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A Deep Study on Machine Learning Techniques for Tool Condition Monitoring in Turning of Titanium-based Superalloys

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Abstract

The current state-of-the-art review on tool condition monitoring for turning of titanium-based superalloys is presented in this paper. Titanium (Ti) superalloys are widely utilised in aerospace industry, automobile industry, petrochemical applications. Ti superalloys are also used in fabrication of biomedical components due to their outstanding combination of mechanical properties and strong corrosion resistance at extreme temperatures. But these superalloys are difficult-to-cut because to their low heat conductivity, low elastic modulus, high strength, and strong chemical resistance. Literature review highlights the drastic reduction in tool life of titanium superalloys at highspeed and feed rates throughout the machining process. The review paper focuses on (i) various reasons to deploy tool condition monitoring; and (ii) study of tool condition monitoring methods based on machine learning techniques to identify the ideal parameters for the prevention of catastrophic tool failure.

1.0 Introduction

Titanium superalloys possess particular advantages when compared to other metals and alloys, and they are presently employed in a broad variety of applications. There are several compositions of Ti superalloys, such as Ti6Al4V, Ti5Al2Sn3Li, Ti6Al6V2Sn, and others, due to their unique features such as high weight-to-strength ratio, exceptionally high corrosion resistance, and low weight. The titanium superalloy Ti6Al4V is the most common. Titanium superalloys are widely employed in the aerospace, automotive, medicinal, and marine industries due to their unique properties[1].

A great deal of study is being done on the machining of titanium superalloys for different operations such as turning, milling, and drilling. Titanium superalloys are more expensive and difficult to work with than other alloys because of their low elastic modulus, great mechanical strength, limited thermal conductivity, high reactivity at higher temperatures, and so on because titanium-based superalloys are difficult to turn, it is recommended that proper tool condition monitoring with suitable techniques as well as machining conditions and cutting factors like speed, feed, and depth of cut must be taken into account[2].

Ti superalloys are most commonly used in applications that require great dimensional accuracy and precision, as well as a smooth surface finish. When machining titanium superalloys, one of the most critical variables to consider is chatter. Chatter is the most annoying feature of machining

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because it affects quality of the product, rate of production, and tool life. To increase product quality and tool life, it is vital to select chatter-free machining settings. The proper machining parameters have to be used to solve this problem[3].

The remaining sections of the paper are grouped as follows:

Section 2 deals with the reasons to deploy tool condition monitoring. Section 3 discusses numerous studies and advancements related to the machine learning approach to anticipate tool failure using an appropriate machine learning algorithm. Finally, Section 4 gives a conclusion.

Section 2: Reason for Tool Condition Monitoring

Mechanical failures are a common phenomenon that occurs in almost all engineering systems (for example, aircraft technologies, nuclear reactors, and industrial machinery) as a result of degradation with operation, aging, or unusual operating conditions. Unusual working circumstances include wear, corrosion, higher operating temperature, high pressure, vibrations, bending, and stress.

Engineering system deterioration, as well as breakdowns, frequently result in increased expenses and reduced output owing to unanticipated machine downtime. It is vital to establish a monitoring plan that will allow companies to organize production stoppages for replaces, inspections, and upkeep so as to increase production rates while keeping maintenance expenditures to a minimum [4].

Traditional maintenance tactics, maintenance methods involve reactionary, preventative as well as predictive maintenance. The fundamental maintenance approach is reactive maintenance planning, sometimes called simply operation-to-failure maintenance management. A reactionary plan for upkeep permits devices to run until defects occur on purpose. The assets are only preserved when they are required. One disadvantage of reactive maintenance is the inability to foresee whenever maintenance assets (such as personnel, machinery cutting tools, and repair spare) would be required for repairs [5].

Preventive maintenance is changing processes or parts on a regular basis to ignore problems that occur often. Though preventative maintenance provides for more constant and precise planned maintenance, it is costly to implement due to the need for frequent component or component substitution at the end of its useful life. Predictive maintenance is a concept for decreasing the large costs of regular maintenance that involves scheduling repair actions based on performance and reliability or circumstances rather than time. The purpose of predictive maintenance is to determine the state of in-service technology and, eventually, to anticipate when a product or system will no longer function as planned [6].

Tool wear will reduce processing accuracy and increasing surface quality throughout cutting operation, and tool loss will have a direct influence on processing efficiency. Tool wear is caused by a combination of temperature and pressure in the cutting action, which is caused by a range of factors. Accurate estimation is difficult to obtain using the traditional mathematical paradigm. As a consequence, in order to fundamentally address these difficulties and accomplish industrial automation, the tool's state must be monitored. Improving manufacturing efficiency, lowering production costs, and ensuring product quality are all critical.

There are two approaches for monitoring tool status: direct and indirect. Tool degradation rate is directly assessed using optical, radioactive, resistive, and computer vision techniques known as machine vision methods. By recognising specific cutting signals linked with wear rate, the indirect approach provides online real-time monitoring. With the advancement of technology and artificial intelligence-based machine learning approaches, tool-based monitoring (TCM) has made considerable gains in the monitoring of tool wear rate [7].

When there is a significant degree of wear, the staff will be prompted to change the tool as soon as possible to avoid component failure, machining slowdown, and a lengthy work duration due to tool failure. According to reports, TCM technology may save up to 40% on manufacturing expenses while increasing cutting speed by 10% to 50% with the right TCM procedures.

Section 3: Machine Learning Approach

In the manufacturing industry, the amount of information generated is at an all-time high. Data from assembly line sensors, environmental parameters, machine tool data, and other sorts of data are provided in a range of forms, meanings, and levels of quality [8].

In the production plant, machine learning techniques are used. These algorithms can detect patterns that are complicated and non-linear in a broad variety of data kinds and sources, and original data is then transformed into feature spaces or models that may be utilised for prediction, analysis, categorisation, regression, or forecasting. [9].

Machine learning techniques have been more popular over the last two decades as a result of a number of variables, including the availability of large amounts of difficult data with little visibility, as well as improved accessibility and capacities of machine learning technologies. Machine learning, in its fundamental form, allows a computer to fix issues without being expressly trained to do so [10].

Machine learning is increasingly widely utilised in production for optimization, control, and debugging, among other things. Identified the complexity of a rapidly evolving, dynamic industrial setting, machine learning (ML), as

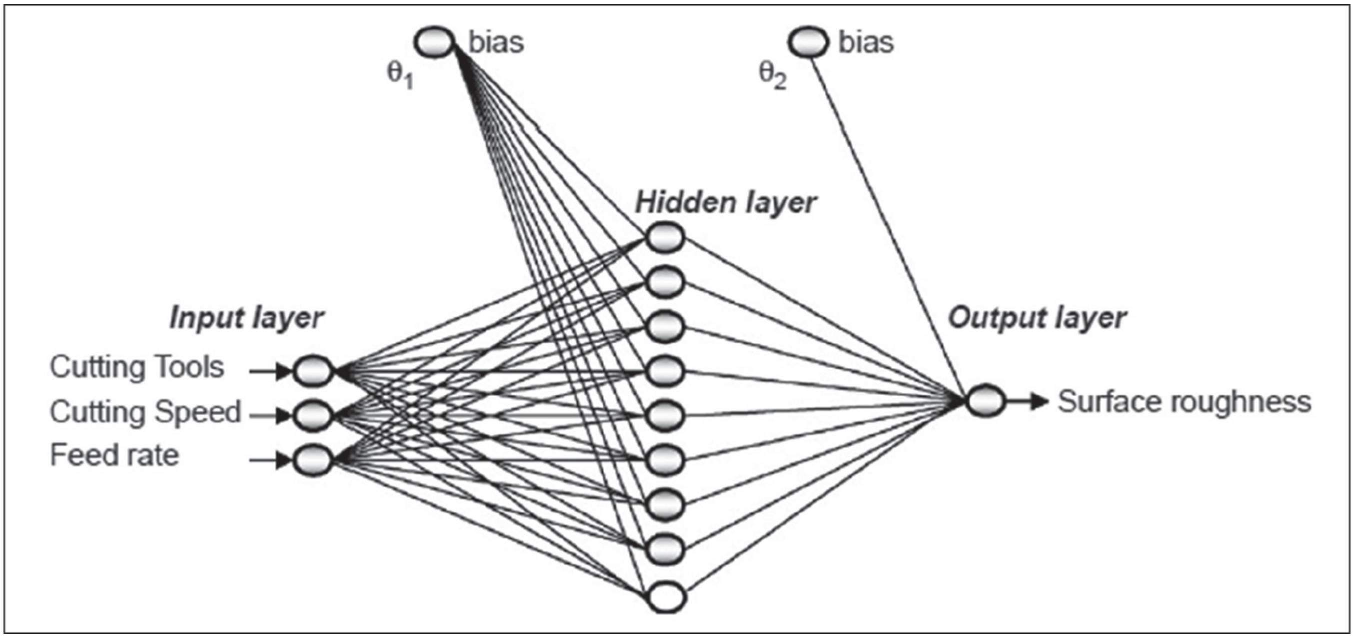

Figure 1: Hidden layer of an ANN design [17]

component of artificial intelligence (AI), has the ability to adapt to alterations, reducing the necessity for system designer to anticipate and respond to every possible scenario. As a consequence of its capacity to automatically learn from and adapt to changing surroundings, as well as its ability to cope with adaptation, ML offers a convincing argument for why it should be utilised in the manufacturing industry [11].

Machine learning algorithms and techniques have been effectively applied in manufacturing process optimization, surveillance and control applications, and condition monitoring. ML approaches were shown to have considerable potential for increased quality assurance improvement in production systems in complicated industrial contexts where discovering the reasons of errors challenging [12].

There are various machine learning algorithms and methodologies available, each has unique advantages and disadvantages. Machine learning has developed into its own research area. As a result, the purpose of this part is to find an appropriate machine learning approach for manufacturing [13].

Many researchers employed various approaches to anticipate tool wear, which are described below. The experiment findings show that machine learning can detect the existing correlation between machining forces and tool flank wear. It has also been demonstrated that this procedure is applicable to any sort of workpiece material. Economically, the cost is slightly higher because to the usage of sensors; nevertheless, it offers several advantages such as strong prediction accuracy and simplicity and ease of implementation [14].

The wear prediction of in-process tools is predicted using an Artificial Neural Network technique. A back propagation artificial neural network is used to train a total of 100 experiment data sets. Cutting forces, feed and dept of cut determined from a dynamometer are the factors considered for this procedure. The test results show that this approach can estimate tool degradation with an accuracy of 0.034 m on an average[15].

Chatter is also observed during the machining process of titanium super alloys. To predict this chatter, a machine learning approach is used, which includes algorithms such as Artificial Neural Network (ANN), Decision Tree (DT), and support vector machining (SVM). The effectiveness of ML techniques in forecasting chatter during super alloy machining was investigated, and ANN was shown to be superior to the others [16].

ANN model is prepared by using experiment patterns as shown in Figure,1 depth of cut, feed rate, cutting speed, and type of cutting tools are used as input layers to the ANN model. On the other hand, surface roughness was the out layer in ANN model.

An ANN-based approach is created and successfully implemented for the examination and modelling of the effects of uncoated PVD and CVD coated carbide tools with variable cutting speeds and feeds, as well as the use of dynamometers and proximity sensors. Figure 2 depicts an ANN technique for predicting tool wear [18].

In this study, the NN technique is extended to predict tool wear and diagnose tool fracture before it happens. A variety of inputs, such as typical cutting input parameters and output

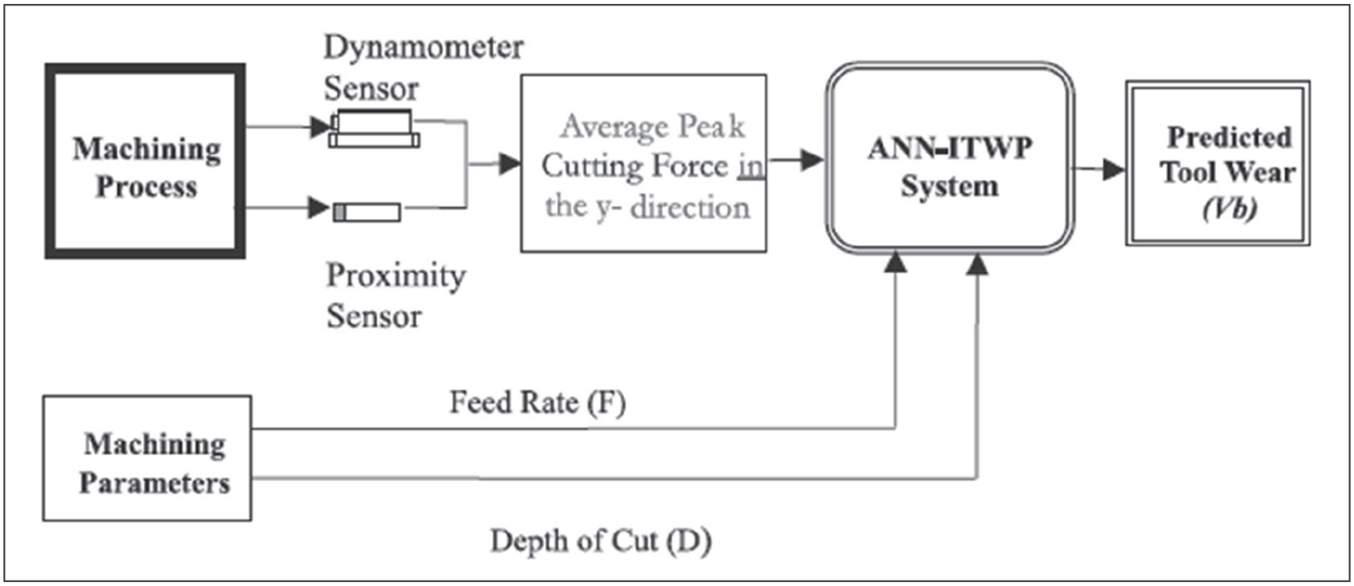

Figure 2: ANN Architecture for tool wear prediction [16]

parameters like as force signals and tool wear, may be considered while training a network. As indicated in Figure 3, the data analysis programme MATLAB, which was employed in this study, has three well-accepted NN methodologies: Levenberg Marquardt (LM), Conjugate Gradient Descent (CGD), and Bayesian Inference (BI), with input and output layers of three forces on cutting tools [19].

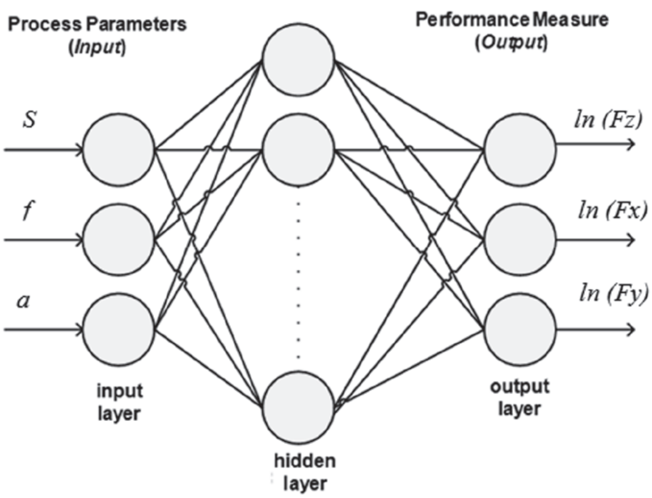

Figure 3: ANN Architecture with forces on cutting tools[20]

Data must be divided into three groups when using NNs:

i. Data for training: The network has been trained, and various weights have been computed and tuned.
ii. Network generalisation is assessed using validation data. When error stops reducing, this data set is utilised to cease training.
iii. Data for testing: The NN's precision is assessed using error values.

Random Forest method is another machine learning approach for predicting tool wear and failure. Table 1 lists two sets of statistical characteristics that were extracted. A dynamometer is used to measure cutting loads in three orthogonal axes (x, y, z), which are then represented as channels and tables. The list of channels is shown in Table 2. The learning technique of this algorithm is to design a club of decision trees by utilizing bootstrap specimens from the collection of training data. Each decision tree generates a reaction based on collection of predictor quantities. Every internal node in a decision tree indicates a characteristic test, each branch reflects the test's outcome, and every leaf node provides a classified label or a regressive response. A "regression tree" is a decision tree with a continual response. Because tool wear symbolises the unavoidability of mechanical failures, so each single decision tree in a randomised forest is a regression tree from the stand point of tool wear analysis. This experiment results using Random Forest approach shows that it can generate, classify, and predict the tool failure accurately [21], [22].

Table 1: Extracted Features

Cutting Force(N)
Maximum
Minimum
Mean
Standard Deviation

Table 2: Data collection from Dynamometer

Signal	Description
1	• Thrust Force (N) in X direction.
2	• Tangential Force (N) in Y direction.
3	• Feed Force (N) in Z direction.

2.0 Conclusions

Based on the evidence supplied in this review, we may draw the following findings. In general, titanium superalloy properties such as high temperature strength, poor elastic elasticity, chemical reactivity, and heat resistance are regarded to be adverse to titanium machinability.

Mechanical failures are common in practically all engineering systems (for example, aircraft technologies, nuclear reactors, and industrial machinery). Degradation and breakdowns in engineering systems often result in increased expenses and lost output owing to unplanned equipment downtime. It is vital to devise a monitoring technique that will keep track of the cutting tool at all times.

Machine learning approaches have been progressively used in manufacturing for continuous tool condition monitoring, optimization, control, and debugging, among other things, over the last two decades. Many researchers employed many approaches to forecast tool wear, including both in and out processes, such as artificial intelligence, neural networks, and ANN algorithms, which are available on many platforms such as Python and MATLAB.

According to study, TCM technology may save up to 40% on manufacturing costs while boosting cutting speed by 10% to 50% with the right TCM methodology and machine learning approaches.

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