Estimation of Residual Life based on Vehicle Tribo Data

D. Valis¹, O. Pokora²
¹Department of Combat and Special Vehicles, University of Defence, Brno, Czech Republic
²Department of Mathematics and Statistics, Masaryk University, Brno, Czech Republic
(david.valis@unob.cz; pokora@math.muni.cz)

Abstract – The aim of the article is to estimate a system technical life. When estimating a residual technical life statistically, a big amount of tribo-diagnostic data is used. This data serves as the initial source of information. It includes the information about particles contained in oil which testify to oil condition as well as system condition. We focus on the particles which we consider to be interesting. This kind of information has good technical and analytical potential which has not been explored well yet. By modelling the occurrence of particles in oil we expect to find out when a more adequate moment for performing preventive maintenance might come. The way of modelling is based on the specific characteristics of diffusion processes, namely the Wiener process. Following the modelling results we could in fact set the principles of “CBM - Condition Based Maintenance”. However, the possibilities are much wider, since we can also plan operation and mission. All these steps result in inevitable cost saving.

Keywords – Field data assessment, off-line diagnostics, first hitting time, residual life, maintenance optimization,

I. INTRODUCTION

Reliability, safety and availability of complex and time dynamic systems – like mechatronic, communication, space and smart systems – has attracted more and more attention in recent years – see, e.g. [1]. The systems we would like to present work in various and mostly adverse operating conditions due to their applications. Therefore it is hardly possible to analyse the reliability of individual system using prior complex reliability tests, the historical pieces of information of other similar systems, or using expert judgement. Dependability characteristics are of our interest as we are concerned of a system reliability and availability level. However, the reliability and availability level of systems under our observation is the area of high interest for designers and engineers so that they could monitor condition and make decisions about maintenance. Based on the practical development in this area, it emerges that condition-based maintenance has become an attractive research area over the last decades – see, e.g. [2-5].

At present there is a tendency to change the format of technical maintenance. Preventive maintenance (PM) at fixed intervals has been abandoned and condition based maintenance has been introduced instead. This trend might be followed only on condition that high-quality data on system condition is available. In technical literature, e.g. [6-9], there are different ways of using direct and indirect diagnostic data. There are introduced the possibilities of vibrodiagnostics, thermal radiation, and also tribo-diagnostics there. As for the vibrodiagnostics and the thermal radiation, they frequently appear in existing publications and scientific papers. Regarding the tribo-diagnostic data, it has been assessed mainly empirically, restrictedly and by specialists.

Since specific types of technical equipment have been observed extensively, a big amount of data is available for the analysis. This special technical equipment is used in very harsh conditions. To have the observed technical equipment operating, it is important not only to have an adequate maintenance system, but also to operate under specific conditions, to plan and complete the mission.

A. Motivation

There were a few reasons for starting this research. The main reason was obviously to save costs during the phase of operation and maintenance of the observed technical equipment. It is rather clear that both the operation and the maintenance have the potential to save costs. The question is how the potential might be identified. The technical literature currently available shows us that the condition based maintenance is a right alternative. However, to introduce this type of maintenance, a certain amount of high-quality data as inputs should be available.

During the operation of the observed technical equipment in previous years, a lot of tribodiagnostic data were obtained. And the truth is that these data have not been used efficiently. The authors of this article identified the potential of these data and applied it in further analysis.

Another reason for assessing and searching for RUL (Residual Useful Life) was to find a lot more adequate model than the ones introduced earlier. Previous models are based on a regression analysis and fuzzy logic which has the potential to support regression models. What we are trying to do in the paper, is to present a new view on the same issue which is supposed to either support the conclusions or disprove them. Therefore we assume that First Hitting Time driven by Wiener process with drift is a suitable tool for Residual Useful Life. Usage of Wiener process was motivation by generalisation of random walk suitable for this technical system.
B. Literature survey

Since in the latest literature publications there is a lot of information about condition based maintenance itself, we decided to consider most recent inspirational sources which deal with Mean Residual Life (MRL), RUL (Remaining Useful Life) and estimation based on data mining, modelling and various approaches. We are also very much preoccupied with diffusion processes, particularly their application in technical practice. Moreover, we take into account deterioration and degradation. The work [6] presents the modelling of residual life (MRL – mean residual life) using a Proportional Hazards model (PH model) in case of indirect condition monitoring, i.e. the state of equipment is not deterministically known. In work [7] we have introduced the possibilities of modelling Remaining Useful Life (RUL) using either a model based approach or a data-driven approach. In work [8] we have developed the approach based on a mathematical model for degradation-based signals from the population of components. In work [9, 10] there are methods used for estimating parameters of condition monitored equipment whose failure rate follows the Cox’s time-dependent Proportional Hazards Model. In [11, 21-24] there are several interesting practical examples of the application of diffusion processes and/or their fragments. In technical applications it is possible to find different examples such as the modelling of work times in a factory assembly line, or fatigue time estimation.

II. OBJECTS OF DIAGNOSTICS AND OIL DIAGNOSTIC METHODS

The assumed objects of diagnostics are in our case engines from heavy tracked vehicles. These engines have not been designed and constructed to use an ON-LINE diagnostic system. However, there are other applications which might be used in practice, e.g. [12, 13, 17-20, 25]. We still apply the OFF-LINE engine diagnostics system when sampling lubrication fluid at certain intervals, and use known and optimised special tribodiagnostic methods [15]. We use the results and information from atomic emission spectrometry (AES). Following this analysis we can obtain the information about the presence of specific individual elements and their amount. The amount is usually the weight of a respective element in one standardised unit of lubricant – e.g. milligrams of iron (ferrum) in one kilogram of oil [ppm]. However, we cannot identify the real origin of the respective elements because of fatigue, cutting or sliding. We also try to identify where these elements might come from. We will work with the idea to increase the potential for maintenance optimisation inputs and cost benefit analysis inputs. During the analysis we will focus on Fe particles, because we suppose that they originate from kinematic parts of a motor. We know the critical value of Fe particles amount.

III. OIL FIELD DATA, ASSESSMENT, MODELLING AND RESULTS

As it has been mentioned before, the data are available in a big amount – it is a statistically important set. The data is collected at intervals and under conditions determined by a methodology. This includes:
- homogenous time intervals given by technical equipment mileage,
- oil temperature and right oil mixing,
- the same place of sample collection,
- the same way of performing the tribo analysis after the sampling.

Based on the data amount, the results are believed to be valuable and statistically reliable. We concentrate in this paper on Fe particles contents only. The example of the data form is in Table I.

Table I. INPUT DATA OF Fe PARTICLES FORM ENGINE OIL - EXAMPLE

<table>
<thead>
<tr>
<th>Sample / Time [Mh]</th>
<th>Fe particles (ppm)</th>
<th>Standard deviation</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/0.15</td>
<td>13.71158</td>
<td>0</td>
<td>4.753368309</td>
</tr>
<tr>
<td>2/0.30</td>
<td>13.72016</td>
<td>0.001014608</td>
<td>4.753368417</td>
</tr>
<tr>
<td>3/0.45</td>
<td>13.73055</td>
<td>0.002029216</td>
<td>4.753368742</td>
</tr>
<tr>
<td>4/0.60</td>
<td>13.74004</td>
<td>0.003043824</td>
<td>4.753369284</td>
</tr>
<tr>
<td>5/0.75</td>
<td>13.74953</td>
<td>0.004058431</td>
<td>4.753370042</td>
</tr>
<tr>
<td>6/0.90</td>
<td>13.75902</td>
<td>0.005073039</td>
<td>4.753371016</td>
</tr>
</tbody>
</table>

A. Utilization of Regression Model

A linear regression model is applied as a basic input characteristic. It helps to determine a linear course of Fe particles generation. The course is completed by dependability intervals for a mean (group) value and for an individual value. These courses are used for setting the point estimations of standard deviations of an individual and mean value for every instant of time – as stated in Table I. These values are later used for Wiener process modelling. In the paragraph below there is an example of this procedure. In view of their random character, a random vector \( \mathbf{X} = (X_1, \ldots, X_k) \) represents independent variables and a dependent variable is represented by a random variable \( Y \). When describing and examining the dependence of \( Y \) on \( \mathbf{X} \), we use a regression analysis, and this dependence is expressed by the following regression function:

\[
y = \varphi(\mathbf{x}, \beta) = E(Y | \mathbf{X} = \mathbf{x}),
\]

where \( \mathbf{x} = (x_1, \ldots, x_k) \) is a vector of numerical variables, \( y \) is a dependent variable, \( \beta = (\beta_1, \ldots, \beta_m) \) is a vector of regression coefficients \( \beta \).

For our data we will look for a regression function in a linear form and we will apply a linear regression model:
$y = \sum_{j=1}^{m} \beta_j f_j(x)$, \hspace{1cm} (2)

where $f_j(x)$ are well-known functions where $\beta_1, \ldots, \beta_m$ are not involved.

For the data we used the following regression functions:
- $m=2$, $f_1(x)=1$, $f_2(x)=x$, regression function: $y=\beta_1+\beta_2 x$
- $m=2$, $f_1(x)=1$, $f_2(x)=x$, regression function: $y=k+\beta_2 x$

The graphical outcomes from the regression analysis for an individual vehicle and a group of vehicles of the same type are presented below in Fig. 1 and Fig. 2. Numerical values have been also recorded and used later for the Wiener process.

**B. Utilisation of Wiener Process**

We assume that the case we observe is a stochastic process with time dependence. The generation of Fe particles is operation time dependant. Therefore the application of a diffusion process seems to be perfectly adequate. Due to normal distribution of random variable and its application capabilities, the Brownian motion might be used universally. The application of the Brownian motion can be found in many areas. Standard use is related to modelling with the use of differential equations. We select one specific example of diffusion processes which is the Wiener process. Rules of the general Wiener process might be specified as follows. A real stochastic process \( \{W(t) \in (0, +\infty) \} \) in a probability space \( (\Omega, A, P) \) is called the Brownian motion or the Wiener process, if the following applies:

1. $W(0) = 0$,
2. $W(t) - W(s)$ has $N(0, t - s)$ distribution for $t > s \geq 0$,
3. For arbitrary $0 < t_1 < t_2 < \cdots < t_n$ increments $W(t_1), W(t_2) - W(t_1), W(t_3) - W(t_2), \ldots, W(t_n) - W(t_{n-1})$, $W(t)$ trajectories are mutually independent random variables and continuous almost everywhere.

Next, it applies that:
1. $E[W(t)] = 0$ for $t \geq 0$
2. $\text{Var}[W^2(t)] = t$ for $t \geq 0$

The Wiener process represents one possible form of diffusion processes. It is actually the integral of what in practical applications is called a white noise. The Wiener process with drift will be used in our application. The initial mean value (drift) is $\beta_1$ and standard deviations for each time increment have been previously calculated – see Table I. For our model we apply Wiener process with drift given by stochastic differential equation.

$$dY(t) = \mu \cdot dt + \frac{\sigma \cdot dW(t)}{\sqrt{t}} \hspace{1cm} (3)$$

where $dW(t)$ is increment of Wiener process and $dt$ is increment of time, $\sigma$ is a standard deviation (either of an individual or a mean value), $\mu$ is a mean value, $t$ is an instant of time, process initial value $Y(0) = \beta_1$. Time increment for modelling was 0.15 Mh. When modelling – simulating, an example of the process course for individual course is shown in Fig. 3, and for a mean value it is in Fig. 4. The critical value of particles amount is 50.
We take into account 95% interval of trajectories which achieve a critical value 50. The vertical line 200 shows a determined interval of PM. These intervals are for the individual and mean value put in Fig. 5 and Fig. 6.

In order to determine the First Hitting Time (FHT) distribution of the individual and mean value, we set histograms and performed tests for a presumed type of distribution. The expected types of probability density distribution such as Gamma (full/firm line), LogNorm (dashed line – overcovered by IGD), Inverse Gaussian (IGD) – dotted line), Normal (dash and dotted line) or Weibull’s were not proved. The courses of these tested distributions are shown in Fig. 7 and Fig. 8. We expect then to obtain FHT distribution only in the form of empiric distribution function.

IV. DISCUSSION

The tested values reached for the individual value the following limits: minimum value = 134 Mh, lower confidence interval 2.5% = 265 Mh, upper confidence interval 97.5% = 524 Mh, mean value = 382 Mh, median = 378 Mh, maximum = 887 Mh.

As to the mean value, the following limits were achieved: minimum value = 258 Mh, lower confidence interval 2.5% = 315 Mh, upper confidence interval 97.5% = 480 Mh, mean value = 385 Mh, Median = 381 Mh, Maximum = 746 Mh.

It follows from the results stated above that the mean value is more or less the same, but the lower threshold of confidence intervals are not. However, the lower confidence intervals are interesting for us in order to determine the possible beginning of PM interval. But if we used the mean value, it would be sufficiently far from the original/fixed PM interval. On the basis of the results we could work with a conservative version and set a new PM interval using the lowest value of lower threshold of confidence interval. This would be 265 Mh (individual value). If we were for a benevolent alternative, we could rely on the mean value and set the PM interval at 380 Mh (more or less the same for both the individual and for the mean value).

When planning a mission, we could work with versions that if common operating conditions were observed, a vehicle could be operated with one oil filling theoretically up to the upper confidence limit 97.5%. Considering conservative or benevolent versions, it would be 480 Mh, or 520 Mh.

V. CONCLUSION

In the article we have introduced possible approaches to modelling indirect diagnostic measures. We were looking for first hitting time distribution which represents a critical limit of Fe particles amount. The modelling is based on the diffusion Wiener process with drift. The
observation and the analysis focused on the individual and mean value of Fe particles amount in oil.

The achieved results complement the set of approaches to the indirect observation of a technical condition. The approaches using purely a regression analysis and fuzzy logic, see [14, 16], have been applied so far. Following the conclusions of modelling with the Wiener process, the results of previous approaches might be completed when searching for:
- optimum interval PM,
- recommended/allowed time for mission completion,
- optimizing dependencies of life cycle cost analyzing.

The approach introduced above opens the possibilities of analyzing other important diagnostic indicators. It is important so that setting the time derived from the histogram and pdf course could be as accurate as possible and undistorted.

In our further analysis we are going to develop this approach even more and complement it with other approaches like ARIMA or ARMA methods.

ACKNOWLEDGMENT

This paper has been prepared with the support of the PRO of K-202 University of Defence, Brno and of the project of Ministry of Defence of the Czech Republic – BOPROS nr. OFVTUV2013002.

REFERENCES


