5235	0.21
7	0.26	0.26	0.21	260000	402.653	35.3546	50.1985	0.22
8	0.27	0.25	0.23	265000	407.653	34.6908	502.096	0.21
9	0.28	0.27	0.21	264000	397.431	35.0776	50.0652	0.20
10	0.24	0.25	0.20	263000	403.542	35.0546	50.0345	0.20
11	0.32	0.33	0.31	275000	505.368	50.0001	100.1345	0.32
12	0.31	0.32	0.32	275000	502.643	50.0478	100.0458	0.32
13	0.30	0.31	0.33	278000	503.653	49.8675	100.0096	0.31
14	0.29	0.32	0.30	272000	506.324	50.0097	100.0342	0.30
15	0.33	0.33	0.34	276000	501.325	50.0986	100.2556	0.30

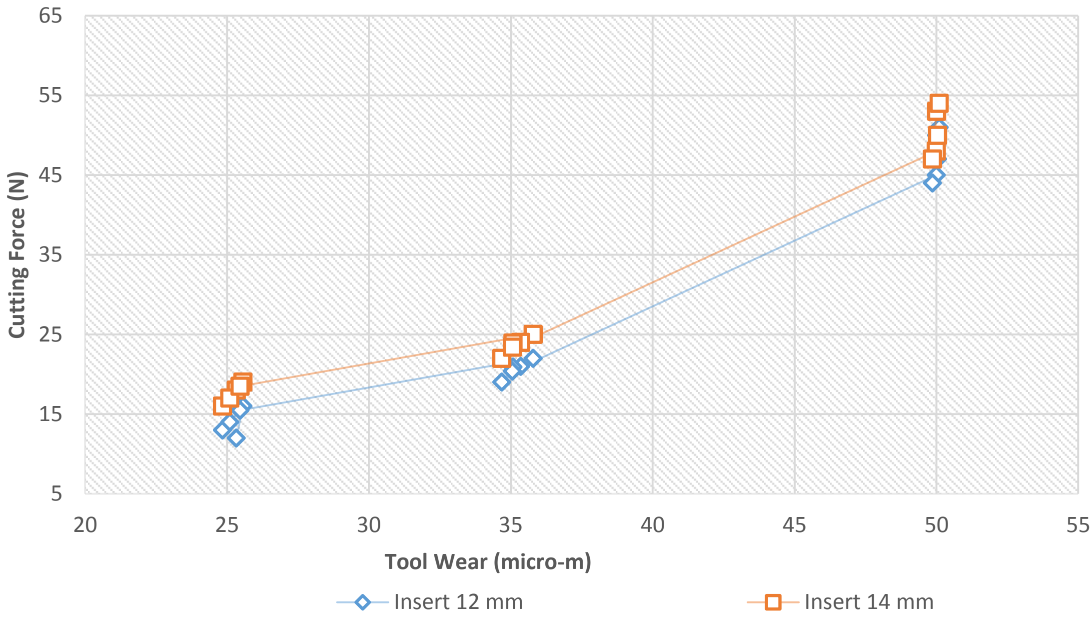

Figure 8. The wear rate using different inserts under cooling conditions.

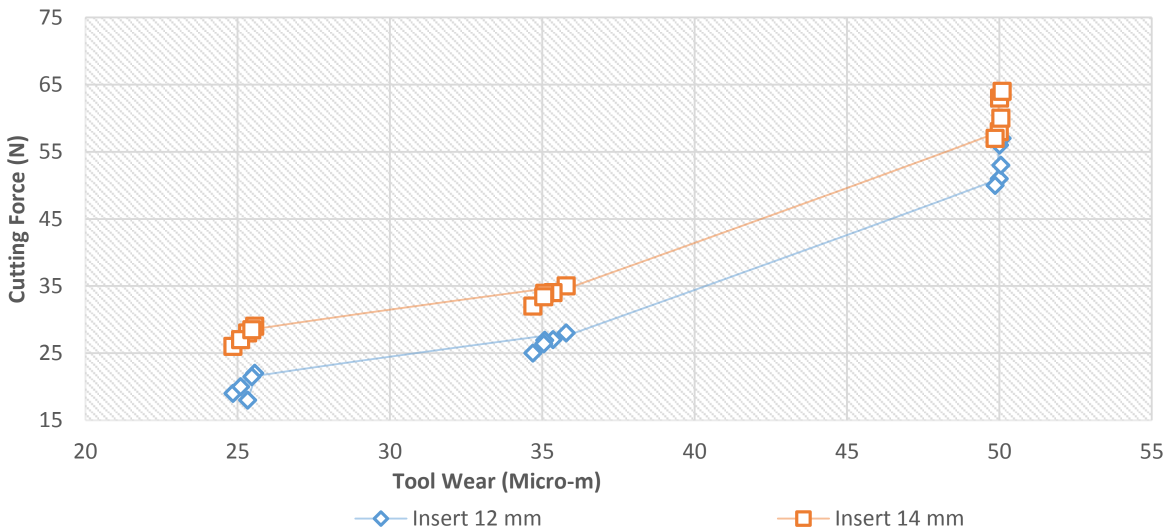

Figure 9. The wear rate using different inserts under dry machining conditions.

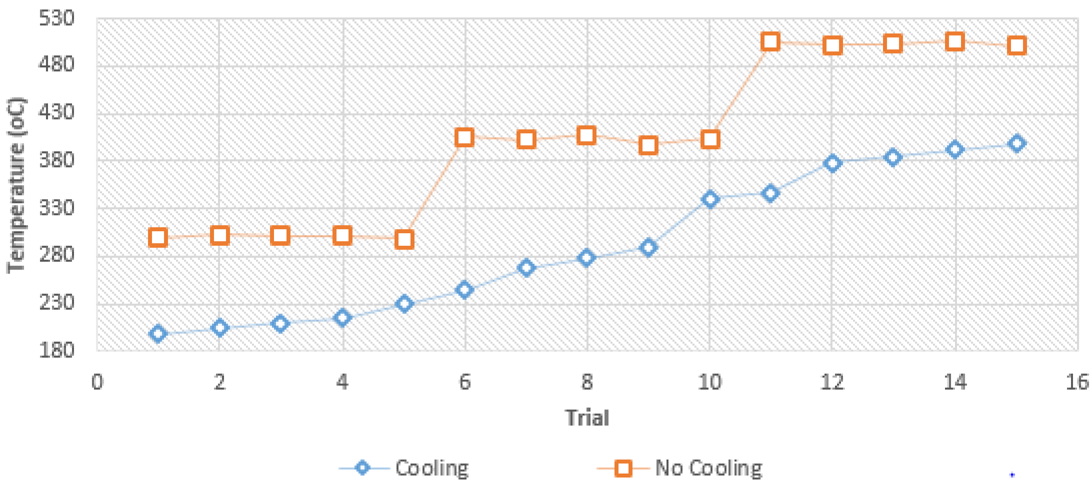

Figure 10. The temperature profile under cooling and dry machining conditions.

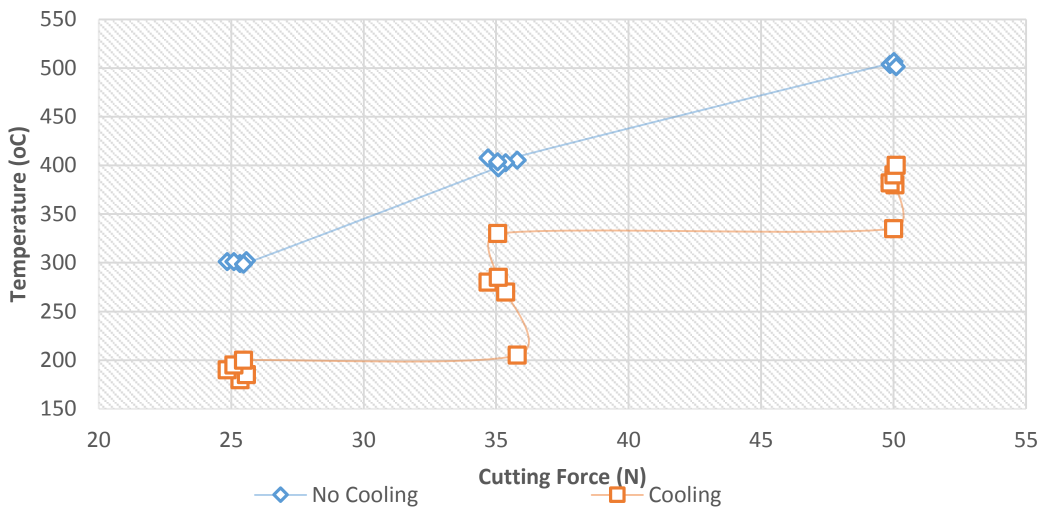

Figure 11. Cutting force-temperature relationship under cooling and dry machining conditions.

IV. Conclusion

The process design for the milling operation of titanium alloy using the artificial neural network was carried out. The Artificial Neural Network (ANN) back propagation and Levenberg-Marquardt algorithm was employed for the correlation of the process parameters. The results obtained indicated that the developed network is highly suitable for corrective and predictive function judging from the correlation coefficients which were close to 1 and the negligible value of the mean square error. Furthermore, from the physical experimentations, an insert of 12 mm produced lower rate of tool wear as opposed to the 14 mm cutting inserts. The tool wear was also observed to increase with an increase in the magnitude of the cutting force. In addition, higher rate of tool wear was observed under dry machining as opposed to the machining under the cooling condition of liquid nitrogen. Hence, this work will assist manufacturers who employs titanium alloy for product development in the quest for the development of an effective process for high performance cutting. The approach will also serve as a decision making tool for the selection of process parameters and control of machining conditions. The small size of the data set employed in this study was a limitation. This is due to the fact that the performance of the ANN improves with an increase in the data size. Hence, further study can consider the implementation of the ANN for process design with a larger data set and comparison analysis with other techniques for process design.

Conflict of Interest

The authors declare no conflict of interest .

Author Contributions

The work is a product of the collective efforts of all the authors.

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References

[1] Y. Ayed, G. Germain, A. M. P. Melsio, P. Kowalewski, and D. Locufier, "Impact of supply conditions of liquid nitrogen on tool wear and surface integrity when machining the Ti-6Al-4V titanium alloy," *The International Journal of Advanced Manufacturing Technology*, vol. 93, no. (1-4), pp. 1199-1206, 2017.

[2] A. Shokrani, V. Dhokia, and S. T. Newman, "Investigation of the effects of cryogenic machining on surface integrity in end milling of Ti-6Al-4V titanium alloy," *J Manuf Process*, vol. 21, pp. 172–179, 2016.

[3] R. R. Rashid, S. Sun, G. Wang, and M. Dargusch, "An investigation of cutting forces and cutting temperatures during laser-assisted machining of the Ti-6Cr-5Mo-5V-4Al beta titanium alloy," *Int J Mach Tools Manuf.* vol. 63, pp. 58-69, 2012.

[4] L. A. Denguir, J. C. Outeiro, G. Fromentin, V. Vignal, and R. Besnard, "Orthogonal cutting simulation of OFHC copper using a new constitutive model considering the state of stress and the microstructure eff ects," *Procedia CIRP*, vol. 46, pp. 238-241, 2016.

[5] J. B. Chen, M. H. Xu, C. Xie, J. K. Du, H. F. Dai, and Q. H. Fang, "A non-uniform moving heat source model for temperature simulation in ultrasonic-assisted cutting of titanium alloys," *Int'l J. Adv. Manuf. Tech.*, 2018, vol. 97, no. (5-8), pp. 3009–3021, 2018.

[6] B. Denkena, T. Grove, M. A. Dittrich, D. Niederwestberg, and M. Lahres, "Inverse determination of constitutive equations and cutting force modelling for complex tools using Oxley's predictive machining theory," *Procedia CIRP*, vol. 31, pp. 405-410, 2015.

[7] X. B. Jing, H. Z. Li, J. Wang, and Y. L. Tian. "Modelling the cutting forces in micro-end-milling using a hybrid approach," *The Intl* Journal *of Adv Manuf Tech.*, vol. 73, no. (9–12), pp. 1647–1656, 2014.

[8] H. Ghorbani and B. Moetakef-Imani. "Specific cutting force and cutting condition interaction modeling for round insert face-milling operation," *The International Journal of Advanced Manufacturing Technology* vol. 84, pp. 1705–1715, 2016.

[9] A. Pramanik. "Problems and solutions in machining of titanium alloy," *Int. J. of Adv. Manuf. Technol.*, vol. 70, pp. 919-928, 2014.

[10] Y. Ayed, G. Germain, W. B. Salem, and H. Hamdi, "Experimental and numerical study of laser-assisted machining of ti6al4v titanium alloy," *Finite Elem Anal Des.* vol. 92, pp. 72–79, 2014.
[11] T. Braham-Bouchnak, G. Germain, A. Morel, and B. Furet. "Influence of high-pressure coolant assistance on the machinability of the titanium alloy," Ti555-3. *Mach Sci Technol.,* vol. 19, no. 1, pp. 134–151, 2015.
[12] J. C. Outiero, D. Umbrello, R. M'Saoubi, and I. S. Jawahir. "Evaluation of present numerical models for predicting metal cutting performance and residual stresses," *Int'l J. Mach. Sci. Technol,* vol. 19, no. 2, pp.183–216, 2015.
[13] H. A. Kishawy, H. Hegab, I. Deiab, and A. Eltaggaz, "Sustainability assessment during machining Ti-6Al-4V with nano-additives based minimum quantity lubrication," *J. Manuf. Mater. Process*. vol. 3, no. 61, pp. 1-12, 2019.
[14] C. Courbon, F. Pusavec, F. Dumont, J. Rech and J. Kopac. "Tribological behaviour of Ti6Al4V and Inconel 718 under dry and cryogenic conditions–application to the context of machining with carbide tools," *Tribology International*, vol. 66, pp. 72–82, 2013.
[15] M. Dhananchezian and M. Pradeep Kumar. Cryogenic turning of the Ti–6Al–4V alloy with modified cutting tool inserts. *Cryogenics*, vol. 51, pp. 34-40, 2011.
[16] A. Elshwain, N. Redzuan, and N. M. Yusof, "Machinability of nickel and titanium alloys under of gas-based coolant-lubricants (CLS)—A review," *International Journal of Research in Engineering and Technology*, vol. 2, pp. 690–702, 2013.
[17] G. Rotella, O. W. Dillon Jr, D. Umbrello, L. Settineri, and I. S. Jawahir, "The effects of cooling conditions on surface integrity in machining of Ti6Al4V alloy," *The International Journal of Advanced Manufacturing Technology*, vol. 71, no. (1–4), pp. 47–55, 2014.
[18] M. Strano, E. Chiappini, S. Tirelli, P. Albertelli, and M. Monno, "Comparison of Ti6Al4V machining forces and tool life for cryogenic versus conventional cooling," in *Proc. the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, vol. 228, pp. 191–202, 2013.
[19] K. H. Park, G. D. Yang, M. Suhaimi, D .Y. Lee, T. G. Kim, and D. W. Kim. "The effect of cryogenic cooling and minimum quantity lubrication on end milling of titanium alloy Ti-6Al-4V," *Journal of Mechanical Science and Technology*, vol. 29, no. 12, pp. 5121-5126, 2015.
[20] C. Shan, X. Zhang, B. Shen, and D. Zhang, "An improved analytical model of cutting temperature in orthogonal cutting of Ti6Al4V," *Chinese Journal of Aeronautics,* vol. 32, no. 3, pp. 759–769, 2019.
[21] I. A. Daniyan, I. Tlhabadira, S. N. Phokobye, M. Siviwe, and K. Mpofu, "Modelling and optimization of the cutting forces during Ti6Al4V milling process using the response surface methodology and dynamometer," *MM Science Journal*, vol. 128, pp. 3353-3363, 2019.
[22] G. Kant and K. S. Sangwan, "Predictive modelling and optimization of machining parameters to minimize surface roughness using artificial neural network coupled with genetic algorithm," *Procedia CIRP*, vol. 31, pp. 453-458, 2015.
[23] I. A. Daniyan, E. I. Bello, T. I. Ogedengbe, and K. Mpofu, "Use of central composite design and artificial neural network for predicting the yield of biodiesel," *Procedia CIRP,* vol. 89, pp. 59-67, 2020.
[24] F. Djavanroodi, B. Omranpour, and M. Sedighi, "Artificial neural network modeling of ECAP process," *Materials and Manufacturing Processes*, vol. 28, no. 3, pp. 276–281, 2013.
[25] I. A. Daniyan, I. Tlhabadira, K. Mpofu, and A. O. Adeodu, "Development of numerical models for the prediction of temperature and surface roughness during the machining operation of titanium alloy (Ti6Al14V)," *Acta Polytechnica Journal*, vol. 60, no. 5, pp. 369–390, 2020.
[26] Y. Xu, Q. Zhang, W. Zhang, and P. Zhang, "Optimization of injection molding process parameters to improve the mechanical performance of polymer product against impact," *The International Journal of Advanced Manufacturing Technology,* vol. 76, pp. 2199-2208, 2014.
[27] S. Kashyap and D. Datta, "Process parameter optimization of plastic injection molding: A review," *International Journal of Plastics Technology*, vol. 19, pp. 1-18, 2015.
[28] M. Mahdavi Jafari, S. Soroushian, and G. R. Khayati, "Hardness optimization for Al6061-MWCNT nanocomposite prepared by mechanical alloying using artificial neural networks and genetic algorithm," *Journal of Ultrafine Grained and Nanostructured Materials,* vol. 50, no. 1, pp. 23-32, 2017.
[29] S. Altarazi, M. Ammouri, and A. Hijazi, "Artificial neural network modeling to evaluate polyvinylchloride composites' properties," *Computational Materials Science*, vol. 153, pp. 1-9, 2018.
[30] U.S. Titanium Industry Inc... Titanium Alloys - Ti6Al4V Grade 5. AzoM, 2017. [Online] Available at https://www.azom.com/properties.aspx?ArticleID=1547 [Accessed July 02, 2019].
[31] I. A. Daniyan, I. Tlhabadira, S. N. Phokobye, S. Mrausi, K. Mpofu, and L. Masu, "Modelling and optimization of the cutting parameters for the milling operation of titanium alloy (Ti6Al4V)," in *Proc. 2020 IEEE 11th International Conference on Mechanical and Intelligent Manufacturing Technologies (ICMIMT 2020)*, Added to IEEE Xplore, pp. 68-73, 2020.
[32] I. A. Daniyan, F. Fameso, F. Ale, K. Bello, and I. Tlhabadira, "Modelling, simulation and experimental validation of the milling operation of titanium alloy (Ti6Al4V)," *The International Journal of Advanced Manufacturing Technology*, vol. 109, no. 7, pp. 1853-1866, 2020.
[33] I. A. Daniyan, I. Tlhabadira, S. N. Phokobye, A. O. Adeodu, and K. Mpofu, "Process design and modelling for milling operation of titanium (Ti6Al4V) alloy using the Taguchi method," *Procedia CIRP*, vol. 91, pp. 348-355, 2020.
[34] I. Tlhabadira, I. A. Daniyan, L. Masu, and K. Mpofu, "Computer aided modelling and experimental validation for effective milling operation of titanium alloy (Ti6AlV)," *Procedia CIRP,* vol. 91, pp. 113-120, 2020.
[35] I. Tlhabadira, I. A, Daniyan, L. Masu, and K. Mpofu, "Development of a model for the optimization of energy consumption during the milling operation of titanium alloy (Ti6Al4V)," *Materials Today: Proceedings,* vol. 38, pp. 614-620, 2021.
[36] I. A. Daniyan, I. Tlhabadira, K. Mpofu, and A. O. Adeodu, "Process design and optimization for the milling operation of aluminum alloy (AA6063 T6)," *Materials Today: Proceedings,* vol. 38, pp. 536-543, 2021.
[37] S. N. Phokobye, I. A. Daniyan, I. Tlhabadira, L. Masu and L. R. vanStaden, "Model design and optimization of carbide milling cutter for milling operation of M200 tool steel," *Procedia CIRP,* vol. 84, pp. 954-959, 2019.
[38] I. A. Daniyan, I. Tlhabadira, O. O. Daramola, and K. Mpofu, "Design and optimization of machining parameters for effective AISI P20 removal rate during milling operation," *Procedia CIRP* vol. 84, pp. 861–867, 2019.

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