Cutting Tool Prognostic using Markov Model

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Abstract

Objectives: Prognosis of a tool is essential for assigning a proper Condition-based Maintenance program for it. Therefore the objective of the present study is to investigate the reliability of a tool using a stochastic Markov Model. **Methods/ Statistical Analysis**: This work proposes a stochastic Markov model for estimating the Remaining Useful Life of the turning tool. In this study, a Mild Steel workpiece was machined to a certain length on a lathe machine using a high-speed steel tool and the Flank Wear Width (FWW) were recorded in every 20 minutes interval. This experiment was conducted for stable feed, stable speed and uniform depth of cut until the failure value of the tool flank wear was achieved, i.e. 0.3 mm. **Findings:** A state based model is developed considering four different degraded stages of the tool. The degradation rates among the states are obtained from the recorded experimental data. The appropriate equations for the four-state Markov model were derived, which show the possibilities of physical changes in the context of time for each level. The set of equations is solved analytically in MATLAB software using Range-Kutta method. After solving these equations, it was concluded that this system is 43% reliable for a 300-minute period and 41% is reliable for 500 minutes time period. **Application/Improvements:** It helps in preventing any kind of production loss. The remaining lifespan of a tool can be predicted by carefully analyzing the data gathered from the trend exploration method such as health monitoring with time.

Keywords: Condition based Maintenance, Cutting Tool, Markov Model, Prognosis, Remaining Useful Life

1. Introduction

The essential prerequisites for the market emulation of an element are its quality, cost and productivity. The product with all these characteristics is manufactured only if the quality of manufacturing is at the highest standard. Due to unanticipated failures of system or degradation of the components, previously mentioned three parameters are severely affected and the quality of manufacturing deteriorates¹. Fierce competition between different manufacturing firms improves the cost, quality, diversity and servicing of the product. The tool used in the manufacturing process has a considerable impact on the quality and speedy production of a final product. Therefore, a tool prognosis is an essential step for the betterment of product as well as industry. Generally, the regular prognosis of tool helps in getting rid of unexpected errors during operation. The proper maintenance of the tool enhances its life, improves access, preserves the exact shape and reduces the overall cycle cost. All

the major maintenance activities are divided into two categories, i.e., curative and preventive maintenance. The curative maintenance is usually performed after failure. On the other hand, the preventive maintenance ensures the legitimate condition of the equipment through systematic or conditional maintenance^{2,3}. The future condition and lifespan of a tool can be predicted precisely using Condition-based Maintenance (CBM)³⁻⁶. In many industries, a large amount of operating expenditure is spent on maintenance activities. Not only downtime or rework can be reduced by proper maintenance of the system, but stability and productivity can also be enhanced effectively^z. Reliable and safe operation of a system could be ensured by identification, categorization and monitoring of defects in very early stages. It will also assist in a precise determination of Remaining Useful Life (RUL) of a system. Prognosis process is a method that analyzes the malfunction of the system and determines the need for timely maintenance, replacement of accessories or just shut down the system to prevent the

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catastrophic failure. The algorithms used for prognosis are either a model-based or data-driven⁸. In these types of approaches, a fault is considered as a continuously variable entity whose evolution is described using deterministic or stochastic law². The RUL of a system should be estimated on the basis of all the available information based on regular inspection and monitoring¹⁰. The condition of a manufacturing system is frequently monitored or examined using a set of sensors. After properly analyzing the information received from the sensors, the determination of the current position of the metal and the RUL can be assessed¹¹. This information is helpful in making proper decision regarding system maintenance. Thus, prognostic can predict the future situation of a system and prevents its unexpected failure¹². Failure prognostic involves estimating the available time before formally failing. Three types of prognostic processes are commonly used to perform this task. Which are as follows: model-based, experience-based and data-driven¹³. Markov model is a stochastic model that is capable of modeling unexpectedly changing systems. It is considered in the Markov model that the future conditions depend only on immediate circumstances, not on the events that happened in the past (Markov property)¹⁴. Ordinarily, this hypothesis enables the model to use reasoning and make an appropriate computation. In the context of predictive modeling and probabilistic forecasting, it is desirable that the model must display Markov property. Markov model mainly recognizes two situations, one of them is a functional state and the second one is a non-functional state. The first condition means that the system is working perfectly without errors and the second condition means the system is faulty or unserviceable¹⁵. Potential failures in future can be estimated by defining the probability of each state and by looking for the possibility of transition in another state from the previous one¹⁶. In this paper, Markov model has been used for the prognosis of a tool. Here, it is assumed that the system could be strictly in one state at a particular time.

2. Experimental Methodology

In this section, the experimental procedure used to collect the tool wear data of selected turning operations has been described. High Speed Steel (HSS) tool and Mild Steel (MS) workpiece have been used to conduct this study. The chemical composition of HSS and MS are given in Table 1 and Table 2. In this experiment, spindle speed and depth of cut were 150 rpm/min and 3 mm, respectively and a single cut of 100 mm length was defined as a single pass. A tool room microscope was employed to illustrate the flank and rake faces of the tool in the enclosure of the lathe machine during the wear testing. The Flank Wear Width (FWW) was identified using calibrated digital images and the tool's wear status was noted for every 20 minutes. The total time required for FWW to reach 0.3 is defined as the life of the tool.

 Table 1. Composition of tungsten high-speed tool

 steels¹⁷

High Speed Steel	С	Si	Cr	V	W	Мо	Со
AISI-T4	0.75	0.30	4.13	1.00	18.25	0.70	5.00

Table 2. Composition of Mild Steel workpiece¹⁸

Mild Steel	С	Cu	Fe	Mn	Р	Si	S
ASTM A36	0.25-0.29	0.20	98.0	1.03	0.04	0.28	0.05

3. Results and Discussion

The system used in this experiment is an open series system and the system's reliability block diagram has been shown in Figure 1.

In this experiment, Flank Wear Width is calculated at every interval of 20 minutes. The calculated values are listed in Table 3. Failure rates are mainly calculated for four stages of this system, i.e. initial (1), 5th, 10th and last (15th) stage. The failure rates of the respective stages are as follows:

 $\lambda 1 = 0.050$ $\lambda 2 = 0.010$ $\lambda 3 = 0.005$ $\lambda 4 = 0.0033$

The probability of each transition state of this system is as follows:

$$\frac{\mathrm{d}y_1}{\mathrm{d}t} = -\lambda_1 y_1 \tag{1}$$

$$\frac{\mathrm{d}\mathbf{y}_2}{\mathrm{d}\mathbf{t}} = -\lambda_2 \mathbf{y}_2 + \lambda_1 \mathbf{y}_1 \tag{2}$$

$$\frac{\mathrm{d}y_3}{\mathrm{d}t} = -\lambda_3 y_3 + \lambda_2 y_2 \tag{3}$$

$$\frac{\mathrm{d}y_4}{\mathrm{d}t} = \lambda_3 y_3 \tag{4}$$

Equations (1) to (4) was solved using the MATLAB software by Runge-Kutta method. These equations were solved for the different time span, i.e. 20, 100, 200, 300 and then the values of all the four stages were produced for the given time. In MATLAB, the results of 1^{st} , 2^{nd} and 3^{rd} stages were added by adding columns of the given stages to calculate reliability using R = y(:1)+y(:,2)+y(:,3) command. Obtained reliability results were plotted in MATLAB in the context of time. The reliability of the system is 43% at the time span of 300 minutes and it is shown in Figure 2. At time span 500 minutes, system is 41% reliable and it is shown in Figure 3. This is very similar to experimentally obtained tool failure time.

As we solve all these equations by Ranga-Kutta method using MATLAB for time intervals of every 20 min. to find out reliability.

$$\lambda 1 = 0.0500$$

$$\lambda 2 = 0.0100$$

$$\lambda 3 = 0.0050$$

$$\lambda 4 = 0.0033$$

$$R = y(:,1)+y(:,2)+y(:,3)$$
(5)



Figure 1. System description for Markov model of given experiment.



Figure 2. Reliability vs. time curve for Markov equation at 300-time span.



Figure 3. Reliability vs. time curve for Markov equation at 500 time span.

We can solve this equation of reliability i.e. Equation (5) on MATLAB for any value of reliability which gives time for that reliability and remaining useful time for this system can be estimated.

4. Conclusion

In this work, prognosis of turning tool is predicted using Markov approach. The data is generated by machining Mild Steel workpiece over a fixed length with constant

Table 3. Flank Wear Width at different time interv	'al
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S. No.	Time	Flank Wear Width (FWW)
1.	20	0.01
2.	40	0.04
3.	60	0.05
4.	80	0.05
5.	100	0.05
6.	120	0.06
7.	140	0.08
8.	160	0.10
9.	180	0.12
10.	200	0.15
11.	220	0.18
12.	240	0.22
13.	260	0.25
14.	280	0.28
15.	300	0.30

feed, speed and depth of cut. The Flank Wear Width is observed in every 20 min of time interval till the tool fails. Four state Markov model considering gradually degraded states is developed. The rate equations are derived for the representing the change of the state probability with respect to time for each state. These expressions derived from the Markov model is solved by Rung-Kutta method using MATLAB software. The reliability of tool at different time span is calculated. A specific level of reliability value 0.3 is set to determine the Remaining Useful Life using Markov model. According to the calculation of Markov model, this tool has a reliability of 43% and 41% for 300 and 500 minutes time interval, respectively.

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