An Expert Based Methodology for Cost Oriented Analysis of Machine Tool Reliability

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Abstract: This paper proposes an improved methodology for machine tool reliability analysis. The overall objective of the proposed methodology is to provide the machine tool manufacturers with the approach that will help them in making cost driven decisions while improving the performance of their machines in the field. The methodology consists of three parts viz., modified fault tree diagram, simulation based data analysis and cost based Failure Modes and Effects Analysis (FMEA). Modified fault tree diagram found useful in providing better insight into the failures and their impact. The simulation based approach helps in obtaining time to failure distribution parameters for each failure events using expert’s judgements. The effect of uncertainty in the experts’ judgements is also quantified in terms of 90 per cent confidence interval values of the parameters. Finally, the cost based FMEA proposed in this paper will help the manufacturer in identifying the critical failure events based on actual cost of failures to the users. The methodology is illustrated with the help of an example of a CNC grinding machine.

Keywords: Failure modes and effects analysis (FMEA), fault tree diagram, reliability, machine tools, quality

1. Introduction

Society of Automotive Engineers (SAE) [1] defines the reliability of machinery and equipment as the probability of failure free operation under the mutually agreed operational and environmental conditions between the users and manufacturers for a specified period of time. Failure of machine tools not only includes complete downing of machine but also includes any event due to which the machine is not capable of producing parts at specified speed and/or quality level.

A component may fail due to more than one cause (end events) and a single failure cause may be responsible for failure in more than one component. Some of them may require minor adjustment or setting like alignment, tightening, etc., while others may require complete replacement of the component. Further, in case of machine tools, the effects of failure is generally in terms of downtime cost, lost production cost, lost quality cost, or repair/replacement cost. These costs of failure along with the failure rates help in determining the optimal preventive maintenance interval. Thus, for the same component, preventive maintenance requirements in terms of maintenance interval, type of maintenance (repair, replacement, oiling & greasing, etc.) and maintenance resources, may be different for each failure event.
A top-down, deductive analysis structured in terms of events rather than components is thus required for reliability analysis of any machine tools. A fault tree analysis is generally used for this purpose. However, conventionally the fault tree analyses do not provide any framework to quantify the end effect of the failure in terms of the cost. Also the quantitative evaluation of the fault tree requires a sound data collection system. The main source of information about the functioning of the equipments is the Technical Assistance Service (TAS) reports. However, this service is often requested during the warranty period and only in cases where the problems cannot be solved by the users. As a result, the manufacturers do not have complete machine functioning data corresponding to its use phase. They only know the warranty period incidents and that too only partially [2]. Performance evaluation from such data may differ from the actual performance of the machine [3]. In such situations any design decision based on such data may not necessarily be effective. Situation becomes more critical in the case of small or medium scale enterprises that, very often, cannot provide machine or facility focused data. However, the experience and knowledge of the employees’ may serve the designer as an alternative data source. Reference [4] presented a methodology to convert the verbal expressions of the maintenance employees into time to failure distribution parameters. However, the experts’ judgements are always probabilistic in nature and thus more work is required to include the uncertainty in the experts’ judgments while estimating failure distribution parameters.

The effects of failure can generally be described purely in economic terms [5]. However, the conventional risk based Failure Modes and Effects Analysis (FMEA) used to prioritize the improvement efforts generally do not provide any quantitative measure in terms of actual cost that may be incurred due to the failure of the machine tool and therefore may not prove to be effective in making cost-driven decisions in many cases. Few cost based FMEA models (for example, Reference [6], [7], and [8]) have also been proposed in the literature to address this problem. However, these models mainly consider the cost of material (components) and labour while the failure of machine tools may cost much more to the users in terms of breakdowns, rejections, rework, and slower production, which is not adequately modelled in the literature.

Following from the above discussion, it seems relevant to address three issues in reliability analysis of the machine tools. These issues are:

1. Representation of machine tool failure process in terms of end events and their impacts.
2. Obtaining failure distribution parameters using probabilistic judgements of the experts’.
3. Mechanism to quantify the failure effects in terms of the cost of failure to users.

In present paper, first a fault tree diagram based framework is presented that can be used to quantify the economic effects of each end events. Expert’s judgement based Monte Carlo simulation approach is then developed to obtain time to failure distribution parameters along with their confidence intervals. The use of such confidence interval in further decision making is also highlighted. Finally, a failure cost-based FMEA is introduced to delineate and evaluate risk of failure more accurately. This eliminates the aforementioned shortcomings of traditional FMEA in the context of machine tools. The proposed approach is illustrated using an example of CNC grinding machine.
Notation

\[ X \]: Most fail life (in years)
\[ Y \]: Maximum life (in years)
\[ FC_{sd} \]: Cost of failure due to system down (in Indian Rupee (Rs.))
\[ FC_{rs} \]: Cost of failure due to reduced speed (in Rs.)
\[ FC_{rq} \]: Cost of failure due to reduced quality (in Rs.)
\[ MTTR \]: Mean time to restore (in hour)
\[ MTBF \]: Mean time between failures (in hour)
\[ PR \]: Average production rate (jobs/hour)
\[ C_{lp} \]: Cost of lost production (in Rs./job)
\[ LC \]: Maintenance labour cost (in Rs./hour)
\[ C_{rej} \]: Cost of rejection (Rs./job)
\[ C_{rep} \]: Repair or replacement cost per failure (in Rs.)
\[ RPR \]: Reduction in production rate (in fraction of \( PR \))
\[ TD_{rrp} \]: Time to detect the reduction in production rate (in hour)
\[ B \]: Type II error of control chart
\[ S \]: Shift in process mean
\[ \sigma_p \]: Process standard deviation
\[ \sigma_{\eta} \]: Process standard deviation
\[ t_s \]: Time between two samples (in hour)
\[ n \]: Sample size
\[ \phi(.) \]: Standard normal cumulative distribution function
\[ EAC \]: Expected annual cost of failure (in Rs.)
\[ N_f \]: Number of failure due to particular failure cause
\[ p_{sd} \]: Probability that a failure cause will bring the system completely down
\[ p_{rs} \]: Probability that a failure cause will reduce the machine speed
\[ p_{rq} \]: Probability that a failure cause will produce more rejection

2. System Description and Fault Tree Diagram Based Framework

The system considered here is a CNC grinding machine used for high precision external grinding operation. However the study presented here is generic in nature and can be applied to any machine tool. The machine has following subsystems:

- Tailstock;
- Work head;
- Wheel head;
- Table (Z-axis);
- Dressing module;
- Carriage (X-axis);
- Coolant unit;
- In Process Gauge (IPG);
- Wheel head;
- Coolant unit;
- In Process Gauge (IPG);

Failure of machine tools is realized by users as one of the following events:
- Machine completely down;
- Machine not producing parts at specified speed;
- Machine producing more rejection;
- Machine producing excessive noise/heat;

The failure is then assigned to one or more of the subassemblies in the system. Failures in each of these subassemblies are further allocated to lower level components and finally to
failure causes. A fault tree is generally used for this purpose [9]. It is prepared based on the field failure records; however in the present work, the fault tree is prepared based on the knowledge of the maintenance engineers from the manufacturer who attend the field complaints. Such information is also obtained from different users using the same machine under same environmental conditions. Thus, it ensures that most of the failures that affect the production capability of the users are included and at the same time removes unnecessary complexity arising from including comparatively insignificant failure events.

A detailed fault tree diagram for the tailstock is shown in figure 1, which is a part of the complete system fault tree diagram of CNC machine considered here. Figure 1 also provides a generalized framework for quantifying the economic effects of the end events by mapping them again to the failure effects with their corresponding probabilities shown on the connecting arrows. The same along with the time to failure distribution of each end events are used in failure cost based FMEA presented in section 4 of this paper.

3. **Weibull Time to Failure Distribution Parameter Estimation**

The failure behavior of a majority of the mechanical systems or components can be modeled by two parameter Weibull distribution, with the probability density function as:

\[
f(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}}, \beta, \eta, t \geq 0
\]

where, \( \eta \) and \( \beta \) are the scale and shape parameters respectively of the Weibull distribution.

The mode of the Weibull time to failure distribution is the value of \( t \) at which the probability of occurrence is maximum. It can be obtained by differentiating (1) with respect to \( t \) and equating the same to zero. It gives:

\[
mod = X = (\frac{\beta-1}{\beta})^{1/\beta} \times \eta
\]

The equation of failure probability for Weibull distribution can be written as:

\[
F(t) = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}}
\]

If the sample size is very large then the probability of survival corresponding to the maximum life will be negligible. In other words the value of \( F(t) \) will be very large. Assigning a very large value to \( F(t) \) (say for example 0.99 here) at maximum life, (3) becomes;

\[
0.01 = e^{-Y/\eta^{\beta}}
\]

Maintenance personnel or the service engineers from the manufacturer who have experience of many years can be expected to have information regarding the failures of a critical component of many years. Their knowledge, if elicited properly, can provide useful information that can be used to determine the time to failure distribution parameters. Experts are first asked about the time when the components mostly fail, which in this case becomes \( X \). Experts are also asked about any incidence when he/she witnessed the longest failure-free operation of the component. The longest failure-free time then becomes the \( Y \). Once the value of \( X \) and \( Y \) are known, the corresponding value to \( \eta \) and \( \beta \) can be obtained using (2) and (4). Longer the experience of an expert larger will be the sample size (total number of replacement/repair observed by an expert) and more accurate will be the assumption of assigning a large value to \( F(t) \) at a life of \( X \). Reference [4] has shown that the sample size does not have significant impact on the
resulting distribution parameters thus justifying the assumption made here. However, in most of the cases the experts fail to give a single value for \( X \) and \( Y \). In such situations an optimistic, pessimistic and a most likely estimate can always be obtained from the experts for these values. Such estimates can also be collected from different users using the same machine under similar environmental conditions and judgments from all the experts can again be divided into three categories as optimistic, pessimistic and most likely.

**Figure 1:** Fault Tree Diagram Based Framework
A beta distribution thus seems to be most appropriate in modeling the experts’ judgments. Using such judgments, a Monte Carlo simulation based approach can be build to obtain parameters for Weibull distribution. Figure 2 shows how the approach works.

![Figure 2: Monte Carlo Simulation Model for Estimating Time to Distribution Parameters](image)

Using the Monte Carlo simulation, a confidence interval for each parameter can also be obtained as shown in Table 1.

### Table 1: Time to Failure Distribution Parameters for Failure Causes of Tailstock Subassembly

<table>
<thead>
<tr>
<th>Component</th>
<th>End cause</th>
<th>( \eta )</th>
<th>( \beta )</th>
<th>Width</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>90% confidence interval</th>
<th>( \mu )</th>
<th>( \sigma )</th>
<th>90% confidence interval</th>
</tr>
</thead>
<tbody>
<tr>
<td>Center</td>
<td>Wear due to usage (C1)</td>
<td>2.41</td>
<td>0.44</td>
<td>3.79</td>
<td>1.02</td>
<td>2.83</td>
<td>0.41</td>
<td>4.12</td>
<td>1.53</td>
<td></td>
</tr>
<tr>
<td>Micro taper</td>
<td>Wear due to usage (C2)</td>
<td>0.84</td>
<td>0.08</td>
<td>1.11</td>
<td>0.58</td>
<td>1.50</td>
<td>0.07</td>
<td>1.74</td>
<td>1.27</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Dust entry (C3)</td>
<td>0.41</td>
<td>0.06</td>
<td>0.60</td>
<td>0.22</td>
<td>1.61</td>
<td>0.27</td>
<td>2.47</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>Linear bearing</td>
<td>Wear due to usage C4)</td>
<td>0.98</td>
<td>0.08</td>
<td>1.22</td>
<td>0.74</td>
<td>1.94</td>
<td>0.16</td>
<td>2.45</td>
<td>1.44</td>
<td></td>
</tr>
<tr>
<td>Bush</td>
<td>Wear due to usage (C5)</td>
<td>0.45</td>
<td>0.09</td>
<td>0.75</td>
<td>0.15</td>
<td>2.30</td>
<td>0.50</td>
<td>3.89</td>
<td>0.71</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Seal 1 failure (C6)</td>
<td>1.05</td>
<td>0.10</td>
<td>1.38</td>
<td>0.72</td>
<td>1.82</td>
<td>0.19</td>
<td>2.42</td>
<td>1.22</td>
<td></td>
</tr>
<tr>
<td>Rack and Pinion</td>
<td>Wear due to usage (C7)</td>
<td>1.82</td>
<td>0.09</td>
<td>2.09</td>
<td>1.55</td>
<td>2.34</td>
<td>0.19</td>
<td>2.94</td>
<td>1.73</td>
<td></td>
</tr>
<tr>
<td>Compression spring</td>
<td>Wear due to usage (C8)</td>
<td>3.14</td>
<td>0.26</td>
<td>3.95</td>
<td>2.33</td>
<td>2.41</td>
<td>0.33</td>
<td>3.47</td>
<td>1.36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Improper setting (C9)</td>
<td>1.40</td>
<td>0.25</td>
<td>2.20</td>
<td>0.60</td>
<td>2.79</td>
<td>0.80</td>
<td>5.34</td>
<td>0.25</td>
<td></td>
</tr>
<tr>
<td>Hydraulic components</td>
<td>Choking of pipe lines (C10)</td>
<td>1.17</td>
<td>0.06</td>
<td>1.36</td>
<td>0.97</td>
<td>2.49</td>
<td>0.21</td>
<td>3.17</td>
<td>1.82</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Choking of relief valves (C11)</td>
<td>1.11</td>
<td>0.10</td>
<td>1.43</td>
<td>0.78</td>
<td>1.86</td>
<td>0.16</td>
<td>2.36</td>
<td>1.35</td>
<td></td>
</tr>
<tr>
<td>Sleeve</td>
<td>Wear due to usage (C12)</td>
<td>1.98</td>
<td>0.23</td>
<td>2.70</td>
<td>1.25</td>
<td>2.27</td>
<td>0.38</td>
<td>3.46</td>
<td>1.07</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Seal 2 failure (C13)</td>
<td>1.46</td>
<td>0.13</td>
<td>1.88</td>
<td>1.04</td>
<td>2.25</td>
<td>0.45</td>
<td>3.69</td>
<td>0.82</td>
<td></td>
</tr>
</tbody>
</table>

**Implication of Confidence Interval**

While mean values of the parameters can be used in further system reliability analysis, confidence interval obtained here can be used to quantify the risk due to uncertainty in experts’ judgment. In cases where cost of failure is significantly higher than cost of preventive maintenance, one may use lower limit value of \( \eta \) for calculating the preventive maintenance interval. Using lower limit of \( \eta \) for calculating optimal preventive maintenance interval will result in an optimal preventive maintenance interval that is comparatively smaller, thereby reducing any risk of failure. Preventive maintenance should be considered for only those components that have \( \beta > 1 \). If the
expert judgment results in to a confidence interval for $\beta$ such that it contains the value 1, it is not a clear mandate in favour of preventive maintenance.

**Some Desirable Properties of a “Good” Estimator**

Convergence and unbiasedness are some of the properties one may look for in a good estimator. If, for a given sample size, the mean value of an estimator equals the true value of the quantity it estimates, then the estimator is called an *unbiased* estimator. Thus, for a given sample size, the difference between the true value and the mean value of an estimator is the bias in the estimation [10]. The ability of an estimator of a parameter $\theta$ to produce estimates that get closer to the true value $\theta_0$ with larger sample sizes is called convergence or consistency of the estimation [10]. Convergence is thus an asymptotic property. Both ‘bias’ and ‘convergence’ are related to the sample size used for estimation, which is not available in case of the expert elicitation based parameter estimation method used in this paper. However, the experience of an expert can be considered equivalent to the sample size. In general it can be assumed that longer the experience, larger will be the sample size being considered by the expert at the time of answering the questions posed on him and in turn lower will be the bias in their judgments. However, apart from years of experience, the ‘bias’ and ‘convergence’ properties of the estimation also depends on psychological aspects. Higher the involvement of the experts with the failure of machine component, lower will be the variability in their judgment and more accurate will be the estimation.

**Robustness of the Expert Judgment based Method**

Accuracy of the expert judgement based method, proposed in this paper, depends on the accuracy of the information obtained from the expert. However, it is highly unlikely that the expert judgement will be totally free from error. On the other hand, the accuracy of all the statistical methods for parameter estimation depends on the amount of data. More the number of data points, higher will be the accuracy in the parameter estimation. In many cases, decision makers are quite often left with only a few data points. In such situations it will be interesting to see how the expert judgement based method for a given level of error in judgement (poor expert judgement) compares with statistical methods for a given number of available data points.

Consider a non-repairable component used in a machine tool, whose time to failure follows a two parameter Weibull distribution with shape and scale parameters as 2 and 200 respectively. The values of mode and maximum life, as obtained from equations 2 and 4, will be 141 and 429 respectively. Assuming that the experts judge the most-fail time ($X$) and maximum life ($Y$) with an error of $\pm$ 15%, judgment for this component can be summarized in terms of upper and lower limits as follows.

- **Time at which most of the components are likely to fail**
  
  \[
  X_{L} = 141 - 0.15 \times (141) = 120 \quad \text{and} \quad X_{U} = 141 + 0.15 \times (141) = 162
  \]
  
  - **Maximum life ever observed by the expert**
    
    \[
    Y_{L} = 429 - 0.15 \times (429) = 365 \quad \text{and} \quad Y_{U} = 429 + 0.15 \times (429) = 493
    \]

  Thus total four combinations are possible with these estimates. Table 2 shows the values of distribution parameters for these four combinations.

  For the same component, the Maximum Likelihood Estimates (MLE) of the life time distribution parameters [11] are also obtained when only few data points are available in field failure record. Let us consider only 10 data points are available. 10 data points are
generated randomly 1000 times and MLE estimates are obtained each time. Table 3 shows these estimates for 10 data points with 90% confidence level.

Table 2: Parameter Estimation When Expert Judgment Contains Error

<table>
<thead>
<tr>
<th>X</th>
<th>Y</th>
<th>Estimates of η</th>
<th>Estimates of β</th>
</tr>
</thead>
<tbody>
<tr>
<td>162</td>
<td>493</td>
<td>229</td>
<td>1.99</td>
</tr>
<tr>
<td>162</td>
<td>365</td>
<td>198</td>
<td>2.5</td>
</tr>
<tr>
<td>120</td>
<td>365</td>
<td>169</td>
<td>1.99</td>
</tr>
<tr>
<td>120</td>
<td>493</td>
<td>201</td>
<td>1.7</td>
</tr>
</tbody>
</table>

Table 3: Parameter Estimation From Maximum Likelihood Method with 10 data points

<table>
<thead>
<tr>
<th>Distribution parameters</th>
<th>Mean</th>
<th>Standard deviation</th>
<th>Lower 90% bound</th>
<th>Upper 90% bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>η</td>
<td>199</td>
<td>32.69</td>
<td>145.5</td>
<td>253</td>
</tr>
<tr>
<td>β</td>
<td>2.38</td>
<td>0.81</td>
<td>1.49</td>
<td>3.75</td>
</tr>
</tbody>
</table>

It can be seen from Table 2 and 3 that for ±15 per cent error in the expert judgment, the accuracy in the parameter estimation is well within the range obtained through MLE method when only 10 data points are available. Thus, the robustness of the method based on expert judgment can be considered satisfactory in situation where there is absence or scarcity of data points. The assumption, of course is that the experts are able to provide the information with reasonable accuracy.

4. Cost based FMEA

Failure Modes and Effects Analysis (FMEA) is a methodology for identifying potential reliability problems early in the product development cycle, where it is easier to take actions to overcome these issues, thereby enhancing reliability through design [9]. Most of FMEA studies rely on the Risk Priority Number (RPN) for identifying high risks and corresponding preventive measures to be taken. At best, RPN provides a qualitative assessment of risk in terms of occurrence, severity and detection whereas the effect of machine tools is generally in economic terms. However, the RPN number does not carry any special meaning, as it does not provide any quantitative measure of actual cost that may be incurred due to the failure.

In the present approach, Expected Annual Cost (EAC) of failure is used to identify the critical failure causes. EAC is the multiplication of the expected numbers of the failure per year and the cost per failure. Cost per failure includes down time cost, reduced speed cost, reduced quality cost and repair/replacement cost. Thus the proposed cost based failure modes and effects analysis approach is a modification of the conventional approach and helps the manufacturer in making cost driven decision while improving the performance of their machine in the field.

Expected Annual Cost Model

As mentioned in section 2, the effects of machine tools failure can be classified as:
- Machine completely down
- Machine not working at specified speed
- Machine producing more rejections
- Machine making excessive noise/heat

Failure effects 1 and 4 are detected immediately as soon as they occur. The cost of failure effect 1 or 4 i.e. system down, will include the cost of lost production for the duration of
repair, the labour cost and repair/replacement cost. Mathematically, this can be expressed as:

$$FC_{ad} = MTTR \times (PR \times C_{ip} + LC) + C_{rep}$$  \hspace{1cm} (5)$$

In case of replacement, $C_{rep}$ will be the cost of the machine component replaced. While failure effects 1 and 4 are observed immediately, effects 2 and 3 are observed with a time lag, during which machine operates at a comparatively degraded performance level. However, it is assumed that as soon as these failure effects are observed, the machine is stopped immediately till repair. The cost of failure effect 2 and 3, in addition to $FC_{ad}$, will include cost consequences during the time lag after which the failure effect is observed. More specifically, the cost of failure effect 2, i.e. machine not working at specified speed, will be the sum of $FC_{ad}$ and the cost of lost production for the time lag for which the machine operates at reduced speed before the same is observed by the users. Mathematically,

$$FC_{rs} = PR \times RPR \times TD_{npr} \times C_{ip} + FC_{ad}$$  \hspace{1cm} (6)$$

Similarly, the failure effect 3, i.e. machine producing more rejections will be detected by the control chart after a time lag. So the cost due to failure effect 3 will be the sum of $FC_{ad}$ and cost of rejected units produced during this time lag. Mathematically,

$$FC_{rq} = N_s \times R_s \times C_{rq} + FC_{ad}$$  \hspace{1cm} (7)$$

where, $N_s$ is the number of units produced during the time required to detect a shift $S$ in process mean due to occurrence of a particular failure cause and $R_s$ is the proportion non conforming units due the process shift. Calculation for $N_s$ and $R_s$ are shown in appendix A. In the present study, it is assumed that the process capability of the in control process is 1 (i.e., the upper and lower specification limits would be at $\pm 3\sigma_p$).

Reduction in production rate and time to detect the same can be obtained from the production records of the users. Similarly, shift in the process mean due to particular failure cause can be obtained from the production control policy of the users. However, in the case study presented in this paper, expert estimates have been collected and used for the calculations. If sufficient past records are available with the users then instead of using average estimates from the experts, a suitable probability distribution can be used to model these parameters. The Expected Annual Cost ($EAC$) of failure due to any failure cause can now be written as:

$$EAC = N_f \left( p_{ad} \times FC_{ad} + (p_{rs} \times FC_{rs}) + (p_{rq} \times FC_{rq}) \right)$$  \hspace{1cm} (8)$$

$N_f$ is calculated in the present paper using ReliaSoft’s Blocksim7 software [12]. Thus, $EAC$ includes the effects of $MTBF$, $MTTR$ and performance degradation and can be used to prioritize the failure causes. A failure cause is economically more severe if its $EAC$ value is high.

**Case Study**

The proposed cost based FMEA is illustrated using an example of a CNC grinding machine. As the objective of this paper is to demonstrate the methodology, cost estimates in this work should be considered as illustrative only, and do not reflect what the actual values are or might be incurred by the user at some time in the future. In order to understand the use of $EAC$ model, calculations for tailstock subassembly is shown in table 4. Similarly, the expected annual cost is calculated for each end events of all the
nine subassemblies in the system. There are in all 63 such end events identified in the system. Table 5 shows the 10 most critical end events in the system identified through cost based FMEA. EAC values are also calculated at subassembly level. It is found that the work head, carriage and tailstock are the most critical subassemblies in the system. They are responsible for 70 per cent of the failure cost. However table 5 gives better picture as it shows the end events that need immediate attention from the manufacturers. It is also interesting to see that these end critical events belong to different subassemblies in the system and are not necessarily limited only to the critical subassemblies (i.e., Work head, Carriage, and Tailstock). Thus, identifying critical subassemblies may be of managerial implication, it gives less input to the designer for further improvement in the system performance. It is thus justified to focus on the end events rather than higher level subassemblies or components.

Table 4: Expected Annual Cost Calculation for Tailstock Subassembly

<table>
<thead>
<tr>
<th>Subassembly</th>
<th>Component</th>
<th>End cause</th>
<th>EAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tailstock</td>
<td>Bush</td>
<td>Wear due to usage</td>
<td>276922</td>
</tr>
<tr>
<td>Work head</td>
<td>Spindle</td>
<td>Seal failure</td>
<td>220236</td>
</tr>
<tr>
<td>Carriage</td>
<td>Slide</td>
<td>Wear due to usage</td>
<td>208068</td>
</tr>
<tr>
<td>Dressing module</td>
<td>Slide</td>
<td>Improper cleaning</td>
<td>205712</td>
</tr>
<tr>
<td>Wheel head</td>
<td>Spindle</td>
<td>Seal failure</td>
<td>204701</td>
</tr>
<tr>
<td>Carriage</td>
<td>Ball screw</td>
<td>Thrust bearing</td>
<td>194017</td>
</tr>
<tr>
<td>Hydraulic system</td>
<td>Rapid cylinder</td>
<td>Wear due to usage</td>
<td>180539</td>
</tr>
<tr>
<td>Tailstock</td>
<td>Micro-taper</td>
<td>Dust entry</td>
<td>159312</td>
</tr>
<tr>
<td>IPG</td>
<td>Other</td>
<td>-</td>
<td>158962</td>
</tr>
<tr>
<td>Table</td>
<td>Other</td>
<td>Improper cleaning</td>
<td>157487</td>
</tr>
</tbody>
</table>

Table 5: EAC Values of Ten Most Critical End Events
Any improvement in system performance can be achieved either by improving the reliability or by changing the preventive maintenance policy against the critical failure events identified through cost based FMEA. However, any improvement in the life of the component will lead to additional cost, which will get added to the component cost. Similarly, inspection and maintenance may bring the machine down and thus result in additional cost to the user in terms of down time cost. Therefore, any improvement must be based on tradeoffs between the cost of improvement and failure cost. Using the proposed cost based FMEA the $EAC$ value can be obtained against any improvement made in the system reliability or maintenance policy. The same can be compared with the existing $EAC$ value and any reduction in the $EAC$ will indicate a better system design or better maintenance policy.

5. Conclusion

Modified fault tree diagram based framework proposed in this paper found useful in providing better insight into the failure and their impact. Two methods have been developed to support the analysis through the above framework. The first method will help the machine tool manufacturers in obtaining the time-to-failure distribution parameters using expert judgement, thereby allowing them to carry out further reliability studies when data is either not available or not sufficient. The approach can be further extended to combine it with the Bayesian approach. First, the expert judgement based method can be used to construct a prior distribution model for the time to failure. As and when data becomes available, it can be used to derive the posterior distribution model for time to failure using Baye’s formula.

Second method proposed in this paper will help in making effective cost-driven decisions while making any improvement in the reliability of the system based on tradeoffs between the cost of improvement and failure cost. The cost models used for calculating the Expected Annual Cost ($EAC$) includes not only the cost of down time but also the cost of rejection and cost of lost production due slower speed to the users. Thus any improvement decision based on $EAC$ value will give better economic performance of the machine to the users. The approaches have been illustrated using an example of CNC grinding machine.

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References

Appendix A

Calculation of $N_s$ and $R_s$

Assume that when process shifts, due to the occurrence of any particular failure event, from in-control state to out-of-control state, the process mean shifts by an amount $S = k\sigma_p$.

If we assume that the process is being monitored by a $\bar{X}$ control chart with control limits at $\pm 3\sigma_{\bar{X}}$, the $B$ (type II) error can be expressed as [13]:

$$B = \phi[3 - k\sqrt{n}] - \phi[-3 - k\sqrt{n}]$$

(9)

The expected number of samples taken before the shift is detected i.e. Average Run Length, $ARL_B = \frac{1}{1 - B}$

The number of units produced during the time required to detect a shift $S$ in process mean due to occurrence of a particular failure cause will be

$$N_s = PR \times \left( \frac{1}{1 - B} \right) \times t_s$$

(10)

Similarly, the proportion nonconforming units due to shift $S$ will be

$$R_s = 1 - \{\phi[3 - k] - \phi[3 + k]\}$$

(11)

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