Preventive and Predictive Maintenance Modeling

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SUMMARY

Customer requirement revolves around the Uptime and Maintenance cost of products for off-highway equipment. Customers experience significant cost when downtime occurs. Appropriate predictive and preventive maintenance strategies are needed to achieve these customer uptime requirements. In our study we presented mathematical models that support the following objectives -

- To estimate effect of maintenance on current age of the system.
- Optimal preventive maintenance schedule to maximize Uptime and minimize maintenance cost.
- Predictive maintenance model to predict failure behavior.

1. ABSTRACT

The measure of success of innovation and customer value for off-highway equipment is through Performance, Uptime and Cost of Operation (PUC). Uptime is a part of the value proposition for all off highway equipment. Voice of customer also have indicated that availability and maintainability are of prime importance. This paper introduces concepts of availability and maintainability.

Availability, as per AIAG D-31, is the probability that the system is operational when called upon to perform its function. Availability calculations consider both Failures and Repairs (Maintenance) of a system. Maintenance is an important function for a system to keep it working without failure. Scheduling good maintenance plan will help in achieving reduction in maintenance cost and high uptime goals.

Predictive maintenance helps in decision making on the issues with an equipment in service by creating alerts to perform a required maintenance activity. This helps to reduce machine downtime during operations and any failure. Within agricultural environment there is limited time available for sowing/planting and same is the case during harvesting of crop, if a performance condition is predicted before the machine goes into field, it will improve uptime of the equipment, reduce losses to the customers as they can carry out the required activities within the required time frame. Predictive maintenance is not only limited to reduce downtime, but also has benefits to optimize overall maintenance management programs.

Various techniques or data-based models can be used to perform predictive maintenance. Some of the techniques like survival analysis where in a lifetime data can be converted into remaining useful life (RUL) or survival data. With this data, predictive maintenance can be scheduled for a specific group of population of machines.

This paper focusses on developing an optimal maintenance schedule and effect of maintenance on the current age of a system. It also talks about the various models which can be used for maintenance modeling, limitations, infrastructure, challenges faced during the journey of preventive and predictive maintenance modeling.

2. INTRODUCTION

Maintenance are the set of activities to be performed on a system to prevent it from failure or make it operational from failure. There are mainly two types of maintenance - Corrective and Proactive[1]:

- Corrective or reactive or replace after failure
- Proactive
  - Preventive or Interval based as suggested by manufacturer
  - Predictive or condition based – Service or replacement based on the current condition

Reactive maintenance refers to repairs that are performed when equipment has already broken down, to restore the equipment to its normal operating condition. This type of maintenance is preferred only when the failure consequences do not have any major safety, downtime, monetary impact.

But with the arrival of modern machines, with built-in complexity for achieving high level customer requirements such as less operational cost, less downtime, reduce unplanned maintenance, etc., an alternate to optimal replacement is preferred. Usually this is addressed by the preventive maintenance techniques.

The condition-based maintenance is a type of predictive maintenance wherein task is performed depending on the current state of the machine. Mostly, maintenance is performed

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only when certain indicators show signs of decreasing performance or upcoming failures. The machine condition can be assessed through visual inspection, test or sensor data of the machine under operation. Sometimes, these data might need to be assessed statistically (predictive maintenance) for judging the level of performance degradation. Based on these results, a maintenance action can be performed before failure.

Predictive maintenance is the science of predicting failures. Using cloud-based infrastructure or IOT, machine performance data is tracked. This data can be used for different types of analysis for proactive product or process improvement.

The challenges of maintenance process in manufacturing industries are high cost, increased downtime due to unscheduled or unplanned failures and loss of brand value making predictive analysis as a clear winner for organizations adopting it.

So, for predictive analysis models to work, the following schematic diagram will show how data is gathered, processed and analyzed to get the desired result.

Fig 1. Schematic for Predictive Maintenance

Maintenance interventions can impact current age of the system depending on the type of repair.

- Perfect repair: This restores the system into "as good as new" condition, this is known as Renewal process. Homogeneous_Poisson_Process is used to model this type of systems
- Minimal maintenance: This restores the system into "as bad as old" condition, known as non-renewal process.
- Imperfect maintenance: This restores the system in between as good as new and as bad as old condition. Generalized renewal process is used to model this type of system

Kijima[2] proposed models to estimate impact of maintenance on current age of the system using time to failure data. According to Kijima's model, system can be maintained with restoration factor varying between 0 and 1. Restoration factor of 1 is for perfect maintenance, 0 for minimal maintenance and between 0 and 1 is for imperfect maintenance.

3. MODELING APPROACHES

For our study we are using deteriorating system for derivation of optimal preventive maintenance interval[3], using imperfect repair models for knowing the impact of repair on current age of the system.

Various algorithms, base life functions, hazard functions, survival analysis and classification analysis, etc. can be used to predict failures and make decision.

3.1 Virtual Life

Real life of a system is defined as the age elapsed since the system was new whereas virtual life defines the restoration level achieved after a repair of a system. It depends on the operation time and on the number of maintenance activities performed.

First focus of this paper is to use Kijima models to estimate the effect of maintenance on current life of the system

3.1.1 Kijima Models

Let a repairable system with successive time to failure t_1, t_2… and time between failures denoted by x_1,x_2…x_n.

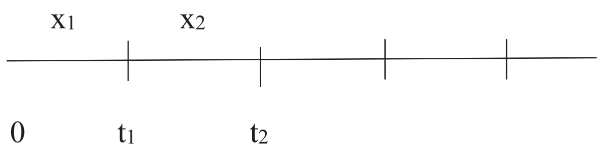

Fig 2. Time to Failure for repairable systems

Thus,

$x_i = t_i - t_{i-1}$ time between failures

If the system virtual life V_{n-1} = y after (n-1)th failure. Then according to conditional probability nth failure time x_n, have the distribution function [4]

$$\Pr(x_n < x | V_{n-1} = y) = \frac{F(x+y) - F(y)}{1 - F(y)} \qquad (1)$$

where *F(x)* is the distribution function of time to failure of the system.

Actual age of the system:

$$x_n = \sum_{i=1}^{n} x_i \qquad (2)$$

Let *q* be the degree of n^{th} repair and *q* varies between 0 and 1

A. Model 1

According to this model, nth repair cannot eliminate the damage incurred before $(n-1)^{th}$ repair. Virtual life of the system becomes

$$V_n = V_{n-1} + q x_n \qquad (3)$$

B. Model 2

According to this, n^{th} maintenance can remove all the damage accumulated up to n^{th} failure, the virtual life after nth repairs becomes

$$V_n = q(V_{n-1} + x_n) \qquad (4)$$

3.2 Optimal Preventive Maintenance

Second focus of this paper is to develop an optimal preventive maintenance schedule for a deteriorating repairable system.

NHPP models in reliability engineering are successfully used for modelling repairable system[5]. These models describe the reliability growth and deterioration. The cumulated number of failures *N(t)* for a given time *t*, for a NHPP process can be given as

$$P(N(t) = n) = \frac{(\rho(t))^{n} * e^{-(\rho(t))}}{n!} \quad (5)$$

The following are the assumption for NHPP

N(0) = 0{N(t), t≥0} failure for t>0 has independent increments

$$P\{N(t + \Delta t) - N(t) = 1\} = \int_{t}^{t+\Delta t} \rho(t)dt$$

$$P\{N(t + \Delta t) - N(t) \geq 2\} = 0$$

The instantaneous failure rate for NHPP is given by *u(t)*

$$u(t) = \lambda\beta t^{\beta-1} \quad (6)$$

$$\rho(t) = E(N(t)) = \int_{0}^{t} u(t)dt = \lambda t^{\beta} \quad (7)$$

ρ(t) - mean value function

u(t) - failure intensity

E(N(t)) – expected number of failures

3.2.1 Maintenance Cost

Cost is an important factor of a system to keep customer satisfied. Maintenance cost includes repair/replacement cost, labor wages, inspection cost, and other costs related to administrations. A balance is required between maintenance cost and customer satisfaction. Thus, we modelled an Optimal preventive maintenance schedule to minimize maintenance cost per unit time.

Fig 3. Optimal Replacement Interval

Assuming first failure has Weibull distribution

$$u(t) = \left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta-1} \quad (8)$$

$$E(N(t)) = \int_{0}^{t} u(t)dt \quad (9)$$

η – Scale Parameter and β – Shape Parameter

A. Total cost per unit time (*C*)

Total cost is the sum of maintenance cost and failure cost.

$$Total\ cost = Maintenance\ cost + Failure\ cost$$

Total cost per unit time is

$$C = \frac{C_{pm} + C_{pl} + E(N(t)) * (C_{cm} + C_{cl})}{t + T} \quad (10)$$

C_{pm} - Cost of Preventive maintenance

C_{pl} - Labor cost for preventive maintenance

C_{cm} - Cost of corrective maintenance

C_{cl} - Labor cost for corrective maintenance

t - Operating time of a system

T - Time taken for maintenance action

Optimal time for maintenance to minimize cost can be obtained by differentiating *C* with respect to *t* and equating to zero.

$$\frac{dC}{dt} = 0 \quad (11)$$

B. Availability (Uptime)

Second important factor is uptime of the machine.

$$Availability = \frac{Time\ Available}{Time\ Avilable + Time\ Not\ Available} \quad (12)$$

$$Achieved\ Availability(A) = \frac{t - (E(N(t)) * t_{co})}{t + T} \quad (13)$$

where t_{co} is time required for corrective maintenance action.

Optimal time for maintenance to maximize uptime can be obtained by differentiating *A* with respect to *t* and equating to zero.

$$\frac{dA}{dt} = 0 \quad (14)$$

3.3 Classification Model

Classification models are used for more complex datasets where relationships are nonlinear. These models have the ability of identifying the significant parameters for the given output based on past data and then using those significant parameters to predict the failures in future. Logistic regression is a statistical model which has been used in our analysis[6].

Logistic Regression: This is a statistical model that in its basic form uses a logistic function to model a binary dependent variable[7]. In regression analysis, logistic regression is estimating the parameters of a logistic model (a form of binary regression). It is denoted as:

$$logit(p) = ln\frac{p}{1-p} \text{ for } 0 < p < 1 \quad (15)$$

$$p = \frac{e^{(a+bx)}}{1+e^{(a+bx)}} \quad (16)$$

where,

p = probability of event happening and

x = the set of independent parameters

a = intercept

b = parameter estimate

3.4 Cox Regression Model:

RUL is the remaining useful life of a component/system. Predicting RUL from system data is a central goal of predictive maintenance algorithms. RUL can be tracked against an assigned goal. When RUL is at x% (comparing it with a predetermined goal), then using machine learning, downtime can be reduced. RUL of a machine is the expected life or usage time remaining before the machine requires repair or replacement.

Let $X_i = \{X_{i1}, \ldots X_{ip}\}$ be the realized values of the covariates for subject i. The hazard function for the Cox proportional hazards model has the form[8]

$$\lambda(t|X_i) = \lambda_0(t)\exp(\alpha_1 X_{i1} + \cdots + \alpha_p X_{ip}) \quad (17)$$

$$\lambda(t|X_i) = \lambda_0(t)\exp(X_i.\alpha) \quad (18)$$

This expression gives the hazard function at time t for subject *i* with covariate vector (explanatory variables) X_i.

$$\lambda(t|X_i) = \lambda_0(t)\exp(\alpha_1 X_{i1} + \cdots + \alpha_p X_{ip})$$

$$\lambda(t|X_i) = \lambda_0(t)\exp(X_i.\alpha) \quad (19)$$

The likelihood of the event to be observed occurring with subject i at time Y_i can be written as:

$$L_i(\alpha) = \frac{\lambda(Y_i|X_i)}{\sum_{j:Y_j \geq Y_i} \lambda(Y_i|X_j)} = \frac{\lambda_0(Y_i)\sigma_i}{\sum_{j:Y_j \geq Y_i} \lambda_0(Y_i|\sigma_j)} = \frac{\sigma_i}{\sum_{j:Y_j \geq Y_i} \sigma_j} \quad (20)$$

3.5 Time Series Model

Time series models[9] forecast future failures. Modeling the dynamic path of a variable can improve forecasts since the predictable component of the series can be projected into the future. There are various models which fall into this, but mostly autoregressive models and moving average models are common.

Autoregressive models of order p are denoted as

$$X_t = c + \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t \quad (21)$$

where $\varphi_1, \ldots, \varphi_p$ are parameters of model ε_t is white noise and c is constant.

Moving Average model of order q is denoted as –

$$X_t = \mu + \left(1 + \theta_1 B^1 + \cdots + \theta_q B^q\right)\varepsilon_t \quad (22)$$

where μ is the mean of the series, the $\theta_1, \ldots, \theta_q$ are the parameters of the model and the $\varepsilon_t, \varepsilon_{t-1}, \ldots, \varepsilon_{t-q}$ are white noise error terms.

4. CHALLENGES

There are many challenges with the implementation and analysis of predictive maintenance. They are mainly as follows:

- Data limitation with number of failures: The data should consist of many failures, but mostly like in practical cases, the number of failures are less. This makes the data skewed. Also, the collection of data should be holistic, but it's often a limitation. Partial information leads to a non-precise prediction.
- Understanding of business tolerance: Usually the nature of business has a tolerance for acceptance of false negatives. For example, a false prediction of aircraft engine can lead to huge downtime, but its required than a catastrophic failure. Thus, actual money which can be incurred for false prediction, should determine if the model needs to be tuned for high precision or high recall.
- Data collection infrastructure: This often becomes challenging due to the number of sensors required, technologies like cloud, etc. Sometimes for some business, it becomes expensive. Also, privacy issues come in picture which need to be catered in.

5. ILLUSTRATIONS

5.1 Case Study I

We did a study on part "X" of a machine. This part has high number of claims and warranty cost. We collected time to failure data and performed life data analysis to understand failure behavior of the part. We have observed shape parameter (β) as 1.5 which indicates wear out phase.

$$\beta = 1.54$$
$$\eta = 984$$

Instantaneous failure rate for the NHPP is given by

$$u(t) = \lambda\beta t^{\beta-1}$$

Assuming first failure follows Weibull distribution following approach was followed for arriving at instantaneous failure rate, expected number of failures, total maintenance cost and uptime of the system -

$$u(t) = \left(\frac{\beta}{\eta}\right)\left(\frac{t}{\eta}\right)^{\beta-1}$$

$$u(t) = \left(\frac{1.54}{984}\right)\left(\frac{t}{984}\right)^{1.54-1}$$

$$E\big(N(t)\big) = \int_0^t u(t)dt$$

$$Total\ cost = Maintenance\ cost + Failure\ cost$$

Total cost per unit time (C)

$$C = \frac{C_{pm} + C_{pl} + E\big(N(t)\big) * (C_{cm} + C_{cl})}{t + T}$$

C_{pm}	\$100
C_{pl}	\$20
C_{cm}	\$157
C_{cl}	\$441
T	1.5 Hours

$$C = \frac{100 + 20 + E\big(N(t)\big) * (157 + 441)}{t + 1}$$

$$\frac{dC}{dt} = \frac{d\left(\frac{100 + 20 + E(N(t)) * (157 + 441)}{t + 1}\right)}{dt} = 0$$

Availability of the system, A:

$$A = \frac{t - E\big(N(t)\big) * t_{co}}{t + T}$$

$$A = \frac{t - E\big(N(t)\big) * 5}{t + 1}$$

$$\frac{dA}{dt} = \frac{d\left(\frac{t - E(N(t)) * 5}{t + 1}\right)}{dt} = 0$$

Below plot shows variation in maintenance cost and total uptime with varying operational time

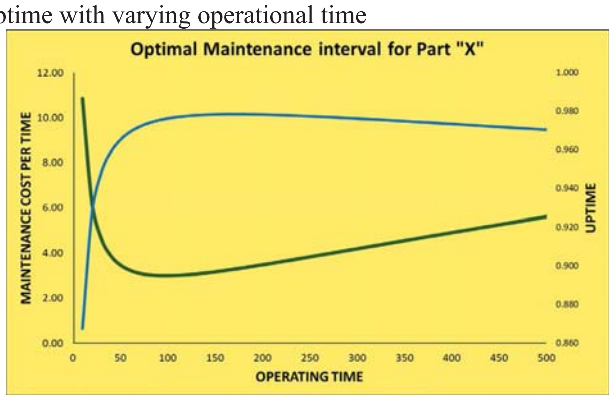

Fig 4. Optimal Replacement Interval (Part X)

5.2 *Case* study

During warranty analysis it was observed that, some analysis can be performed on the cost of recall which is a special type of warranty. The cost could be optimized based upon study by identifying serial numbers prone to failure.

To demonstrate predictive maintenance study, a case study was performed on sample data set where in real time data (telematics data) of engine parameters x_1, x_2, x_3 and x_4 were monitored on engines in an agricultural environment. The output of the model required to have a probability of failure and non-failure. Hence, the best option was to use logistic regression maintenance model. Using the equation below, the estimates and intercepts were calculated.

$$p = \frac{e^{(a+b_1x_1+b_2x_2+b_3x_3+b_4x_4)}}{1+e^{(a+b_1x_1+b_2x_2+b_3x_3+b_4x_4)}}$$

where p is the probability of non-failure. Thus, (1-p) is the probability of failure.

All machines were calculated for a probability of failure. The cut-off of probability is taken as 8%, above which the cases were marked as failure data. Actual data on failure versus predicted output was compared using confusion matrix. The confusion matrix below gives the accuracy of the model.

Act\Pred	F (Predicted)	NF (Predicted)
F (Actual)	73	23
NF (Actual)	168	772

Table 1. Failure Prediction Accuracy

$$Accuracy = \frac{True\ positive + False\ negative}{Total\ number\ of\ Cases}$$

$$Accuracy = \frac{73+772}{73+23+168+772} = 0.82 = 82\%$$

5.3 Steps further:

After the model is developed, here are few steps which need to be completed:

- Apply machine learning techniques for the model to determine a probability of failure
- Generate real time machine monitoring and identify high probabilities of failure.

6. CONCLUSION

Within agricultural, construction & forestry equipment environment, preventive and predictive maintenance models can be adopted to improve uptime and the owning and operating cost of machine for customer. The good accuracy of these models was demonstrated with the help of two case studies.

The optimal preventive maintenance policy is been carried out at part level to determine maintenance interval. This will enhance availability, identify failures proactively and reduce maintenance cost.

Predictive maintenance with the advent of machine learning, is used to identify failures based on past failure trends. Predictive modeling improves the life of the system by performing condition-based maintenance activities.

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