<u>CERTIFICATE</u>

Date:-_________

This is to certify that report entitled **“Remaining Useful Life Estimation for cutting tools by Statistical Trend Exploration and Stochastic Markov Approaches”** by **Mr. Prashant Bhardwaj** is the requirement of the partial fulfillment for the award of Degree of **Master of Technology (M.Tech.)** in **Production Engineering** at **Delhi Technological University**. This work was completed under my supervision and guidance. He has completed his work with utmost sincerity and diligence. The work embodied in this project has not been submitted for the award of any other degree to the best of my knowledge.

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STUDENT’S DECLARATION

I, Prashant Bhardwaj, hereby certify that the work which is being presented in the major project-II entitled “Remaining Useful Life Estimation for cutting tools by Statistical Trend Exploration and Stochastic Markov Approaches”, is submitted, in the partial fulfilment of the requirements for degree of Master of Technology at Delhi Technological University is an authentic record of my own work carried under the supervision of Mr. Girish Kumar. I have not submitted the matter embodied in this seminar for the award of any other degree or diploma also it has not been directly copied from any source without giving its proper reference.

Prashant Bhardwaj
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Abstract

This thesis deals with development of methodology to obtain Remaining Useful Life (RUL) of a turning tool using two different approaches; statistical trend exploration technique and stochastic Markov method. An experiment is performed by HSS tool to machine a mild steel work piece for a constant length on lathe machine. Flank wear width for different number of passes of tool over work piece is recorded for constant feed, speed and depth of cut up to failure value of tool flank wear i.e. 0.5 mm. In statistical trend exploration technique, the behavior of flank wear width is plotted on different curve against number of passes. Best fitted curve behavior is studied and equation of that curve is generated which gives us RUL for different number of passes of tool as input value.

In stochastic Markov method, a state based model is developed considering four gradually degraded stages of the tool. The degradation rate among states are obtained from the data of the experiment. The rate equations are derived for the four state Markov model representing the change of the state probability with respect to time for each state. The set of equations is solved analytically by Range-Kutta method using MATLAB software. The analytical results are verified by Monte Carlo Simulation.

The estimation of remaining tool life is important in planning condition based maintenance program and helps us by preventing any loss during production.

Keywords: - Remaining useful life, cutting tool, trend exploration technique, Markov model, Monte-Carlo simulation.

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Notations

$R(t)$ = Reliability function

$f(t)$ = density function

$\frac{dp}{dt}$ = Probability of each transition state

λ = Denotes the failure rate; the rate at which a system fails

μ = confidence interval for the population mean

σ = population standard deviation

C_1, C_2 & C_3 = Integrating constants

Appendix A1

MATLAB program for solving Markov equation by Runge-Kutta method

```
function dydt = rul(t,y)

lmbda1=0.0138;

lmbda2=0.0208;

lmbda3=0.0416;

dydt = [-lmbda1*y(1);

-lmbda2*y(2)+lmbda1*y(1);

-lmbda3*y(3)+lmbda2*y(2);

lmbda3*y(3)];
```

Appendix A2
MATLAB program for reliability using Monte-Carlo simulation

```
function montecarlo()

clear all

close all

clc

totalRuns = 0;

totalSuccess = 0;

runs=300;

matrix = zeros(1,runs);

for i=1:1:runs

x1 = random('uniform',0,1);

x2 = random('uniform',0,1);

x3 = random('uniform',0,1);

lambda1 = 0.0138;

lambda2 = 0.0208;

lambda3 = 0.0416;

t1 = (-1/lambda1) * log(x1);

t2 = (-1/lambda2) * log(x2);

t3 = (-1/lambda3) * log(x3);

t = t1 + t2 +t3;
```

```
if t < 145

    success = 0;

else

    success = 1;

end

totalRuns = totalRuns + 1;

totalSuccess = totalSuccess + success;

reliability = totalSuccess / totalRuns;

matrix(1,totalRuns) = reliability;

fprintf('Success = %d Total Runs = %d \n' , success,totalRuns);

fprintf('Reliability =  %.15f \n\n\n ' ,reliability);

end

x = 1:1:runs;

y = matrix(x);

plot(x,y);
```

Chapter-1

Introduction

A brief introduction to the importance of reliability analysis, RUL estimation and performance improvement of systems or components is discussed in this chapter. It covers the underlying background and problem areas of the research study. It also discusses the research questions and the scope of the research. Finally the structure of the thesis is discussed.

1.1. Background of Research:

The major role of maintenance in industry is to improve the availability, reliability and security, with reduction of the cycle cost. The main types of maintenance are curative and preventive maintenances. In the curative, the maintenances are done only after the failure, whereas in the preventive, it is done either systematically or conditionally to the health condition of the system. This type of maintenance is commonly termed as a Condition Based Maintenance (CBM). The condition of the system is continuously monitored and inspected by a set of sensors. The data is recorded and processed in order to estimate the current health state and to estimate its failure time. The estimated states are used to take appropriate maintenance decisions. Diagnostic aims at assessing the component's current condition and identifying the cause of its failure, whereas prognostic is used to predict its future health state in order to anticipate the failure. Formally, failure prognostic consists of estimating the time before failure or the Remaining Useful Life (RUL). It can be done by three ways like,

- Model-based prognostic,
- Experience-based prognostic and
- Data-driven prognostic.

1.2. Methodology of Research:

Model based prognostic consists of studying each component or sub-system in order to establish for each one of them a mathematical model of the degradation phenomenon. The derived model is then used to predict the future evolution of the degradation and thus the related RUL value. Experience-based prognostic methods used mainly probabilistic or stochastic models of the degradation phenomenon, or of the life cycle of the components, by taking into account the data and knowledge accumulated by experience during the whole exploitation period of the industrial system. Data-driven prognostic is based on the transformation of the monitoring data into relevant behavioral models permitting to predict the RUL and the associated confidence. RUL is illustrated in figure1.1 below.

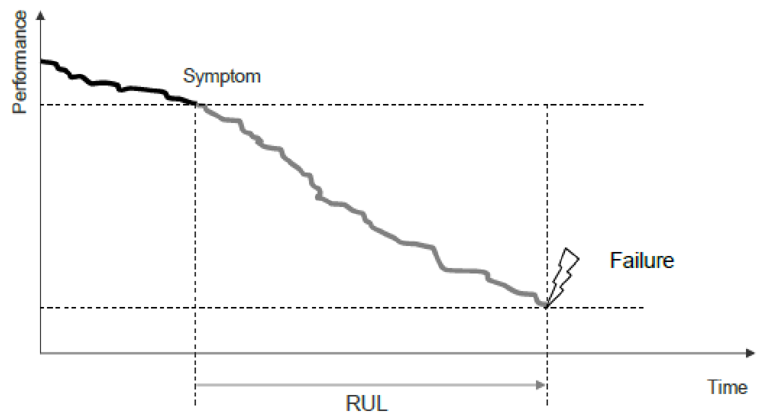

Figure 1.1: Remaining Useful Life illustration

Trend exploration technique is a type of a statistical method and is simplest form of estimating RUL. It is based on simple trend analysis of a single parameter which affects remaining life by single sensor or from a number of sensors. This one parameter is then plotted with time. A failure level is pre-established. A trend is then calculated with time. Failure limits also need to be decided carefully. When data is obtained, the behavior fits the trend and so RUL is simply calculated.

1.3. Research Method:

Tool life can be defined as the usable time that has remaining before the cutting tool has failed to machine work piece. The standard definition of tool life is the time remaining until a defined amount of wear has occurred in the rake face or flank face of the cutting tool. For a tool RUL can be calculated by behavior of tool wear for time duration during machining.

After this statistical method we can also verify the results by stochastic method. We can generate a Markov model of this and can get desired results. Markov models assume that at any instant system or component can be in one of the finite states. Probabilities of future failure of system can be calculated by defining that of each state and that of each transition between one another. Future state in Markov models is depends only upon the most recent past state. A Markov chain is a stochastic process. Markov chains can be discrete, having finite number of states or continuous with infinite number of states. For prognostics, steady state probabilities for a Markov process are independent of initial conditions but the rate of steady state depends on both the initial conditions and the transition probabilities. The number of states represents the number of components of the system. For prognostics, Markov analysis assumes that

- Each state's status can be only failed or available.
- Probabilities of moving from one state to another do not change with time.
- Time in a particular state is exponentially distributed with a constant rate.
- The sum of all transition probabilities must be equal to one.
- Future states are only dependent on the immediately preceding state.

These results can be validated by Monte-Carlo simulation method. Monte Carlo methods are a broad class of computational algorithms that rely on repeated random sampling to obtain numerical results; i.e., by running simulations many times over in order to calculate those same probabilities heuristically just like actually playing and recording your results in a real casino situation. They are also used in physical and mathematical problems and are most suited when it is impossible to obtain a closed-form expression or infeasible to apply a deterministic algorithm. Monte Carlo methods are mainly used in three distinct problems: optimization, numerical integration and generation of samples from a probability distribution.

CHAPTER II: Literature Review

CHAPTER III: Remaining Useful Life Estimation Methods

CHAPTER IV: Experiment procedure and System modelling

CHAPTER V: Results and Discussions

CHAPTER VI: Conclusion and Future Scope

Chapter-2

Literature Review

Many publishers published their paper on maintenance engineering. Maintenance can be defined as a combination of all technical and associated administrative action intended to retain an item or a system in, or restore it to, a state in which it can perform its required function. Commonly maintenance is categories into four categories: Corrective, preventive, predictive and proactive. Maintenance is the most important factor to improve the system availability. Some of these papers are reviewed and discussed in this chapter.

2.1. Review on Reliability:

To reduce maintenance cost and to optimize maintenance strategies, it is necessary to understand reliability and its variations, the consequences of failure, the factor affecting maintenance and its relationship between the maintenance task and production or other performance of assets to be maintained. Reliability is the ability of a system to perform a required function under stated conditions for a given period of time. Second mathematical way to explain reliability is in terms of failure distribution function or failure density function. Failure means that a system fails to meet its performance requirement. Many publishers expressed their view on this topic.

Dhillon [1992] evaluated reliability and availability of the system with warm standby and considering common cause of failure. The standby and switching mechanism of considering two unit parallel system reliability. Laplace transform of system state probability are used for availability, MTTF and MTBF consideration.

Roberto-de-Lieto and Davoli [2010] estimated plant reliability installed in hospital by constructing RBD of all components working in the system and in this RBD MTTR, MTBF and MDT are evaluated and system reliability is estimated by using Markovian chain and constructing probabilistic differential equations.

Sharma et al. [2011] published a paper on “Reliability analysis of complex multi-robotic system using GA and fuzzy methodology” in which various reliability parameters of robotic system by using Real Coded Genetic Algorithms (RCGAs) and Fuzzy Lambda-Tau Methodology (FLTM) is proposed. Optimal value of Mean time to Failure and Mean time between Failures is obtained by using genetic algorithm. Triangular fuzzy numbers are used to enhance the reliability of the system. Petrinets are considered to represent the relation between different components of the system.

Yingkui and Jing [2012] proposed multistate system reliability by considering multiple possible state of the system. This model allows both system and its component to consider more than two level of performance. Multi-state reliability models provide more realistic and more precise representations of reliability.

Fink et al. [2013] published a paper on “Predicting component reliability and level of degradation with complex-valued neural networks” in which multi-layer feed forward neural networks based on multi-valued neurons (MLMVN),a specific type of complex valued neural networks are used to evaluate reliability of the system. Reliability model is formulated in the form of time series to extract complex dynamic pattern to predict long term system reliability.

2.2. Review on Maintenance

Maintenance is a conceptual model and process which guideline on how to conduct maintenance effectively through proper integration of various maintenance model and methodology. This section classifies and compares the characteristics and general idea of different maintenance framework. Maintenance optimization is the objective of maintenance while reliability prediction and risk assessment lays a basis for optimal maintenance decision making.

Wu and Chan [2003] proposed importance of a component state in Multi State systems and explained the solution of this multistate system by using heuristics, met heuristics, neural networks and fuzzy techniques.

Cher et al. [2006] proposed a model on practical framework of predictive maintenance of scheduling of multi state system. By this scheduling system-perspective using the failure times of the overall system as estimated from its performance degradation trends can be derived.

Gurler and Kaya [2008] proposed maintenance policy with multistate system whereas Huang and Yuan [2009] proposed two state preventive maintenance policy for multistate deterioration system under periodic inspection of the system with multiple action of preventive maintenance.

Yuan [2013] presented a two-stage preventive maintenance (PM) policy for the multi-state deterioration system under periodic inspection and with multiple candidate actions for PM. they assumed that: (1) such actions except replacement are imperfect, (2) the inspection and action times can be ignored, (3) the system can be modeled by a multi-state discrete time Markov chain whose transition probabilities will change and be updated only at the instant after completing each PM, and (4) the risks of such imperfect actions will be updated only at the instant after completing each PM.

2.3. Review on Remaining Useful Life:

Remaining useful life prediction is of crucial importance in condition based maintenance to reduce the maintenance cost and to improve reliability. Prognostic of system life time is a basic requirement for condition based maintenance in many application domains where safety, reliability and availability are considered of first importance. Many publishers expressed their different views on the method of RUL estimation. In this thesis remaining useful life of a cutting tool is estimated by running that on lathe machine over different interval of time then a state-space probabilistic Markov model is generated to evaluate the RUL of the system.

Ahammed [1998] presented a methodology for the assessment of remaining useful life of a pressurized pipeline containing active corrosion effects. A probabilistic approach is used for this assessment and associated variables are represented for non-linear probabilistic distributions. Because of the presence of non-linearity and non-normal variables in limit state functions advanced first order second moment iterative method is used for reliability evaluation. This methodology also allows calculation of the reliability index, failure probability,and relative contribution of the random variables and also allows study of the effect of variation of the variance of the random variables on the overall pipeline reliability.

Essawy [2001] proposed methodology to estimate machine RUL using history data. This was an indirect methodology in which parameters related to critical machine operating regions and transitions were defined first. The prediction models were built using these parameters. Fuzzy logic decision-making system was used to locate current machine operating region with a probability. Then neural networks were used to estimate the RUL of the machine with known tolerance limit.

Frank et al. [2001] developed robust analytic methods for predicting remaining useful life of mechanical systems. The project is focused specifically on the investigation of a generalized statistical method for characterizing and predicting system degradation. Prognostic process is used for predicting the future state of the system. Effective prognostics will result in reduced numbers and severity of failures (especially failures in the field), optimizing operational performance, extending the time between needed maintenance activities and reducing life-cycle costs.

Frank and Thomas [2001] proposed robust analytic methods for predicting remaining life of mechanical systems. This method is used for analyzing system status and heath for estimating life expectancy. By doing this system can be more powerful, reliable. Prognostic system is used for estimating the life of the component, in this system high level architecture or framework is constructed for RUL.

Shao and Nezu [2003] proposed a new concept of progression-based prediction of remaining life to estimate the RUL of a bearing. Compound model of a neural network is used in this method. In this method different logistic rules to check the bearing initial stage then trend prediction model in real time is used for RUL estimation.

Liao et al. [2005] estimated the RUL of ball bearing by using both a proportion hazards model and a logistic regression model. In this method multiple degradation feature of the system is used for reliability analysis. Now RUL can be estimated by fitting the degradation feature in graph. This model is better than logistic regression model as it ignores prior degradation features.

Kharoufeh and Cox [2005] proposed that by considering two kinds of sensors data, environment observations and degradation measures in their stochastic failure models to numerically compute the RUL distributions and their moments. However, the number of the states in a Markovian model was estimated by a K-mean clustering algorithm which implied that there must be sufficient data on failures and degradation to estimate the model parameters. His work was also extended by proving several limit theorems related to a time-scaled version of the degradation process and a space-scaled version of the unit's random lifetime. But the main disadvantage of this process was that it was less flexible for shock inter arrival time which was not exponentially distributed.

Gebraeel et al. [2005] proposed a Bayesian updating approach that incorporates real-time condition information into residual-life models. This method assumes that the stochastic component of a degradation model follows a normal prior. Gebraeel et al. does not apply when the prior is highly skewed.

According to Jardine et al. [2006], Altay and Green, [2006] It is critically important to assess the RUL of an asset while in use since it has impacts on the planning of maintenance activities, spare parts provision, operational performance, and the profitability of the owner of an asset.

Kothamasu et al. [2006] was the only one who suggested managerial problems in health diagnostic and prognostic without discussing the modelling issue of the problem.

Mazhar et al. [2007] said that RUL estimation has also an important role in the management of product reuse and recycle which has strategic impacts on energy consumption, raw material use, pollution and landfill.

Steven et al. [2007] proposed an idea in which Hidden Markov models are used as tools for pattern recognition in a number of areas, ranging from speech processing to biological sequence analysis for estimating remaining useful life. In this paper a comparison is made between maximum likelihood estimation to fully Bayesian estimation of parameters for profile hidden Markov models with a small number of parameters. We find that, relative to maximum likelihood methods, Bayesian methods assign higher scores to data sequences that are distantly related to the pattern consensus, show better performance in classifying these sequences correctly, and continue to perform robustly with regard to misspecification of the number of model parameters. Monte-Carlo approach is also used for reliability estimation.

Mazhar et al. [2007] proposed Weibull analysis method for remaining useful life estimation. It proposed an integrated approach to estimating the remaining useful life of components for reuse. It is applied to the time-to-failure data to assess the mean life of components. The advantages of this approach over traditional approaches employing multiple regression analysis are highlighted with empirical data from a consumer product. Finally, the Weibull analysis and the ANN model are then integrated to assess the remaining useful life of components for reuse.

Enrico and Francesco [2009] proposed a fuzzy network for RUL estimation. Data from failure dynamic scenarios of the system are used to create a library of reference trajectory patterns to failure. By this failure system remaining life can be predicted by fuzzy similarity analysis. The prediction on the failure time is dynamically updated as time goes by and measurements of signals representative of the system state are collected.

Wahyu et al. [2009] proposed Monte-Carlo method for reliability and health prediction of the system. By predicting the degradation of working conditions of machinery, it can organize a predictive maintenance program and prevent production loss. For complex systems, the trending data of the performance degradation is nonlinear over time known as a time series. Monte-Carlo method is used for evaluating RUL by nonlinear system without considering the assumption of linearity.

Santanu et al. [2009] proposed a research on using degradation models to compute residual life distributions for degrading components. In this paper RUL is estimated by considering stochastic parameters.

Abd kadir et al. [2010] proposed artificial neural network method for prediction of RUL of bearing for condition based maintenance. This method is used to improve accurate RUL of the system. ANN model uses time and fitted measurements Weibull hazard rates of root mean square (RMS) and kurtosis from its present and previous points as input and life percentage is obtained as output. It degraded the failure and noise of the bearing. This CBM improved reliability and cost of maintenance.

Sikorska et al. [2010] published a paper on “Prognostic modelling options for remaining useful life estimation by industry” prognostic model is used for RUL prediction. In this paper business issues are discussed for appropriate modelling approach for trial. In this paper combination of Knowledge-based (expert and fuzzy), Life expectancy (stochastic and statistical), Artificial Neural Networks, and Physical models are used for reliability and RUL prediction. This paper also explores strength and weakness of main prognostic model.

Lee et al. [2010] incorporated the Markov property into a regression model and presented a new model for the survival analysis called Markovian chain. In regression model subject’s health followed a stochastic process and failure occurred when the process first reached a failure state. In this model regression can be done by linear order differential equations and RUL can be estimated.

Jihong et al. [2010] published a paper on "A dynamic multi-scale Markov model based methodology for remaining life prediction" in which it was proposed that RUL can be estimated by multi-feature fusion techniques to represent deterioration severities of facilities and an improve Markov model is presented for estimation of RUL. Based on both historical and real time data a dynamic prediction method is introduced into Markov model by a weighted coefficient. Markov Model is used with the combination of Fuzzy-C algorithm. A dynamic multi scale Markov model is presented to solve state division problem of multi-sample prediction.

Chaochao et al. [2011] proposed an integrated adaptive neuro-fuzzy and high-order particle filtering approach for RUL estimation in which high-order particle filtering is used which forecasts the time evolution of the fault .indicator and estimates the probability density function of RUL. This approach estimated RUL with the help of part data and real time data. The high-order particle filter integrates with higher order Markov model to carry out long term prediction which give accurate result of RUL probability density function.

Xiao-Sheng et al. [2011] proposed that RUL is typically random and unknown, and as such it must be estimated from available sources of information such as the information obtained in condition and health monitoring. Its estimation is central to condition based maintenance and prognostics and health management.

Tobon-Mejia et al. [2011] proposed present paper is a contribution on the assessment of the health condition of a computer numerical control (CNC) tool machine and the estimation of its remaining useful life (RUL).In this approach both on line and off line phases are used for RUL estimation .In on line phase data is collected by the system and in the second phase these data are used in simulation and modelling. A condition monitoring, diagnostic and prognostic data-driven method is used for modelling and simulation. Dynamic Bayesian method is used for RUL estimation under current working condition.

Baojia et al. [2011] published a paper on "Reliability estimation for cutting tools based on logistic regression model using vibration signals" in which it was proposed that reliability of the system is the main factor of system stability and manufacturing effectiveness. This study propose a novel reliability estimation approach to the cutting tools based on logistic regression model by using vibration signals. Three steps for reliability analysis is considered, first online vibration signal ,second wavelet packet transform, and third step is correlation analysis is also used to select the salient feature parameters which are composed of feature band energy, energy entropy and time-domain features and finally reliability analysis is carried out by regression method.

Scanlon et al. [2011] used sound pressure measurements for developing an automated degradation analysis system to estimate the RUL of the rolling element bearings. By using high frequency resolution effective automated monitoring can be done. Acoustic data from the sensors are collected then with the help of Fourier transformation was applied to deduce the frequency and mutual information is applied and RUL of the rolling bearing can be estimated.

Bin Li [2012] made a thorough understanding of the material removal process in cutting is essential in selecting the tool material and in design, and also in assuring consistent dimensional accuracy and surface integrity of the finished product. Hidden Markov models (HMMs) were introduced to estimate tool wear in cutting, which are strongly influenced by the cutting temperature, contact stresses, and relative strains at the interface. The main objective of this work is to evaluate the RUL of the tool by using HMM and improve it by simulation technique with the combination of FEM. Finally it was concluded that a Markov chain is a random process of discrete-valued variables involving a number of states linked by a number of possible transitions. At different times, the system is in one of these states each transition between the states has an associated probability, and each state has an associated observation output for tool wear estimation.

Chao Hu et al. [2012] published a paper on “Ensemble of data-driven prognostic algorithms for robust prediction of remaining useful life” in which k-fold cross validation was proposed to evaluate the error of the system. Three weighting schemes, namely the accuracy-based weighting, diversity-based weighting and optimization-based weighting, are proposed to determine the weights of member algorithms and these three algorithm give more accurate result of RUL than any other sole algorithm and give the results for reliability improvement.

Khanh et al. [2012] published a paper on “Remaining useful life estimation based on stochastic deterioration models” it was proposed that prognostic of system lifetime is a basic requirement for condition-based maintenance in many application domains where safety, reliability, and availability are considered of first importance. A stochastic process (Wiener process) combination with data analysis method is used for deterioration of the system and RUL prediction.

Jaydeep et al. [2012] published a paper on “Prediction of remaining useful life for fatigue-damaged structures using Bayesian inference” in which it was proposed that Structural health monitoring enables fatigue damage for in-service structures to be evaluated and the remaining useful life to predict. In this paper, Bayesian inference using a random walk method was implemented to predict the remaining useful life of an aircraft fuselage panel subjected to repeated pressurization cycles and the effect of the likelihood on the remaining useful life predictions was also evaluated. The proposed method takes into account model uncertainties as well as the presence of noise and bias in the measurement data.

Guofeng and Xiaoliang [2012] proposed linear chain conditional random field model for RUL estimation of tool and improving the efficiency of the machining process. This model is proposed to overcome the shortcomings of hidden Markov model. The main feature of this method is method is that the estimation of the model parameters depends not only on the current feature vectors but also on the context information in the training data. So it present the relationship between field vector and tool wear. Acoustic emission data are collected to check the effectiveness of this process.

Xiao-Sheng et al. [2012] estimated remaining useful life as one of the most central component in prognostic and health management. According to Xiao-Sheng Si RUL estimation can prevent failure in more controllable manner. Degradation path-dependent approach was proposed for RUL estimation with the combination of Bayesian updating and expectation maximization (EM) algorithm. A linear degradation model and an exponential-based degradation model are used for the algorithm and these two models are helpful to illustrate exact RUL distribution.

Vantung et al. [2013] suggested proportional hazard model and support vector machine for Machine performance degradation assessment and remaining useful life prediction. Machine performance degradation assessment and remaining useful life (RUL) prediction are of crucial importance in condition-based maintenance to reduce the maintenance cost and improve the reliability. Three stage method is used for reliability assessing and forecasting of RUL. in the first stage only dynamic behavior of the system is studied, in second stage the Cox's proportional hazard model is generated to estimate the survival function of the system and in last stage support vector machine is used for RUL estimation.

Miltiadis et al. [2014] propose regression to fuzziness method for RUL estimation of power plant components. The methodology is used to compensate for a potential lack of historical data by modeling an expert's operational experience and expertise applied to the system. With the help of the past data fuzzy sets are constructed which span the entire parameter range. This model is then synergistically used with linear regression and a component's failure point to estimate the RUL. In this method real world examples are taken to predict RUL. The main advantage of this system is that it also estimate the uncertainty of the system.

Chapter-3

Remaining Useful Life Estimation methods

In this chapter all the methods used for estimating RUL are classified and explained. And all the tools used in our experiment are also explained s Markov modelling and Monte-Carlo simulation etc. Some Reliability tool and MTTF calculation methods and their confidence interval calculation methods and their significance is also explained.

3.1. Diagnostic v/s Prognostics

Diagnostics involves the identifying and quantifying the failure or damage that has occurred to the component, while the prognostics is concerned with the prediction of the damage that is yet to occur. Although diagnostics may provide useful outputs on its own, whether prognostics relies on diagnostic outputs and therefore cannot be done in isolation.

To understand the models of diagnostics and prognostics, it is important to identify the various steps involved in obtaining an RUL estimate and its confidence limits. Consider the process of a component undergoes between a healthy state and final failure. Each failure mode may have different reasons to initiate the failure and thereafter have a different degradation behavior in same operating conditions. Therefore, to determine remaining useful life of a component, it is important to know:

- Is a component in the degraded state?
- Which failure mode has initiated the degradation?
- How severe is the degradation?
- How quickly is degradation expected to progress from its current state to functional failure?
- What novel events will change this expected degradation behavior?
- How may other factors affect our estimate of RUL?

3.1.1. The diagnostic prognostic process

- Diagnostic: These are the main steps of diagnostic.
    - Fault detection: Detecting and reporting an abnormal operating condition.
    - Fault isolation: Determining which component is failing or failed.

- Fault identification: Estimating the nature and extent of the fault.

- Prognostic: These are the main steps of prognostic.
  - Remaining useful life prediction: Identifying the lead time to failure.
  - Confidence interval estimation: Estimating the confidence interval associated with the RUL prediction.

3.2. Classification

Remaining life estimation methods are mainly classified in four main groups and many sub groups as follows:

- Knowledge-based models:

Estimate the similarity between an observed situation and previously defined failures and calculate the remaining life from previous events. It consists the following systems:

- Expert systems.
- Fuzzy systems.
- Life expectancy models:

Estimate the remaining life of components with respect to the expected risk of degradation under known operating conditions. Sub-categories are as following:

- Stochastic models: These are the main functions of this model.Aggregate reliability functions.
- Conditional probability methods, including the RUL probability density function and Bayesian Networks.
- Statistical models: These are the main functions of this model.
  - Trend extrapolation.
  - Auto-regressive Moving Average (ARMA) models and variants.
  - Proportional Hazards Modelling (PHM).

- Artificial Neural Networks:

  Estimate the remaining useful life of a component from a mathematical representation of the component from observation data rather than a physical understanding of the failure processes. Further classified as follows:

  - Direct RUL forecasting.
  - Parametric estimation for other models.

- Physical models:

  Estimated the remaining useful life of a component from a mathematical representation of the physical behavior of the deterioration processes.

3.2.1. Knowledge based model

Estimate the similarity between an observed situation and previously defined failures and calculate the remaining life from previous events.

3.2.1.1. Expert system

An expert system in a particular field, performance of human experts is simulates by software program. It consists of a knowledge base experience from subject matter experts and a rule base for applying that knowledge to particular problems known to the software system and are formulated as precise IF-THEN statements.

3.2.1.2. Fuzzy systems

Fuzzy set theory overcomes the drawbacks of expert system by allowing partial set membership based on a variable's 'degree of truth' as in expert system logics work on only TRUE and FALSE logics. Fuzzy logic systems use simple IF-THEN rules. A typical fuzzy process logic statement may look like 'IF (process is too hot) AND (process is heating rapidly) THEN (cool the process quickly)'.

3.2.2. Life expectancy models

Estimate the remaining life of components with respect to the expected risk of degradation under known operating conditions.

3.2.2.1. Stochastic models

Reliability-related information is provided by stochastic models, such as Mean Time to Failure (MTTF) as probabilities of failure w.r.t. time. It works on some assumptions that the time to failure of identical components is considered statistically identical and independent random variables and described by a probability density function.

3.2.2.1.1. Aggregate reliability functions

It involves analyzing the time to failure of a population of equipment and probability density function and related hazard function for the population can be determined. A single fault progression from incipience to final failure cannot be represented by this probability density function, which follows an exponential curve. When failures are expected to occur then it provides information about this. Various distributions can be used, including the Exponential, Normal, Lognormal, Gaussian and Weibull.

3.2.2.1.2. Conditional probability models

A number of stochastic model describes a current state in the form of a condition reliability function and use the Bayes theorem to and probabilistic future behavior is estimated. Thus, they are called as Bayesian models.

RUL probability density function

RUL probability density function is the simplest Bayesian approach. It is an extension of aggregate reliability analysis. Probability density function of the relevant failure mode is required. Information to locate a specific item on this general distribution is obtained. The distribution is recorded by this information using Bayes theorem. This process is repeated each time for new observation. This process is called Bayesian updating. The resulting distribution is known as the predictive density function.

Static Bayesian Networks

Bayesian Networks is a probabilistic acyclic graphical models represents a set of random variables and their probabilistic interdependencies. They are also called as Bayesian Belief Networks. Depending on the type of information used to develop the network it can be knowledge-based, stochastic or hybrid approaches.

Dynamic Bayesian networks

In Dynamic Bayesian networks the directed BN arcs flow forward in time. Therefore useful for modelling time series data. RUL estimation is by using time series forecasting. The most common variants are used in engineering prognostics include Markov models, Kalman filters and Particle filters.

Markov and semi-Markov models

Markov models assume that at any instant system or component can be in one of the finite states. Probabilities of future failure of system can be calculated by defining that of each state and that of each transition between one another. Future state in Markov models is depends only upon the most recent past state. A Markov chain is a stochastic process. Markov chains can be discrete, having finite number of states or continuous with infinite number of states. For prognostics, steady state probabilities for a Markov process are independent of initial conditions but the rate of steady state depends on both the initial conditions and the transition probabilities. The number of states represents the number of components of the system.

Semi-Markov models differ from basic Markov chains. In Semi Markov they do not require the exponentially distributed time spent in a particular state. It can be in any distribution. Thus Semi Markov are more useful for estimating RUL than Markov models.

Hidden and semi-hidden Markov models

A HMM is explained by five parameters. Two parameters and three probability distributions:

- Number of model states
- Number of distinct observation symbols per state
- State transition probability distribution
- Observation symbol probability distribution
- Initial state distribution.

To overcome the lack of transition information to and from hidden states. The stochastic model is trained with data representing faults of interest.

Semi-Hidden Markov Models differ from HMMs is not worked on assumption of constant failure rate. They allow the modelling of state duration with explicit distribution that need not be exponential. This is advantageous for estimating remaining useful life hence preferred more for prognostics.

Bayesian estimation with Kalman filters

The Kalman filter is efficient recursive digital processing technique used to estimate the state of a dynamic system from a series of incomplete and noisy measurements in way that minimize mean squared error. At any instant, the Kalman filter is defined by its state estimate and error covariance.

Bayesian estimation with particle filters

After Kalman filters for estimating the posterior distribution in Bayesian network models. This is not bound by any linearity or Gaussian noise assumptions which are Particle filters. They are also called Monte Carlo simulation methods. They are particularly useful for situations where the posterior distribution is multivariate and non-standard.

3.2.2.2. Statistical models

Statistical models is the estimation of the damage initiation and its progression based on previous inspection results on similar machines. Forecasting of future degradation is often undertaken by comparing results with models representing ‘good’ performance. They are used as an alternative to ANN.

3.2.2.2.1. Trend evaluation

The simplest form of prognostic RUL prediction. It is based on simple trend analysis of a single monotonic parameter of remaining life. This parameter may have developed from sensors aggregated into a single variable and this parameter is then plotted as a function of time. An alarm level is pre-decided. End of life is considered equal to that level being reached. A trend is then calculated based on this data using regression methods.

3.2.2.2.2. Autoregressive models

Autoregressive moving average (ARMA), Autoregressive integrated moving average (ARIMA) and ARMAX models are mainly used for modelling and forecasting data for time series. ARMA and ARMAX models can remove temporal trends. A time series is designated to be stationary if its first two moments are time-invariant under translation.

3.2.2.2.3. Proportional hazards modelling

Proportional Hazards Modelling (PHM) models the way explanatory or concomitant variables and referred to as covariates which affect the life of the equipment. As it is opposite to linear regression methods, PHM assumes a multiplicative relationship. It models system degradation as the product of baseline hazard rate and positive function which reflects the effect of the operating environment on the baseline hazard. It is described by a vector of covariates and an associated vector of regression parameters and remaining useful life can be estimated.

3.2.3. Artificial neural networks

Artificial Neural Networks estimate output for the remaining useful life of a component from a mathematical representation of the component which is derived from observation data. They are effective and efficient at modelling complex non-linear systems. A number of different data can be used as inputs. Outputs depend on the aim of the modelling process, such as maintenance remaining useful life.

3.2.3.1. Direct RUL forecasting

Direct forecasting of an RUL value used for prognostic utilizing ANNs. By using a neural network it predict the next point of a temporal data series. This data series corresponds to some measure of remaining useful life. Physical or an arbitrary output of pre-processing routine. Data is extrapolated till final failure value. Then the RUL is the time until that point is reached.

3.2.3.2. RUL via parameter estimation

The second use of neural networks in RUL prediction involves estimation of the parameters of a known function that has usually been derived using physics of failure techniques.

3.2.4. Physical models

Physical models characterize the behavior of a failure mode using physical laws. It thoroughly understands the system behavior in response to stress, at both macroscopic and microscopic levels. Physical models assumes that this behavior of any component can be described accurately and analytically. By solving a deterministic equation for the derived from extensive empirical data of physical models remaining useful life of a component can be estimate as an output.

3.3. Reliability Measures

Reliability is the analysis of failures, their causes and consequences. It is the most important characteristic of product quality as things have to be working satisfactorily before considering other quality attributes. Usually, specific performance measures can be embedded into reliability analysis by the fact that if the performance is below a certain level, a failure can be said to have occurred. Reliability is the probability that the system will perform its intended function under specified working condition for a specified period of time. The reliability function R(t) is the probability that a system will be successfully operating without failure in the interval from time 0 to time t,

$$R(t) = P(T > t),\ t \geq 0$$

Where T is a random variable representing the failure time or time-to-failure. The failure probability, or unreliability, is then

$$F(t) = 1 - R(t) = P(T \leq t)$$

Which is known as the distribution function of T. If the time-to-failure random variable T has a density function f (t), then

$$R(t) = \int_{t}^{\infty} f(x)dx$$

This can be interpreted as the probability that the failure time T will occur between time t and the next interval of operation, $t + \Delta t$. The three functions, R(t), F(t) and f(t) are closely related to one another. If any of them is known, all the others can be determined.

3.4. Markov Model Fundamentals

For any given system, a Markov model consists of a list of the possible states of that system, the possible transition paths between those states, and the rate parameters of those transitions. In reliability analysis the transitions usually consist of failures and repairs. When representing a

Markov model graphically, each state is usually depicted as a “bubble”, with arrows denoting the transition paths between states, as depicted in the figure 3.1 below for a single component that has just two states: healthy and failed.

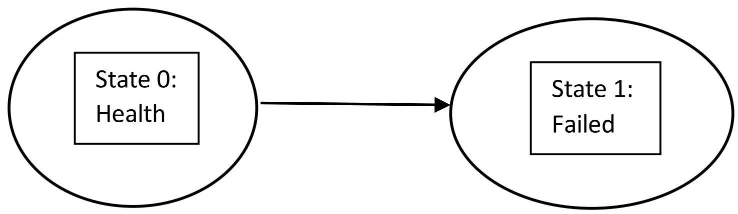

Figure 3.1: System having two states healthy and failed

The symbol l denotes the rate parameter of the transition from State 0 to State 1. In addition, we denote by P(t) the probability of the system being in State j at time t. If the device is known to be healthy at some initial time t = 0, the initial probabilities of the two states are $P_0(0) = 1$ and $P_1(1) = 0$. Thereafter the probability of State 0 decreases at the constant rate l, which means that if the system is in State 0 at any given time, the probability of making the transition to State 1 during the next increment of time dt is ldt. Therefore, the overall probability that the transition from State 0 to State 1 will occur during a specific incremental interval of time dt is given by multiplying (1) the probability of being in State 0 at the beginning of that interval, and (2) the probability of the transition during an interval dt given that it was in State 0 at the beginning of that increment. This represents the incremental change dP0 in probability of State 0 at any given time, so we have the fundamental relation

$$\frac{dP_0}{dt} = -\lambda P_0$$

This signifies that a transition path from a given state to any other state reduces the probability of the source state at a rate equal to the transition rate parameter l multiplied by the current probability of the state. Now, since the total probability of both states must equal 1, it follows that the probability of State 1 must increase at the same rate that the probability of State 0 is decreasing. Thus the equations for this simple model are

$$\frac{dP_0}{dt} = -\lambda P_0$$

$$\frac{dP_1}{dt} = \lambda P_0$$

$$P_0 + P_1 = 1$$

The solution of these equations, with the initial conditions $P_0(0) = 1$ and $P_1(0) = 0$, is

$$P_0(t) = e^{-\lambda t}$$

$$P_1(t) = 1 - e^{-\lambda t}$$

The form of this solution explains why transitions with constant rates are sometimes called "exponential transitions", because the transition times are exponentially distributed. Also, the total probability of all the states is conserved. Probability simply "flows" from one state to another. It's worth noting that the rate of occurrence of a given state equals the flow rate of probability into that state divided by the probability that the system is not already in that state. Thus in the simple example above the rate of occurrence of State 1 is given by $(lP_0)/(1-P_1) = l$.

3.5. Mean time to failure (MTTF)

Usually we are interested in the expected time to next failure, and this is termed as mean time to failure. The mean time to failure *(MTTF)* is defined as the expected value of the lifetime before a failure occurs. Suppose that the reliability function for a system is given by $R(t)$, the MTTF can be computed as

$$\text{MTTF} = \int_0^\infty t.f(t)dt = \int_0^\infty R(t)dt$$

3.6. Confidence interval

A confidence interval gives an estimated range of values, which is likely to include an unknown population parameter. The estimated range being calculated from a given set of sample data. If independent samples are taken repeatedly from the same population, and a confidence interval calculated for each sample, then a certain percentage of the intervals will include the unknown population parameter.

For instance, a confidence interval for the mean of a population specifies a range of values within which the true, but unknown, mean may lie. In other words, if we draw 100 different samples from a population and calculate a 95% confidence interval for each sample, then 95 of these confidence intervals will contain the true.

The width of the confidence interval gives us some idea about how uncertain we are about the unknown parameter. A very wide interval may indicate that more data should be collected before anything very definite can be said about the parameter. Confidence Limits are the lower and upper boundaries of a confidence interval, that is, the values which define the range of a confidence interval.

Confidence intervals for the failure rate (λ) and MTTF (Mean) of an Exponential distribution. When the population standard deviation (σ) is known, a 100(1-α) % confidence interval for the population mean (μ) of a Normal distribution is given by:

$$\left[\bar{x} - Z_{\propto/2}\left(\frac{\sigma}{\sqrt{n}}\right)\right] < \mu < \left[\bar{x} + Z_{\propto/2}\left(\frac{\sigma}{\sqrt{n}}\right)\right]$$

3.7. Monte-Carlo Simulation

A Monte Carlo technique is any technique making use of random numbers to solve a problem. The Monte Carlo method is defined as representing the solution of a problem as a parameter of a hypothetical population, and using a random sequence of numbers to construct a sample of thepopulation, from which statistical estimates of the parameter can be obtained. Let us express the solution of the problem as a result F, which may be a real number, a set of numbers, a yes/no decision, etc. The Monte Carlo estimate of F will be a function of, among other things, the random numbers used in the calculation. The introduction of randomness into an otherwise well-defined problem produces solutions with rather special properties which, as we shall see, are sometimes surprisingly good.

Monte Carlo simulations usually employ the application of random numbers which are uniformly distributed over the interval [0, 1]. These uniformly distributed random numbers are used for the generation of stochastic variables from various probability distributions. These stochastic variables can then be used to approximate the behavior of important system variables. In this way one can generate sampling experiments associated with the modeling of system behavior. The statistician can then apply statistical techniques to analyze the data collected on system performance and behavior over a period of time. The generation of a system variable behavior from a specified probability distribution involves the use of uniformly distributed random numbers over the interval [0, 1]. The quantity of these random numbers generated during a Monte Carlo simulation can range anywhere from hundreds to hundreds of thousands. Consequently, the computer time necessary to run a Monte Carlo simulation can take anywhere from minutes to months depending upon the both the computer system and the application being simulated. The Monte Carlo simulation produces various numerical data associated with both the system performance and the variables affecting the system behavior. These system variables which model the system behavior are referred to as model parameters. The study of the sensitivity of model parameters and their effect on system performance is a large application area of Monte Carlo simulations.

Chapter-4

Experiment Procedure and System Modelling

This chapter summarises how the experiment is performed and what are the outputs we got from the experiment. This experiment is done to estimate the remaining useful life of a cutting tool. HSS tool is used to evaluate the RUL. On the basis of this experiment a state space Markov model is generated to represent the various failure and working stages of the model. Simulation of this experiment is also done by Monte-Carlo technique.

4.1. Procedure

The experimental steps followed to collect the tool wear data for selected turning operations are described in this section. The tool was a HSS and the work piece material was MS from the workshop. The initial outer diameter of the steel work piece was 300 mm. The depth of cut was 1 mm. A single pass was defined as a single cut of length 100 mm. The spindle speed was 250 rpm/min. A tool room microscope was used to image the flank and rake surfaces within the lathe enclosure during the wear testing. The wear status of the tool was recorded after each pass and recorded as shown in table 4.1 and the calibrated digital images were used to identify the flank wear width (*FWW*). Tool life was defined as the time required for the flank wear width (*FWW*) to reach 0.5 mm**.** Figure 4.1 shows the variation of FWW with the number of passes for each test conditions.

Table 4.1: flank wear width at different number of passes

Number of passes	Flank wear width (in mm)
Initial	0.00
1	0.10
2	0.10
3	0.10
4	0.10

5	0.10
6	0.10
7	0.10
8	0.10
9	0.10
10	0.23
11	0.28
12	0.53

From SPSS software this variation between flank wear width and number of passes is plotted over a graph in which flank wear width increases with number of passes.

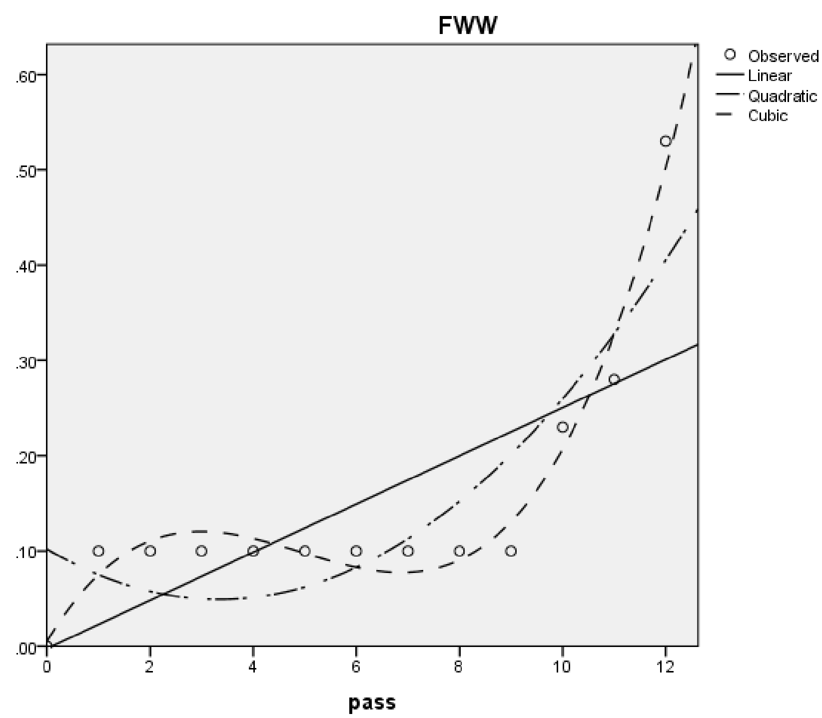

Figure 4.1: Behavior of different curve on experimental points of flank wear width at different no. of passes

From these various curves cubic curve is best fitted with these values and the equation of this curve is obtained from the output as shown in table 4.2 below:

Table 4.2: model summary and parameters estimates by SPSS

Model Summary and Parameter Estimates

Dependent Variable: FWW

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.547	13.263	1	11	.004	-.002	.025		
Quadratic	.759	15.711	2	10	.001	.102	-.032	.005	
Cubic	.968	91.336	3	9	.000	.005	.090	-.022	.001

The independent variable is pass.

Equation (i) is the cubic equation between FWW and number of passes where Y is FWW and X is number of passes in which value of Y varies by changing the value of X.

$$Y = 0.001x^3-0.022x^2+0.090x+0.005 \quad \text{(i)}$$

We can solve this eq (i) for any value of flank wear width i.e. Y and find out the roots of the equation (X) i.e. number of passes by which we can estimate the remaining useful life of the tool.

4.2. System Description

System which is used in this experiment is an open series system and reliability block diagram of this system is as shown in figure 4.2 below:

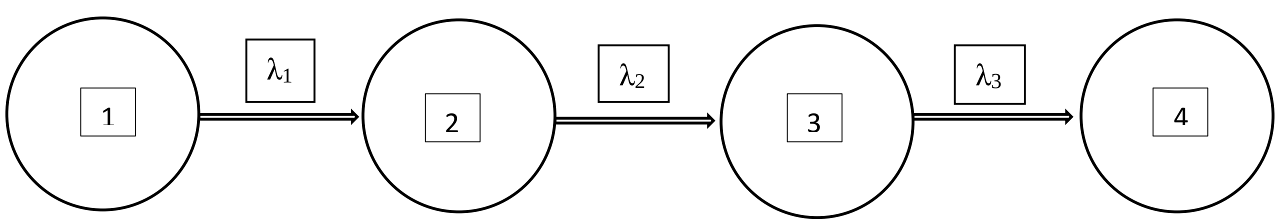

Figure 4.2: System description for Markov model of given experiment

Time taken for single pass in this experiment is 12 min and in this system we took 4 stages of system i.e. initial (1st), 6th, 10th and last (12th). Failure rate for different stages is calculated

$\lambda_1 = 0.0138$

λ_2= 0.0208

λ_3= 0.0416

And probability of each transition state of this system is as follow:

$$\frac{dy_1}{dt} = -\lambda_1 y_1 \qquad \text{(ii)}$$

$$\frac{dy_2}{dt} = -\lambda_2 y_2 + \lambda_1 y_1 \qquad \text{(iii)}$$

$$\frac{dy_3}{dt} = -\lambda_3 y_3 + \lambda_2 y_2 \qquad \text{(iv)}$$

$$\frac{dy_4}{dt} = \lambda_3 y_3 \qquad \text{(v)}$$

Solving these equations (ii) to (v) from MATLAB software by Runge-Kutta method. Solving this equation for different time span i.e. 100, 144, 150 respectively and then values of all the four stages are produced for given time span. Now results of 1st, 2nd and 3rd stages is added by adding columns of the given stages to calculate reliability using R = y(:,1)+y(:,2)+y(:,3) command in MATLAB.

These reliability results are plotted against time in MATLAB.

At time span 100 reliability is 63% as shown in figure 4.3 below.

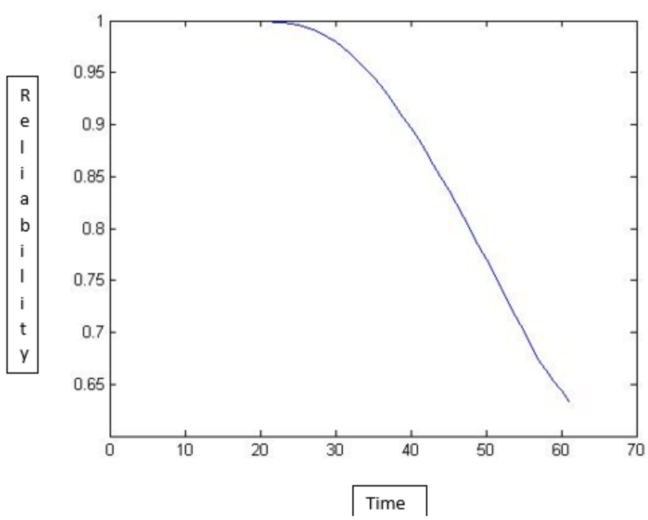

Figure 4.3: Reliability v/s time curve for Markov equation at 100 time span

At time span 144 minutes system is 41% reliable as shown in figure 4.4. (Which is tool failure time experimentally)

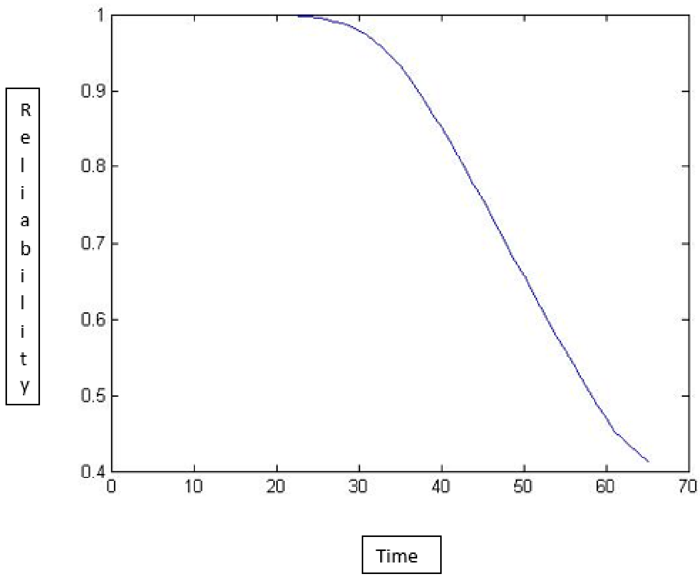

Figure 4.4: Reliability v/s time curve for Markov equation at 144 time span

Chapter-5

Results and Discussion

This chapter summarises the solutions of the equations generated from the Markov model. MTTF and its interval is calculated at different confidence level. Results are verified by simulation by Monte-Carlo technique. All the results are also discussed in this chapter.

5.1. Reliability Calculation

All the equations of probability of first three working states are integrated and added to get the value of reliability.

Integrating equation (ii) probability of 1st transition state, we get

$$\int \frac{dy_1}{dt} = \int -\lambda_1 y_1$$

$$\log y_1 = -\lambda_1 t + c_1$$

At boundary conditions t = 0 and y_1 = 0, C_1=0

$$y_1 = e^{-\lambda_1 t} \qquad \text{(vi)}$$

Integrating equation (iii) probability of 2nd transition state, we get

$$\int \frac{dy_2}{dt} = \int (-\lambda_2 y_2 + \lambda_1 y_1)$$

$$y_2 = \frac{\lambda_1}{\lambda_2 - \lambda_1} + c_2$$

At boundary conditions t=0 and y_2=0, $c_2 = -\frac{\lambda_2}{\lambda_2 - \lambda_1}$

$$y_2 = \frac{\lambda_1}{\lambda_2 - \lambda_1}(e^{-\lambda_1 t} - e^{-\lambda_2 t}) \qquad \text{(vii)}$$

Integrating equation (iv) probability of 3rd transition state, we get

$$\int \frac{dy_3}{dt} = \int (-\lambda_3 y_3 + \lambda_2 y_2)$$

$$y_3 = \frac{\lambda_1\lambda_2}{\lambda_2 - \lambda_1}\left(\frac{e^{-\lambda_1}}{\lambda_3 - \lambda_1} - \frac{e^{-\lambda_2}}{\lambda_3 - \lambda_2}\right) + e^{-\lambda_3 t}c_3$$

At boundary conditions t=0 and y_3=0, $c_3 = -\frac{\lambda_1\lambda_2}{\lambda_2-\lambda_1}(\frac{1}{\lambda_3-\lambda_1} - \frac{1}{\lambda_3-\lambda_2})$

$$y_3 = \frac{\lambda_1\lambda_2}{\lambda_2-\lambda_1}\left(\frac{e^{-\lambda_1}}{\lambda_3-\lambda_1} - \frac{e^{-\lambda_2}}{\lambda_3-\lambda_2} - (\frac{1}{\lambda_3-\lambda_1} - \frac{1}{\lambda_3-\lambda_2})e^{-\lambda_3 t}\right) \qquad \text{(viii)}$$

Reliability can be calculated by adding equation (vi), (vii) & (viii) as $R=y_1+y_2+y_3$ and values of failure rate is used as pre calculated.

λ_1 = 0.0138

λ_2= 0.0208

λ_3= 0.0416

$$R(t) = 4.446e^{-0.0138t} + 0.0496e^{-0.0416t} - 3.942e^{-0.0208t} \qquad \text{(ix)}$$

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

Some results for time at different reliability is calculated as shown in table 5.1 below:

Table 5.1: Tool running time for different Reliability value by equation developed by Markov model.

Reliability (R)	Time (t)
At 0.99	19.34
At 0.95	36.60
At 0.41	144.23 (tool failure time experimentally)

These results of reliability can be plot with time as shown in figure 5.1 below:

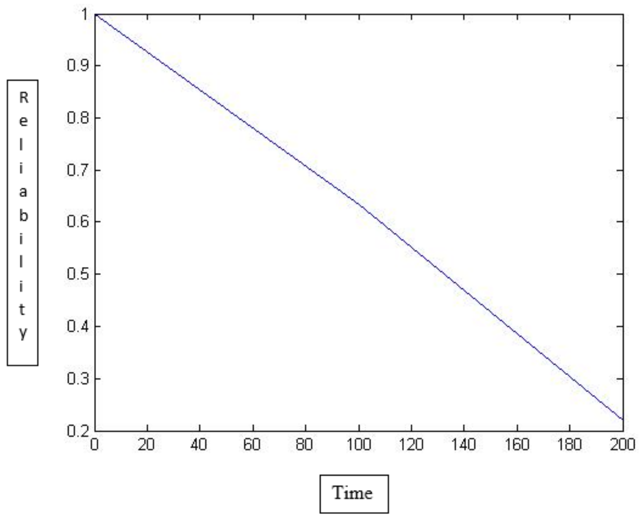

Figure 5.1: Reliability time curve of manually solved reliability equation of Markov model

5.2. MTTF calculation

The mean time to failure *(MTTF)* is defined as the expected value of the lifetime before a failure occurs. Suppose that the reliability function for a system is given by $R(t)$, the MTTF can be computed as:

$$\mathrm{MTTF} = \int_0^{\infty} t.f(t)dt = \int_0^{\infty} R(t)dt$$

Integrating equation (ix) with in the limit of 0 to ∞ we can calculate MTTF.

$\mathrm{MTTF} = \int_0^{\infty} \mathrm{R(t)dt} = \int 4.446\mathrm{e}^{-0.0138\mathrm{t}} + 0.0496\mathrm{e}^{-0.0416\mathrm{t}} - 3.942\mathrm{e}^{-0.0208\mathrm{t}}$

MTFF =144.57 (x)

Now, density function f(t) is

$\mathrm{f(t)} = -\frac{\mathrm{dR(t)}}{\mathrm{dt}}$

By equation (ix)

$$f(t) = \frac{4.446e^{-0.0138t} + 0.0496e^{-0.0416t} - 3.942e^{-0.0208t}}{dt}$$

$$f(t) = 0.0613e^{-0.0138t} + 0.021e^{-0.0416t} - 0.082e^{-0.0208t}$$

Now, $E(t^2) = \int_0^\infty t^2 f(t)dt$

$E(t^2) = 29009.15$ (xi)

Variance, $\sigma^2 = E(t^2) - (MTTF)^2$

By using equation (x) &(xi)

$\sigma^2 = (29009.15) - (144.57)^2$

$\sigma^2 = (29009.15) - (144.57)^2$

$\sigma^2 = 8108.67$

Standard deviation, $\sigma = \sqrt{8108.67}$

$\sigma = 90.05$ (xii)

Now, Confidence interval can be calculated by

$$\left[\bar{x} - Z_{\propto/2}\left(\frac{\sigma}{\sqrt{n}}\right)\right] < \mu < \left[\bar{x} + Z_{\propto/2}\left(\frac{\sigma}{\sqrt{n}}\right)\right]$$

For confidence level 95%, Z = 1.96. Taking sample size (n) = 800 and using equation (x) & (xii),

$$\left[144.57 - 1.96\left(\frac{90.048}{\sqrt{800}}\right)\right] < \mu < \left[144.57 + 1.96\left(\frac{90.048}{\sqrt{800}}\right)\right]$$

$138.32 < \mu < 150.81$ (xiii)

& for confidence level 90%, Z = 1.64. Taking sample size (n) = 800 and by equation (x) & (xii),

$$\left[144.57 - 1.64\left(\frac{90.048}{\sqrt{800}}\right)\right] < \mu < \left[144.57 + 1.64\left(\frac{90.048}{\sqrt{800}}\right)\right]$$

139.35< μ< 149.79 (xiv)

Equation (xiii) & (xiv) gives range of tool life at 95% and 90% confidence level respectively.

Now we can validate these results by Monte-Carlo simulation for mission time 145 minutes. Simulation is run over 300 trials.

And final reliability at the end of Monte-Carlo simulation produced in MATLAB is 40.33% and simulation results are shown in figure 5.2 below:

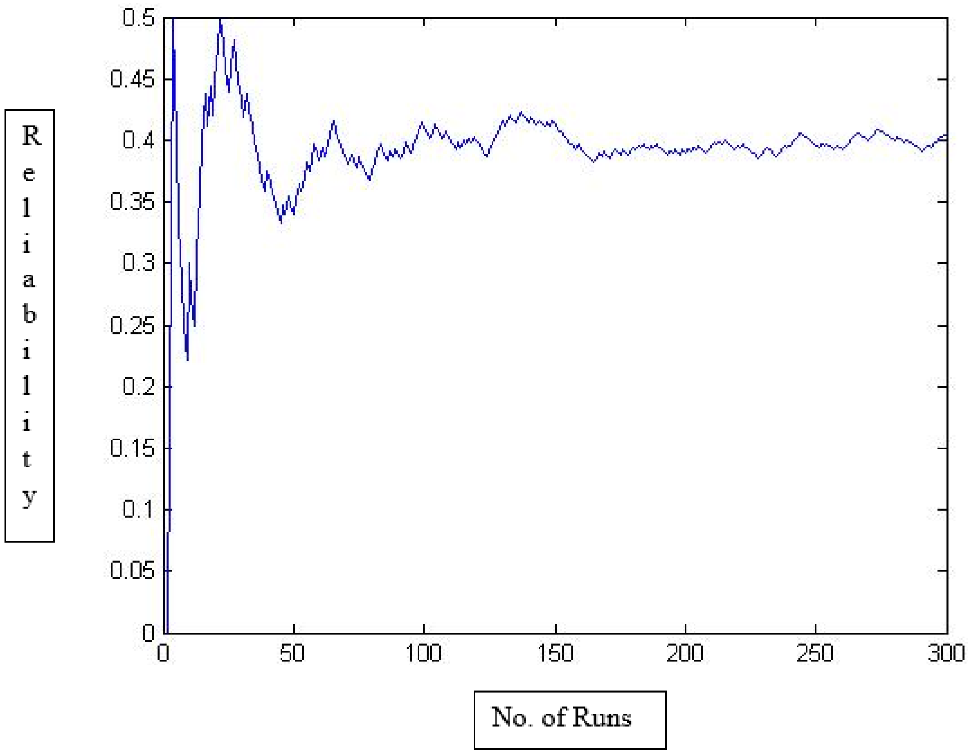

Figure 5.2: Reliability v/s no. of runs curve for Monte-Carlo simulation

5.3. Result

The results of the experiment performed above is presented in this chapter. The results obtained provide a definite indication of the trend in the availability for different maintenance policies. Remaining useful life estimation is done by statistical, stochastic, and all the results are also validated with Monte-Carlo simulation.

Experiment gives an equation by which can give remaining working time of tool at any flank wear of tool. Markov model is generated for this experiment. Equation from this estimate remaining life of tool and its reliability. Now, by calculating mean time to failure (MTTF), at different confidence level, a range of a working tool life is calculated.

The results obtained by Markov model is validated by Monte- Carlo Simulation. Markov model at the MTTF gives approx. equal reliability i.e. 40%.

Chapter 6
Conclusion and Future Scope

6.1. Conclusion

In this thesis, RUL of turning tool is predicted using two different approaches i.e. statistical trend exploration and stochastic Markov approach. For model development, the data is generated by machining mild steel work piece over a fixed length with constant feed, speed and depth of cut for number of times till the tool fails.

In statistical trend exploration approach a regression model is developed by the behaviour of the tool wear which is plotted against the number of passes. Best fit curve is obtained using SPSS software. It gives an equation by which the remaining possible number of passes at any value of flank wear can be obtained.

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 Runge-Kutta method using MATLAB software. The reliability of tool at different time span is calculated. A threshold level of reliability value 0.4 is set to determine the remaining useful life. By using reliability time equation MTTF and its interval at different confidence level is obtained. By using Monte-Carlo simulation results of reliability obtained from the Markov approach are verified.

The proposed analysis of predicting remaining tool life will help to know its failure time so that the tool can be changed before it fails. Also, after knowing the RUL, required maintenance actions can be planned.

6.2. Future Scope

This section presents a brief on potential future directions.

- Tool degradation behavior is modeled with exponential distribution so that Markov approach can be applied. But in real life the exponential distribution is not appropriate for mechanical systems. So, in real mechanical system there is a need to develop a model with non-exponential distributions such as Weibull.

- Many other parameters for tool degradation i.e. noise, vibration etc. can also be studied to get exact tool degradation behavior and estimation of RUL is much accurate than this model.
- Number of experiments can be performed to get the best behavior of the tool wear.
- For better results semi-Markov or hidden-Markov approaches can be used.

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