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Tool Condition Monitoring for Turning Operation of Titanium-based Super Alloys by Artificial Neural Network Approach

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Abstract

The research work is focused on Tool Condition Monitoring (TCM) of Titanium-based Superalloys and turning operations to improve the machining process and to predict tool wear and failure. Titanium (Ti) based superalloys are widely adapted in aerospace and automotive industries because of their outstanding combination of mechanical properties and high-temperature corrosion resistance. These superalloys, however, are difficult to cut due to their poor heat conductivity, low elastic modulus, high strength, and superior chemical resistance. Also during the machining of Ti superalloys at high cutting speeds and feed rates, the life of the cutting tool is drastically decreased. Tool life is shortened, and adequate surface quality is sometimes impossible to achieve due to the poor machining cutting properties of uncoated cutting tools. As a result, adopting a Physical Vapor Deposition (PVD) coated carbide cutting tool can increase cutting tool life and cutting qualities. In the turning process, a lathe tool dynamometer is set up to measure the cutting forces. The findings indicate that such cutting forces and wear data, when combined with machine learning approaches based on Neural Networks, may be utilized for actual monitoring of tool wear/breakage and control mechanisms, thereby enhancing digital manufacturing techniques.

Keywords

Titanium superalloy, Tool condition monitoring, Physical vapor deposition, Neural network, Cutting forces, Tool wear.

1.Introduction

Ti superalloys are available in a variety of compositions (such as Ti6Al4V, Ti5Al2Sn3Li, and Ti6Al6V2Sn) due to their unique properties of high weight-to-strength ratio, high corrosion resistance, and low weight (Abdulgadir et al. 2019). The Ti6Al4V titanium superalloy is the most common and widely used material in automotive, aerospace, medical, as well as marine industries. But these are more expensive and challenging to work with than other alloys due to their low elastic modulus, strong mechanical strength, limited thermal conductivity, and significant reactivity at higher temperatures, among other characteristics (Castellanos et al. 2018). Hence it is advised to consider and study the machining conditions and cutting variables such as feed rate, speed, and depth of cut (Oke et al. 2020; Pervaiz et al. 2014; Yang & Liu 2012).

The state of the equipment is critical in machining operations because it affects both the quality of the end product as well as the efficiency of the operations. Two elements determine the state of a tool wear and breakage of tools (the progressive degradation of the tool over time and a sudden change that leads to the end of life of a tool) (Aramesh et al. 2018). Tool breakage occurs due to tool wear, and tool change is necessary as a result of tool breakage. When the equipment breaks, the workpiece is harmed and the efficiency of the operation decreases (Balaji et al. 2013; Kulandaivelu et al. 2013). The goal of this research is to better understand and assess the value of wear and cutting force data for actual TCM during the turning operation of a Ti-based superalloy adapted in applications requiring great dimensional accuracy and pristine surface finish (Fan et al. 2020). The machining operations are performed by altering the speed and depth of the incision. The Dynamometer provided data regarding the cutting force. Then, in order to anticipate wear rate progression, premature failure, and tool life, tool wear and force data were fed into a neural network for functional processing (Cheng et al. 2020; Ulutan & Ozel 2011). Section 2 focuses on the literature study, followed by the Materials and Experimental setup in Section 3. Section 4 presents the Neural Network architecture. Sections 5 and 6 are focused on the discussion and conclusion of the result respectively.

2. Literature Review

Titanium and its superalloys have properties like high strength at high temperatures, low thermal conductivity, and poor elasticity (Gupta et al. 2018). Their chemical reactivity also makes them hard to machine. When titanium superalloys are machined, they can fail in many ways. These are called crater wear, flank wear, notching, chipping, and mostly catastrophic failure (Andriya et al. 2012; He et al. 2021).The substance of cutting tools used in the machining of titanium superalloys is crucial. There are several types of tool materials available on the market, including carbide, ceramics, polycrystalline cubic boron nitride (PCBN), cubic boron nitride (CBN), and polycrystalline diamond (PCD). Utilizing superior cutting tool materials and coated tools can boost the performance of titanium superalloys during machining (Ginting et al.2018). Due to enhanced tool performance, the advantages of coating may surpass the expenses, despite the fact that coating costs are growing (Bag et al. 2020; Koseki et al. 2015).

When it comes to machining titanium superalloys, coated carbide tools work better than uncoated tools because the high heat generated during machining comes into direct contact with the cutting tools (Velmurugan & Venkatesan, 2021). Coating these cutting tools avoids direct heat contact with the tools (Nalbant et al. 2009). So, this cuts down on tool wear and makes tools last longer. Cutting fluids and coolants don't have to be used if the tools are coated. This makes machining safer, cleaner, and better for the environment (Zhao et al. 2020).To predict tool wear, a number of measurement technologies are used (Chen & Chen 2005). Piezo sensor-based dynamometers have proven to be the best way to measure force and keep an eye on the cutting process. There are two methods for monitoring the state of an instrument: direct and indirect (Prengel et al. 2001). Using optical, radioactive, resistive, and computer vision techniques known as machine vision technologies, the rate of tool deterioration is directly measured. The indirect method enables live, real-time monitoring by recognizing unique cutting signals associated with the wear rate (Krishnakumar et al. 2015). Tool-based monitoring has made significant strides in the monitoring of tool wear rate as a result of technological and artificial intelligence-based machine learning advancements (Karam et al. 2016). With the proper TCM methods, TCM technology may reduce production costs by as much as 40% while boosting cutting speed by 10 to 50% (Ezugwu et al. 2008).

3. Materials and Experimental Setup

In the experiment, a titanium superalloy rod of Grade 5 was employed, and its dimensions were 10 centimeters in length and 5 centimeters in diameter, as shown in Figure 1(a), Titanium superalloys are utilized frequently in the automotive, aerospace, medical, and maritime industries as a result of the exceptional qualities that they possess (Andriya et al.2012). The chemical elements that make up titanium grade 5 materials are illustrated in Table 1.

Table 1. Chemical composition of Ti Grade-5

Content	C	Fe	N	O	Al	V	H	Ti
Composition	0.05	0.09	0.01	-	6.15	4.4	0.005	Balance

The Titanium material is turned on a CNC machine with PVD (Physical Vapor Deposition) coated TNMG carbide turning inserts as shown in Figure 1(b), a tool holder as shown in Figure 1(c), and the different process variables are summarized in Table 2.

a b c

Figure 1. Materials

The experimental setup for turning Ti superalloy is shown in Figure 2, as a schematic. Data about cutting force was acquired from the dynamometer. Ti rod is machined using the settings indicated in Table 2,

Table 2. Machining Parameters

Parameters	Value
Chuck Speed(rpm)	250,400,600,900
Feed (mm/rev)	0.02
Depth of Cut (mm)	0.1, 0.2, 0.3, 0.4, 0.5
Cutting Force	Fx, Fy, Fz

and the turning process is repeated until the insert tool fails and all data is gathered. SEM images (Scanning Electron Microscope) are used to measure wear, and wear is measured using ImageJ software. Figure 3 depicts the SEM images. All of this information is fed into the Neural Network, which is discussed in the next section (Cheng et al., 2020).

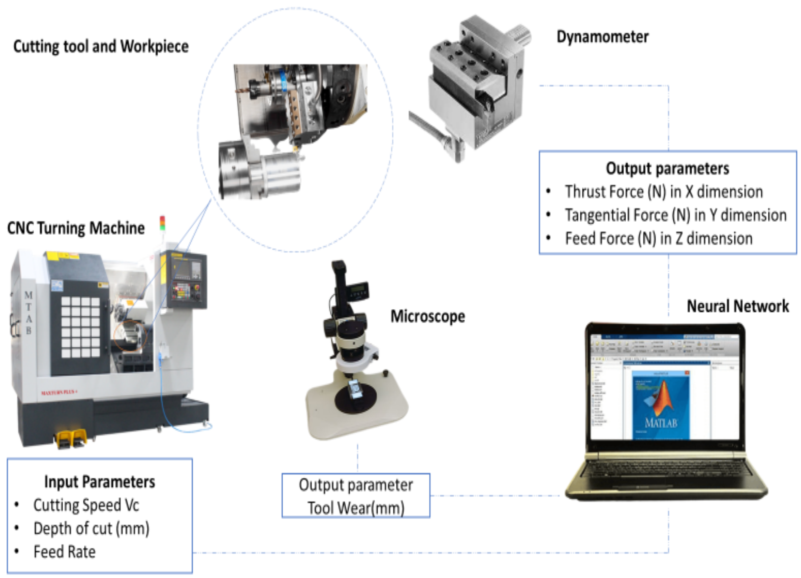

Figure 2. Schematic Representation

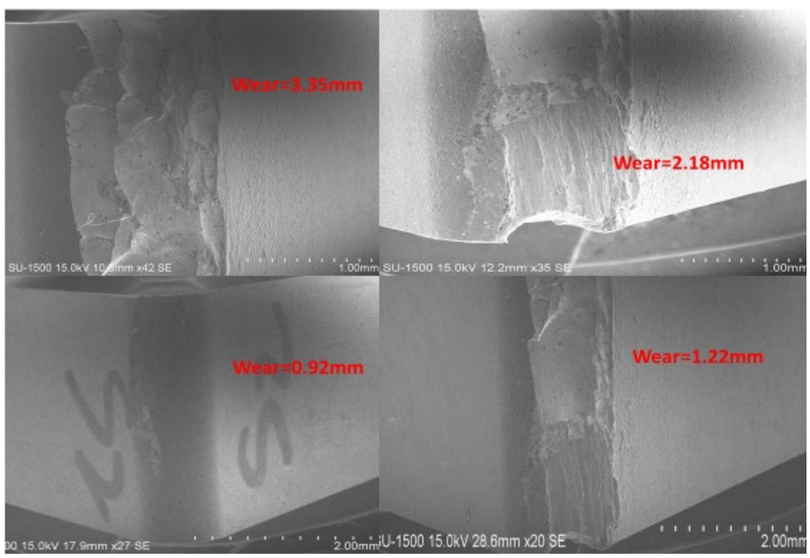

Figure 3. SEM Images

3.1 Neural Network Architecture

An artificial neural network (ANN) was constructed as part of the current modeling study to provide accurate predictions regarding the cutting force and tool wear that occurs during the turning of titanium-based superalloys (Wu et al., 2017). These three cutting variables Speed, depth of cut as well as feed were employed as an input factor in the ANN model depicted in Figure 4, which also included cutting force and tool wear as output parameters (Gouarir et al., 2018).

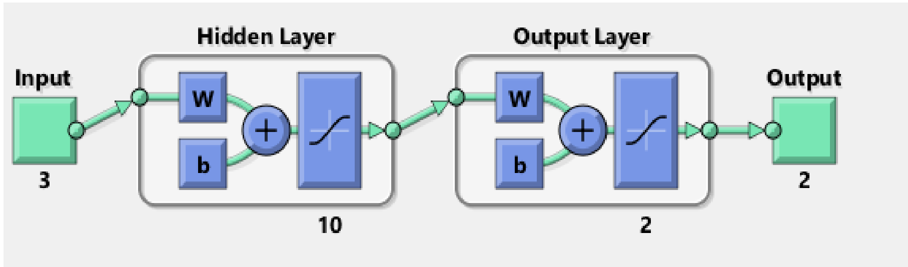

Figure 4. ANN Architecture

The training samples, validation samples, and testing samples were divided into three categories of experimental data. During training, the network is provided training samples and is updated depending on how incorrect it is (Dudzik & Labuda 2020). Validation data are used to assess how effectively a network generalizes and even to determine when training should be stopped when generalization no longer improves (Joshi & Kulkarni 2021). Because testing samples have no effect on training, they may be used to assess how effectively the network functions both during and also after training (confirmation runs) (Zacharia & Krishnakumar 2020). In this study, NN (neural network) technique is expanded so that it can be used to predict how tools will wear and break before they do. In this study, the data is analysed using well-known NN methods such as, Scaled Conjugate Gradient (SCG), Levenberg Marquandt (LM) and Bayesian Inference (BI). The flow chart below (Figure 5) shows how MATLAB software is used to analyse and make predictions. With NNs, you have to divide your data into three groups (Corne et al. 2016):

i) Data for training: After the network has been trained, different weights have been generated and tuned.
ii) Validation data: The generalization of the network is quantified. When error stops reducing, this data set is utilized to cease training.
iii) Data for testing: The NN's precision is assessed using error values.

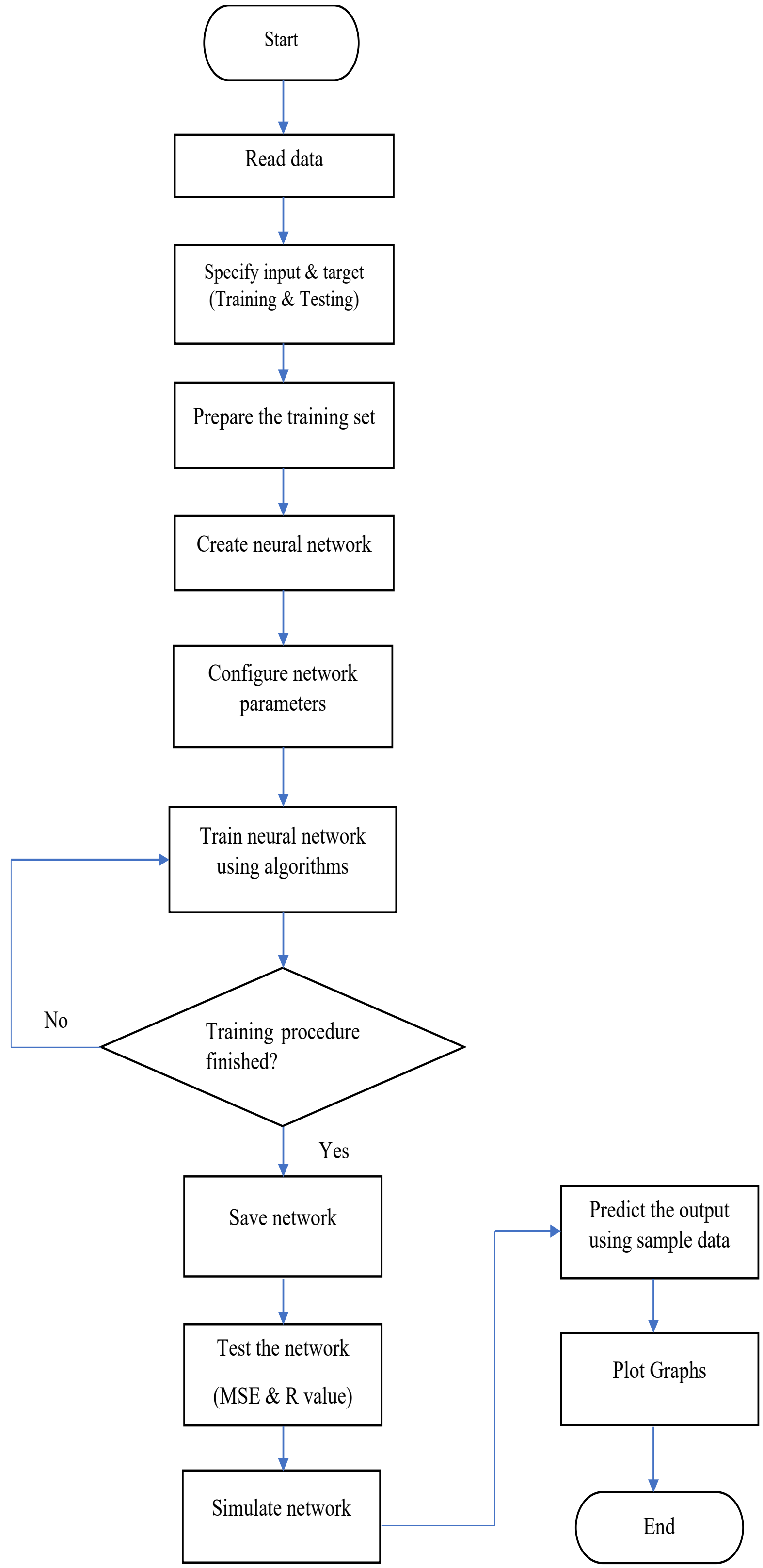

Figure 5. Flow chart

4.0 Results & Discussion

The neural network is trained using the Levenberg Marquandt (LM) method, which maps predictions to continuous outputs. There are two types of MSE: mean squared error (MSE) and mean squared deviation (MSE). Lower numbers are preferable. A value of 0 indicates that there is no mistake. When using epoch 4, you get the greatest validation performance of 0.0035 (see Figure 6 and Figure 7).

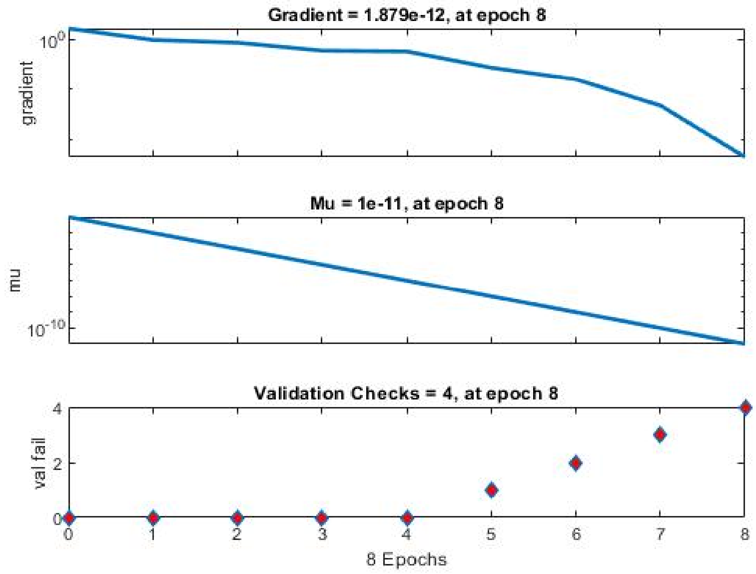

Figure 6. Testing

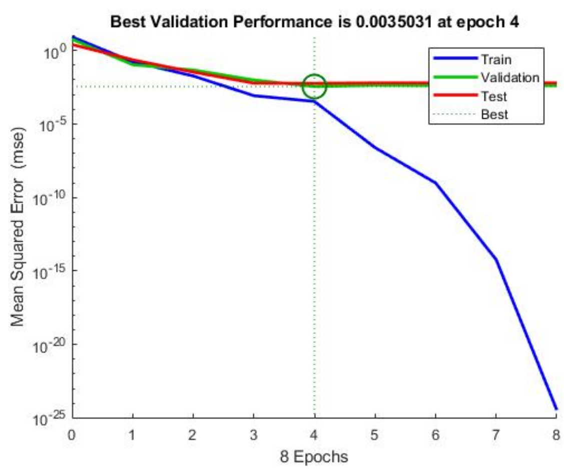

Figure 7. Performance

The regression (R), shown in Figure 8, is another way to measure how well the network works. Regression values show how closely output values and goals match up. An excellent connection between the output as well as the goals was found throughout training (R=0.99), validation (R=0.99) and evaluation (R=0.99).

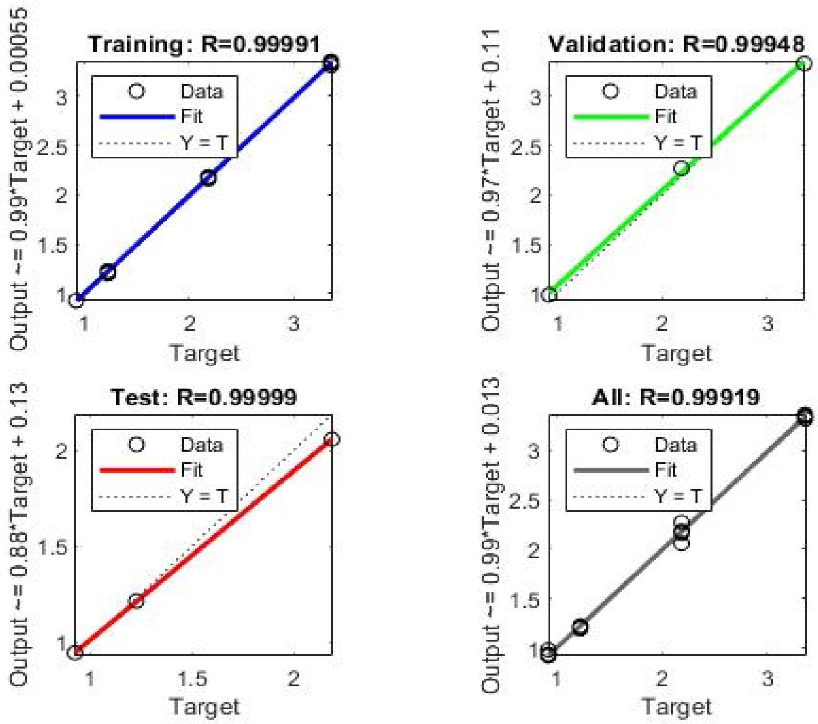

Figure 8. Regression Plots

The neural network is also trained using two different techniques, namely Scaled Conjugate Gradient (SGD) and Bayesian Inference (BI), moreover, the outcomes are shown in Table no.3.

Table 3. Performance comparison of three NN algorithms

	Training		**Validation**		**Testing**	
Algorithm	**MSE**	**R**	**MSE**	**R**	**MSE**	**R**
Levenberg Marquandt (LM)	0.0003	0.99	0.0035	0.99	0.0058	0.99
Bayesian Inference (BI)	1.18×10^{-8}	1.0	NA	NA	4.05×10^{4}	0.95
Scaled Conjugate Gradient (SCG)	1.29×10^{4}	0.97	6.40×10^{4}	0.94	5.63×10^{4}	0.92

Table 4. R^2 value of three NN algorithms

Algorithm	**R**	**R^2**	**R^2 (%)**
Levenberg Marquandt (LM)	0.99	0.98	98
Bayesian Inference (BI)	0.95	0.90	90
Scaled Conjugate Gradient (SCG)	0.92	0.84	84

The R-squared of the linear regression model is a measure of how well its "fits" a dataset, and it's also called rho wherein it measures how much of the response variable's variation can be described by the predictors. Table 4 shows the R^2 values of the algorithms indicated below.

5. Conclusion

This study evaluates and analyses cutting force and wear data for tool condition monitoring during the turning of a Ti-based superalloy. The primary objective was to estimate tool wear and cutting forces to save machining costs and time. Based on the data, the following conclusions may be drawn:
When turning materials, especially superalloys like titanium, the cutting force rises very quickly and steeply. This is a sign of catastrophic tool failure, but tools can also fail early. This shows how important it is to use TCM in real-world business settings.

To train the neural networks, MATLAB'S neural network toolbox was used with experimental data from real trials. While Bayesian inference as well as the Scaled Conjugate Gradient techniques have higher R^2 values, the Levenberg Marquart approach (R^2 =98%) is the best choice for wear forecasting when utilizing neural networks. This application is anticipated to need a maximum number of 10 neurons.

The obtained findings show that the proposed modeling technique might be utilized successfully to predict the tool wear as well as cutting force at the turning operation of Titanium Grade 5 superalloy, hence aiding decision-making during process planning and giving a feasible means of avoiding costly and time-consuming tests.

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