Comparison and ensemble of temperature-based and vibration-based methods for machinery prognostics

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ABSTRACT

This paper presents a comparison of a number of prognostic methods with regard to algorithm complexity and performance based on prognostic metrics. This information serves as a guide for selection and design of prognostic systems for real-time condition monitoring of technical systems. The methods are evaluated on ability to estimate the remaining useful life of rolling element bearing. Run-to failure vibration and temperature data is used in the analysis. The sampled prognostic methods include wear-temperature correlation method, health state estimation using temperature measurement, a multi-model particle filter approach with state equation parameter adaptation utilizing temperature measurements, prognostics through health state estimation and mapping extracted features to the remaining useful life through regression approach. Although the performance of the methods utilizing the vibration measurements is much better than the methods using temperature measurements, the methods using temperature measurements are quite promising in terms of reducing the overall cost of the condition monitoring system as well as the computational time. An ensemble of the presented methods through weighted average is also introduced. The results show that the methods are able to estimate the remaining useful life within error bounds of $\pm 15\%$, which can be further reduced to $\pm 5\%$ with the ensemble approach.

1. INTRODUCTION

In the last decade, maintenance focus has shifted towards prognostic health management where maintenance action is taken based on the current health state of a system and its estimated remaining useful life. In addition, new technical systems, referred to as self-optimizing mechatronic systems with the ability to adaptively control reliability have been developed (Sondermann-Wölke & Sextro, 2010; Meyer & Sextro, 2014). These systems are able to react to changed operating conditions or faults within the system through behavior adaptation based on multi-objective optimization and consequently require accurate estimation of the current health state and the remaining useful life. The overall objective of this approach is to increase reliability, availability and safety of technical systems.

A number of methods for estimating the remaining useful life (RUL) have been proposed. These methods can be divided into three broad categories: 1) reliability based, which rely on failure times of similar units, 2) model based, which rely on mathematical models based on physics of failure and 3) data driven methods, which rely on raw sensory data obtained from a system during operation (Tobon-Mejia, Medjaher, & Zerhouni, 2011). Reliability based methods are the simplest to employ since they do not require condition monitoring data. However, their accuracy is relatively low, especially for systems subjected to varying operating conditions and consequently displaying varying lifetimes. Model-based methods though found to be very accurate, are system or component specific and are not easily adaptable to different systems. In addition, due to the complexity of modern day systems, the system models are very complex and computationally intensive. Data driven methods have received considerable efforts since they can be adapted to different systems. Data driven methods employ mainly statistical based algorithms such as support vector machines (SVM) and hidden Markov models (HMM) or artificial intelligence methods such as artificial neural networks (ANN) (Tobon-Mejia et al., 2011). These algorithms require a lot of data for training and this involves conducting run-to-failure tests to generate the training and validating data. The performance of these algorithms also depend on suitability of the features extracted from the raw data (Kimotho & Sextro, 2014a). For classification of health states, good features should demonstrate separability between different health states while for regression approach where the features are mapped to a function (either a health index or RUL), then the features should have the ability to capture the degradation trend, preferably monotonic change. For rotating machinery, the most common condition monitoring data utilized are vibration signals.

Temperature measurements have been recognized as a condition monitoring tool but their application in estimating the remaining useful life has not been fully realized. One of the identified limitations of temperature in machinery diagnosis and prognosis is the inability to identify faults at the development stage. However, this limitation can be overcome by strategic positioning of the temperature sensors. A number of sensors for condition monitoring of technical systems have been developed. A wireless temperature sensor for condition monitoring of bearings operating through thick metal plates was proposed by (Gupta & Peroulis, 2013). The sensor consists of a temperature-sensitive permanent magnet which is attached to the inner ring of the bearing, thus allowing the bearing temperature to modulate the produced magnetic field. Joshi et al, (Joshi, Marble, & Sadeghi, 2001) demonstrated the application of radio telemetry for bearing cage temperature measurement for use in condition monitoring of bearings. The cage telemetry was found to capture faults such as loss of lubrication much faster than housing thermocouple. Brecher et al, (Brecher, Fey, Hassis, & Bonerz, 2014) demonstrated the use of a customized telemetry system for measuring a bearing's inner ring temperature for high speed applications. The analysis showed that the inner ring temperature was vital in accurately monitoring the health of the bearing. These developments could prove useful in enhancing fault identification and estimation of remaining useful life in bearings as well as reducing the overall cost of the condition monitoring system.

In this paper, five methods for estimating the remaining useful life of bearings are evaluated and compared in terms of performance based on prognostic metrics and computational time. The first approach involves correlating wear with temperature rise due to frictional heating. The method uses run-to failure temperature measurements to obtain coefficients which can be used with the temperature measurements at any given time to estimate the remaining useful life. The second approach involves estimating the health states of a bearing from the temperature measurements and deducing the remaining useful life from the current health state. The third approach involves the application of multi-model particle filter with model parameter adaptation to propagate a health index derived from temperature measurements to a predetermined threshold. The fourth approach involves estimating the health states of a degrading component using features extracted from vibration measurements (Kimotho, Sondermann-Wölke, Meyer, & Sextro, 2013). Classification algorithms are used to identify the current health state. The probability of each health state together with the percentage remaining useful life at each health state of similar units are utilized in estimating the remaining useful life. The last approach involves mapping features extracted from vibration measurements to the remaining useful life at any given time. Regression algorithms are used in this approach (Kimotho & Sextro, 2014a). The last two methods based on vibration signals have been previously discussed in (Kimotho, Sondermann-Wölke, et al., 2013; Kimotho & Sextro, 2014a) and are only briefly introduced for comparison and ensemble purposes.

All the methods are evaluated using ball bearing run-to-failure data for training and truncated run-to-failure data for testing obtained from the 2012 PHM data challenge (Nectoux, Medjaher, Ramasso, Morello, & Zerhouni, 2012). The data is obtained through highly accelerated run-to-failure experiments conducted at three different operating conditions shown in Table 1. Due to the highly accelerated degradation, the data sets are characterized by high variability in experiment durations, ranging from 1 to 8 hours. In this work, only data sets from test 1 are analyzed.

Table 1. Operating conditions of the test bearings

Test	Speed (rpm)	Load (kN)
1	1800	4.0
2	1650	4.2
3	1500	5.0

2. PROGNOSTIC METHODOLOGIES

The following subsections outline different methodologies that have been evaluated on their suitability to estimate the remaining useful life of technical systems. An ensemble approach of combining the estimations of different approaches is also explored.

2.1. Wear - Temperature Correlation - Method 1

During operation, rolling element bearings encounter resistance to rotation which consist of rolling and sliding friction. This resistance occurs at the rolling contacts, contact areas between the rolling elements and the cage, as well as the guiding races (Harris & Kotzalas, 2006). The frictional forces perform work which is dissipated in form of heat, consequently increasing the bearing temperature. The frictional heat generated depends on the applied load, rotational speed, the type and size of bearing, properties and quantity of lubricant as well as the rate of heat dissipation. The rise in temperature reduces the viscosity of the lubricant which leads to a reduction in the lubricant film thickness. This results to higher asperity contact, increased heat generation due to increased friction and consequently increased wear (Joshi et al., 2001). Wear results to continued loss of geometric accuracy of the rolling and gradual development of other faults such as micro-pitting (Harris & Kotzalas, 2006). Since it is assumed that wear can be prevented by proper attention to the bearing, no considerable effort has been made to estimate the remaining useful life of bearings related to wear and change in temperature (Harris & Kotzalas, 2006). Johnson (Johnson, 1985) investigated the temperature produced by frictional heating in sliding contact by examining the temperature produced in a half space by a heat source which moves on the surface. The maximum temperature occurs towards the rear of the heated zone which has the longest exposure, as shown in Figure 1 (Johnson, 1985). For a bearing rotating at constant

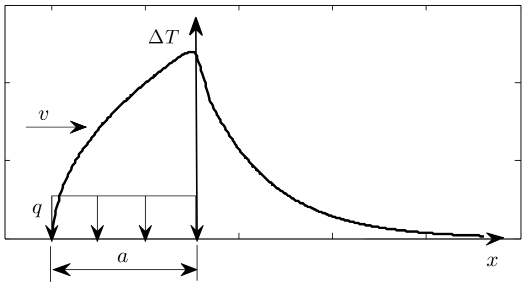

Figure 1. Temperature distribution due to uniform moving heat source, where q is the heat source, ΔT is the temperature difference, a is the half contact length and v is the velocity.

speed, frictional heat is generated at all contact points leading to an overlap in the maximum temperature throughout the bearing. This would result to an almost constant temperature distribution. Therefore, the temperature will not be a function of position but the factors mentioned previously. The bearing operating temperature will also depend on the balance between the heat generated and the heat removed from the bearing through conduction, convection and radiation. In most cases the temperature of the bearing increases rapidly during initial operation and then increases slowly to a steady state temperature as shown in Figure 2. The rate of rise depends on the rate of heat removal. When a bearing is run con-

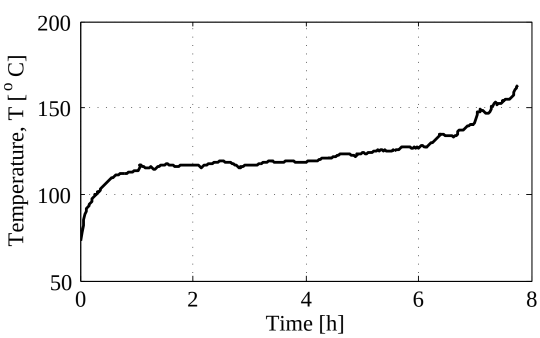

Figure 2. Typical run-to-failure temperature curve of a rolling element bearing.

tinuously to failure, at constant speed, the rate of temperature rise changes rapidly initially, and then decreases to an almost constant value. Just before failure, the temperature rise again changes rapidly. This behavior is shown in Figure 2. The behavior is also consistent with degradation of bearings, where degradation is high initially, followed by gradual degradation and finally high degradation towards failure. This indicates that temperature can be used to effectively track degradation of components occasioned by wear.

Assuming that the heat removal rate is constant for a given system, then it is possible to track bearing degradation from temperature measurements. Since wear is approximately proportional to the work done by the frictional forces which give rise to frictional heat, then it may be assumed to be directly proportional to the temperature rise in the component. This relationship can be formulated as shown below:

$$\frac{\Delta \dot{m}}{\Delta A} \propto \frac{\Delta P_R}{\Delta A}(T(t) - T_o), \tag{1}$$

where $\Delta \dot{m}$ is the material removal rate, ΔP_R is frictional power, $T(t)$ is the current temperature, T_i is the room temperature and ΔA is the contact area. Taking the initial temperature as the datum for temperature change and considering that wear is approximated by the material removal rate yields

$$m_{EOL} = \rho \Delta A \Delta z = \int_0^{t_{EOL}} \dot{m}(t)dt = k \int_0^{t_{EOL}} \Delta T(t)dt, \tag{2}$$

where ρ is the density of the material, ΔA is the contact area, Δz is the approximate wear depth, t_{EOL} is the time at the end of life of the component, k is proportionality constant, m_{EOL}, is the allowable mass that can be removed through wear before a component is considered to have failed. The ratio of allowable mass to the proportional constant can be obtained from the training data as by

$$\frac{m_{EOL}}{k} = \int_0^{t_{EOL}} \Delta T(t)dt. \tag{3}$$

Considering the current time, t_c, Eq. (3) can be rewritten in cumulative form as:

$$\frac{m_{EOL}}{k} = \int_0^{t_c} \Delta T(t)dt + \int_{t_c}^{t_{EOL}} \Delta T(t)dt. \tag{4}$$

During testing or online prognosis, the second term of Eq. (4) is unknown. This term is proportional to the remaining allowable wear before the component fails. Therefore this factor can be referred to as the remaining wear coefficient. Eq. (4) can be rearranged as:

$$\int_{t_c}^{t_{EOL}} \Delta T(t)dt = \frac{m_{EOL}}{k} - \int_0^{t_c} \Delta T(t)dt. \tag{5}$$

The term $\int_{t_c}^{t_{EOL}} \Delta T(t)dt$ can be used as a health index HI, defined as follows

$$HI = \frac{\int_{t_c}^{t_{EOL}} \Delta T(t)dt}{\frac{m_{EOL}}{k}}. \tag{6}$$

Division by $\frac{m_{EOL}}{k}$ normalizes the health index such that HI

is within the range $0 \leq HI \leq 1$, with $HI = 1$ for a healthy component and $HI = 0$ for a failed component. Figure 3 shows the health index of the two bearings used to generate the training data sets. The term $\frac{m_{EOL}}{k}$ is computed from

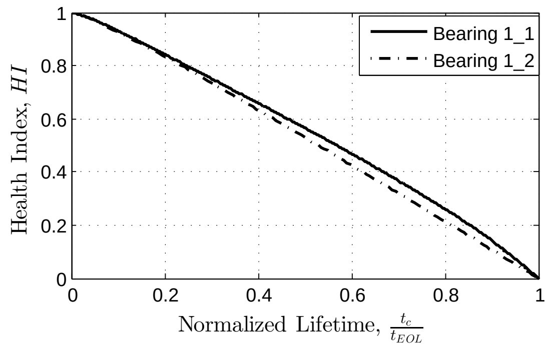

Figure 3. Health index computed from the training bearings.

the training data sets which contain run-to-failure temperature measurements. The health index of the test bearing at the current time is computed using Eq. (6), with $\frac{m_{EOL}}{k}$ obtained from the training data sets. To obtain the time to end of life, t_{EOL} of the test bearing, a polynomial curve of order 2 is fitted to the calculated health index and extrapolated to the point where the health index is zero. The RUL can then be calculated as shown in Figure 4. The performance of

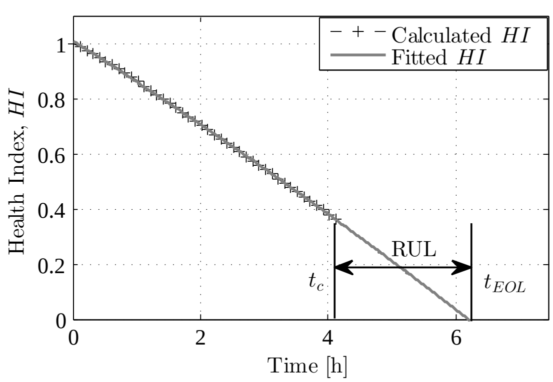

Figure 4. RUL prediction of bearing 1_7.

the method can be evaluated through prognostic performance metrics such as percentage error computed as follows

$$\text{Error} = \frac{\text{RUL}_{actual} - \text{RUL}}{\text{RUL}_{actual}} \times 100, \quad (7)$$

where RUL_{actual} is the actual remaining useful life and RUL is the estimated RUL. Table 2 shows the % Error computed for the different test bearings. The results show that the proposed method is a promising approach in prognostics with the estimation error below 15%.

Table 2. % Error of RUL estimation of the proposed method.

Test bearing	Actual RUL (h)	Estimated RUL (h)	Error (%)
Bearing 1_4	0.094	0.083	11.82
Bearing 1_5	0.446	0.400	10.45
Bearing 1_6	0.392	0.334	14.89
Bearing 1_7	2.103	1.983	5.71

2.2. Health State Estimation using Temperature Measurements - Method 2

This method involves estimating the health states of a degrading component using temperature measurements. Based on the current health state, a health index can be defined from which the remaining useful life can be estimated. k-means clustering algorithm is employed to discretize the temperature data into a number of clusters and an energy factor for each health state is calculated from the temperature change using Eq. (8)

$$\left(\frac{\Delta m_{EOL}}{k}\right)_{HSi} = \int_{t_{HSi-1}}^{t_{HSi}} \Delta T(t)dt. \quad (8)$$

A health index at each health state is then obtained as follows

$$(HI)_{HSi} = 1 - \frac{\int_{t_{HSi-1}}^{t_c} \Delta T(t)\, dt}{\left(\frac{\Delta m_{EOL}}{k}\right)_{HSi}}. \quad (9)$$

A total of 4 health states were identified from the training data. For test data, the current health state is estimated using classification algorithms such as support vector machines, which output the health state probability. Figure 5 shows a plot of the correlation coefficient for bearing 1_6. The right hand axis shows the normalized temperature change curve. To obtain the time to end of the current health state, a poly-

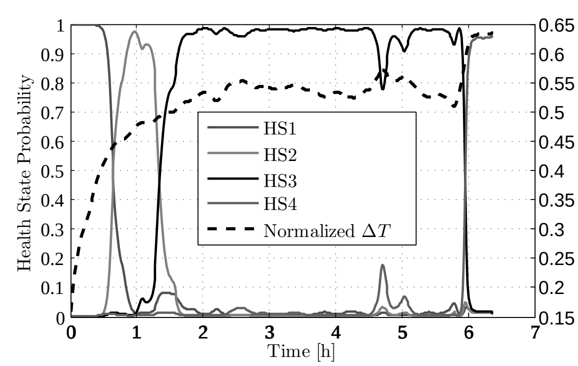

Figure 5. Health states of bearing 1_6

nomial curve of order 2 is fitted to the calculated health index and extrapolated to the point where the health index is zero. This point signifies the transition to the next health state or end of life if the current health state is the last health state (HS4 in this case). The remaining useful life can then be calculated using Eq. (10)

$$\text{RUL} = (t_{HSi} - t_{ci}) + \sum_{j=i+1}^{n} \frac{RL_j}{1 - RL_j} \cdot t_{HSi}, \tag{10}$$

where t_{ci} is the current time in health state i, t_{HSi} is the time at the end of health state i, RL_j is the percentage of remaining useful life of health state j, obtained from the training data and n is the total number of health states. If the current health state is the last health state, then $RL_j = 0$ and Eq. (11) reduces to

$$\text{RUL} = (t_{HSi} - t_{ci}). \tag{11}$$

Figure 6 shows the plot of the calculated health index and fitted health index for bearing 1_6, which was identified to be in health state 4. Table 3 shows the performance evaluation

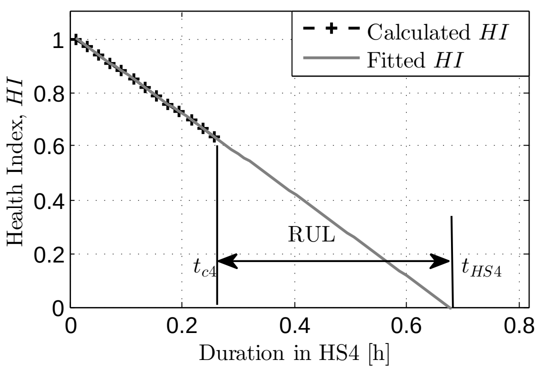

Figure 6. The estimated RUL at health state 4 for bearing 1_6.

of this method based on the percentage error, calculated from Eq. (7). One advantage of this method is the ability to identify current health state, which would be important for maintenance action recommendation or for adaptive systems utilizing discrete health states to adapt the operating regime. In addition, the method can be adapted to systems with varying operating conditions by defining different wear factors based on the operating regime and health state.

Table 3. % Error of RUL estimation of the proposed method.

Test bearing	**Actual RUL (h)**	**Estimated RUL (h)**	**Error (%)**
Bearing 1_4	0.094	0.083	12.70
Bearing 1_5	0.446	0.485	-8.74
Bearing 1_6	0.392	0.343	12.53
Bearing 1_7	2.103	2.162	-2.79

2.3. Temperature based Particle Filter Approach with Parameter and Model Adaptation - Method 3

Particle filter is a general Monte Carlo (Sampling) method for estimating the state of a system that changes over time using a sequence of noisy measurements obtained from the system (Arulampalam, Maskell, N., & T., 2002). The state of the system is considered to evolve according to

$$x_k = f(x_{k-1}, t_{k-1}, t_k) + n_k, \tag{12}$$

where x_k is the state of the system at time k and f is the transition function that propagates x_{k-1} to x_{k-1}, and n_k is the process noise. The state vector is assumed to be unobservable and its information is only obtained through noisy measurements of its observation z_k which is obtained by

$$z_k = g(x_k) + \nu_k, \tag{13}$$

where g is the observation model and ν_k is the measurement noise. The filtering process involves the estimation of the state vector at time k, given all the measurements up to time k, denoted by $z_{1:k}$. From a Bayesian setting, this problem involves recursively calculating the distribution $p(x_k|z_{1:k})$ which is done in two steps (Arulampalam et al., 2002).

1. Prediction Step, where $p(x_k|z_{1:k-1})$ is computed from the filtering distribution $p(x_{k-1}|z_{1:k-1})$ at time $k-1$ as follows:

$$p(x_k|z_{1:k-1}) = \int p(x_k|x_{1:k-1})p(x_{k-1}|z_{1:k-1})dx_{k-1}, \tag{14}$$

   where $p(x_{k-1}|z_{1:k-1})$ is assumed to be known due to recursion and $p(x_k|x_{k-1})$ is given in Eq. (12) (Arulampalam et al., 2002). The distribution $p(x_k|z_{1:k-1})$ is known as a prior over x_k before receiving the most recent measurement z_k.

2. Update step, where the prior is updated with the new measurement z_k using Bayes' rule to obtain the posterior over x_k

$$p(x_k|z_{1:k}) = \frac{p(z_k|x_k)p(x_k|z_{1:k-1})}{p(z_k|z_{1:k-1})}. \tag{15}$$

The computations in the prediction and update steps Eqs. (14-15) can be done using approximation methods such as Monte Carlo sampling (Arulampalam et al., 2002). A detailed description of this approach can be found in (Arulampalam et al., 2002).

When using this approach for prognostics, there is no new measurement available and hence the update step is not carried out. The system state is propagated until a predefined threshold is reached. This approach has been employed in prognostics of various technical systems such as batteries (Lee, Cui, Rezvanizaniani, & Ni, 2012; Xing, Miao, Tsui, & Petch, 2011), fuel cells (Jouin, Gouriveau, Hissel, Pera, & Zerhouni, 2014; Kimotho & Sextro, 2014b), gears (He, Bechhoefer, Dempsey, & Ma, 2012) and bearings (Wang & Gao, 2013).

In the context of this work, a health index is selected as the state of the system ($x_k = HI_k$) and defined by normalizing the temperature change such that $0 \leq HI \leq 1$ based on the maximum and minimum values of the training data which consists of run-to-failure temperature measurements as shown in Eq (16)

$$HI = \frac{\Delta T - \Delta T_{min}}{\Delta T_{max} - \Delta T_{min}}. \quad (16)$$

Two state equation were selected based on the temperature trend. The first part of the curve was approximated using a logarithmic equation while the second part was approximated using an exponential equation. The transition point was taken as the point where the rate of change of the health index (filtered using a kernel-based smoother) is zero, that is, $\frac{dHI}{dt} = 0$. Figure 7 shows the selection of state equations based on training data set from bearing 1_1. The selected

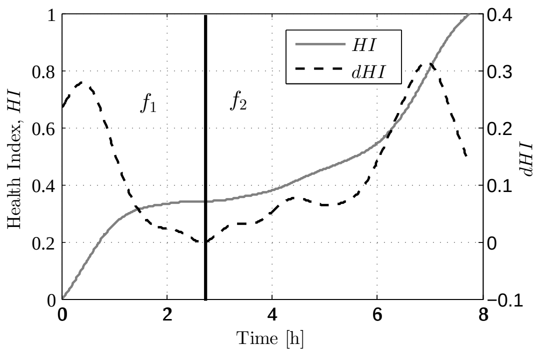

Figure 7. Health index with different state models.

state equations are shown below

$$f_1 = \alpha \cdot \ln\left(\frac{t_k}{t_{k-1}}\right) + HI_{k-1}, \quad (17)$$

$$f_2 = HI_{k-1} \cdot \exp(\beta(t_k - t_{k-1})), \quad (18)$$

where, α and β are state equation parameters to be fitted from the training data.

To evaluate the performance of the approach on the training data and the suitability of the selected state equation parameters, the available training data is truncated at different fractions of the component's lifetime. The health index is then computed and propagated until it reaches a threshold. The RUL is then calculated as shown in Figure 8. The process is done for several runs and a statistical value such as mean or median is taken as the overall RUL as shown in Figure 8. Figure 9 shows the performance of the approach based on the training data at different truncation intervals. Most of the particle filter approaches employed in literature use single state equation parameters when propagating the state of the system. However, as seen in Figure 9, due to the non-linearity of the degradation trend, it is difficult to obtain parameters

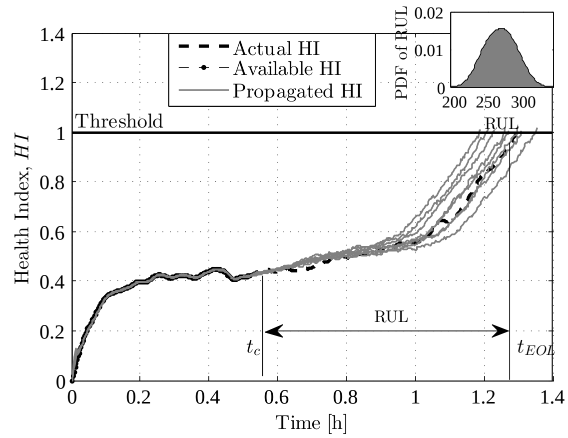

Figure 8. RUL estimation for bearing 1_1 at $t_c = 0.4 t_{EOL}$.

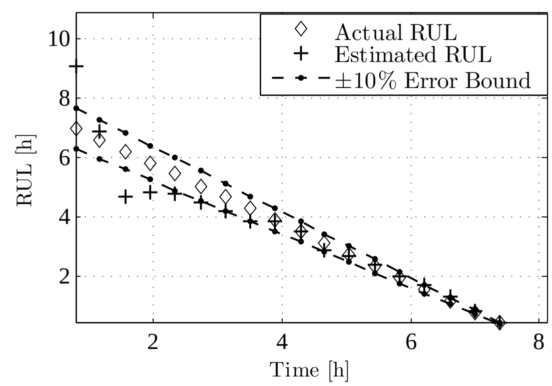

Figure 9. Estimated RUL at different fractions of lifetime without parameter adaptation.

that are able to track degradation of the systems accurately throughout its lifetime. The parameters are accurate at certain degradation stages and inaccurate at others. This limitation can be addressed by adapting the parameters to the rate of degradation. Figure 10 shows the RUL estimation with state equation parameter adaptation based on the rate of change of the health index. With this approach, the estimated RUL is approximately within ± 10 confidence bounds at all degradation stages. Once suitable state equation parameters have been identified, the method is then applied to truncated test data or data acquired in real-time. This involves normalizing the change in temperature of the test data using Eq. (16) together with the maximum and minimum values obtained from the training data. The particles are propagated with resampling until the available data is exhausted after which the model is used to propagate the health index up to the threshold. Figure 11 shows estimation of RUL through this approach for bearing 1_7. The method was applied to other test bearings and a performance analysis conducted and presented in Table 4. With this approach, errors less than 15% can be attained. The approach is more robust since measurement and

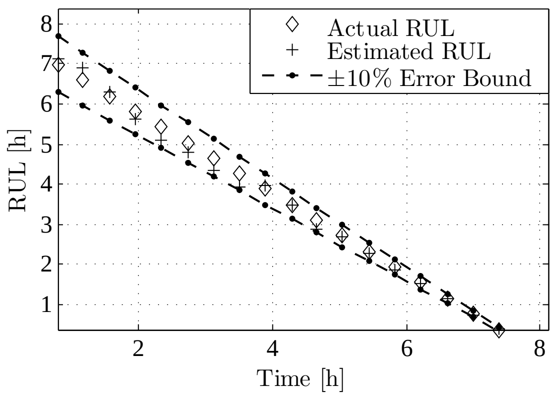

Figure 10. Estimated RUL at different fractions of lifetime with parameter adaptation.

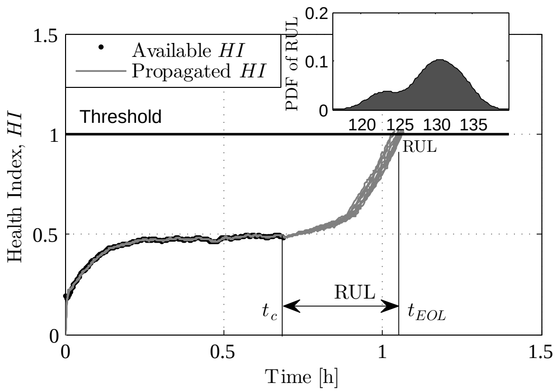

Figure 11. RUL estimation for bearing 1_7.

state propagation uncertainties are taken into account. The prediction accuracy also increases as the component nears failure due to resampling.

Table 4. % Error of RUL estimation using particle filter approach

Test bearing	Actual RUL (h)	Estimated RUL (h)	Error (%)
Bearing 1_4	0.094	0.106	-12.50
Bearing 1_5	0.446	0.433	2.99
Bearing 1_6	0.392	0.417	-6.38
Bearing 1_7	2.103	2.008	4.52

2.4. Prognostic Approach based on Health State Estimation - Method 4

Most technical systems undergo through a series of discrete health states before failure, with east health state indicating the severity of faults or degradation. RUL estimation based on this approach involves extracting relevant features from the raw run-to-failure data and discretizing the features into a number of clusters representing different health states within the lifetime of the system. This can be done by employing clustering algorithms to identify the classes within the features. Algorithms such as k-means and self-organizing maps (SOM) neural networks can be employed to identify the health states in the features. Figure 12 is a feature plot (skewness and clearance factor) showing clustering of data for different health states during degradation of a ball bearing. Machine learning algorithms are then trained to map the input

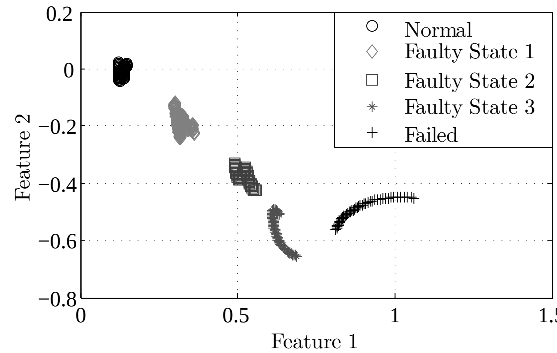

Figure 12. Clustering of data according to the health state.

features to the fault classes (health states). The workflow of this approach is summarized in Figure 13. The probability of a data point belonging to a given class is then computed from which the remaining useful life is calculated as follows:

$$\text{RUL}_c = \frac{t_c}{1 - \sum_{i=1}^{N} P_i \cdot RL_i} \sum_{i=1}^{N} P_i \cdot RL_i - d_c, \qquad (19)$$

where t_c is the current time, P_i is the probability of the system being in health state i, such that $\sum_{i=1}^{N} P_i = 1$, N is the total number of health states, RL_i is the historical fractional RUL of similar systems and d_{cj} is the duration of stay in the current health state. Various classification algorithms such as support vector machines (SVM), random forests (RF), neural networks (NN) can be employed with this approach. A data point is assigned the class with the highest probability. Figure 14 shows the health state probability for training bearing 1_1 as it degrades with time. Table 5 presents the performance analysis of this approach based on the works of the authors in (Kimotho, Sondermann-Woelke, et al., 2013; Kimotho & Sextro, 2014b).

Table 5. % Error of RUL estimation of the proposed method

Test bearing	Actual RUL (h)	Estimated RUL (h)	Error (%)
Bearing 1_4	0.094	0.086	9.03
Bearing 1_5	0.446	0.438	1.87
Bearing 1_6	0.392	0.411	-4.81
Bearing 1_7	2.103	2.123	-0.97

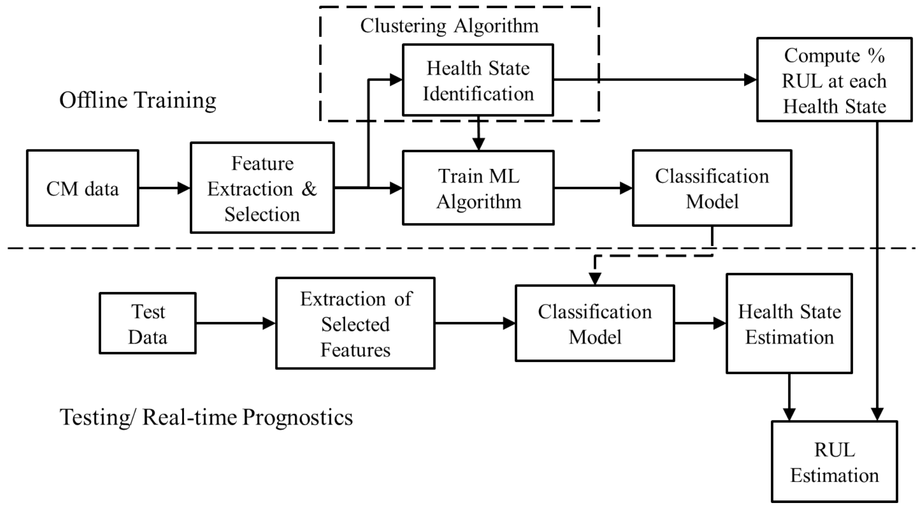

Figure 13. Health state approach to estimating RUL.

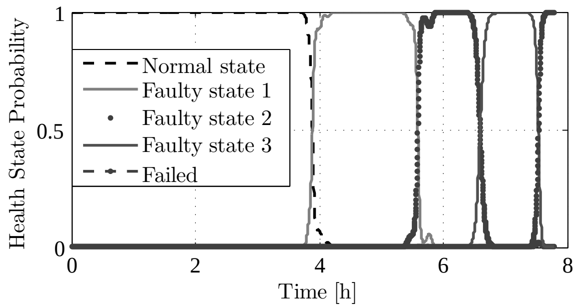

Figure 14. Health state probability of a bearing as it wears with time.

2.5. Mapping Extracted Features to RUL - Method 5

If the run-to-failure data condition monitoring data and corresponding failure times of similar units are available, then machine learning algorithms can be applied to map the extracted feature to the remaining useful life as shown in Figure 15. Machine learning algorithms such as support vector regression, regression trees, neural networks, extreme learning machines, etc, using regression approach can be employed. This approach is very sensitive to the trendability of the data and as such data processing approaches and feature selection to obtain monotonically changing features should be employed (Kimotho & Sextro, 2014a).

Kimotho et al (Kimotho & Sextro, 2014a) developed a prognostic approach for non-trending data. The approach involves applying an autoregressive model to the extracted features to obtain a monotonically changing feature which is used as the input to extreme learning machine (ELM) algorithm. Normalized RUL of similar units is used as the target in order to carter for units with varying lifetimes. The RUL at the current time is then computed through Eq. (20) which is derived from Figure 16. Given the current time, t_c, and the normalized RUL, F_c, the estimated remaining useful life RUL can be obtained by similar triangles as follows

$$\mathrm{RUL} = t_{EOL} - t_c = \frac{t_c}{1 - F_c} F_c. \tag{20}$$

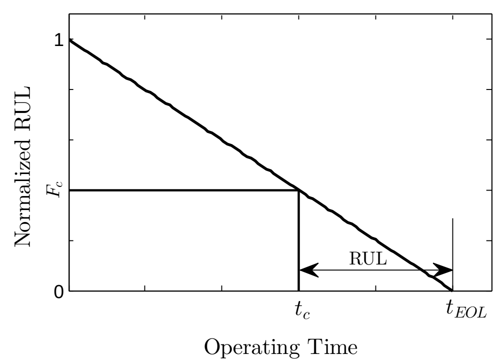

Figure 16. Estimating the RUL from the current time and normalized RUL.

ELM is a single layer feedforward neural network that utilize generalized inverse matrix operation to compute the weights output weights in a single calculation while the input weights are randomly generated (Huang, Zhu, & Siew, 2006). As a consequence, it does not require adaptation of weights and biases thus significantly reduces the computation time for both training and testing. Table 6 shows the performance analysis of this approach based on the works of (Kimotho & Sextro, 2014a).

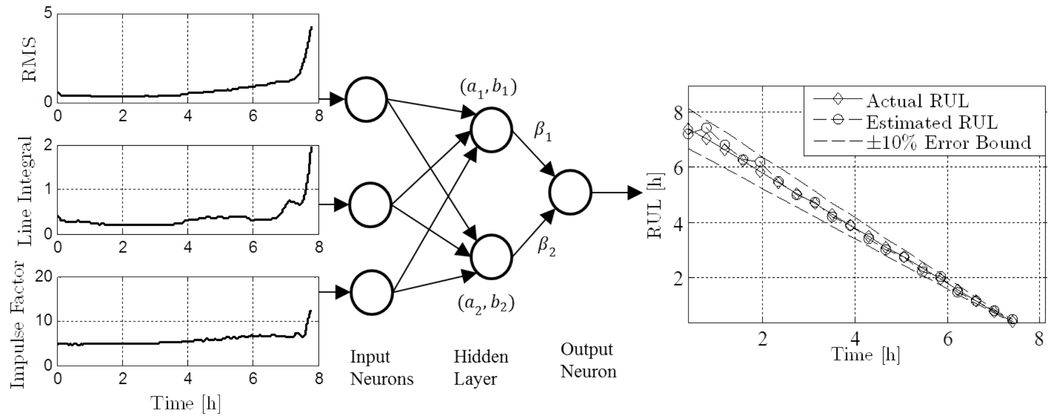

Figure 15. Mapping of extracted features to RUL using extreme learning machines (ELM)

Table 6. % Error of RUL estimation of the proposed method

Test bearing	Actual RUL (h)	Estimated RUL (h)	Error (%)
Bearing 1_4	0.094	0.09	5.31
Bearing 1_5	0.446	0.467	-4.63
Bearing 1_6	0.392	0.425	-8.41
Bearing 1_7	2.103	2.025	3.71

3. DISCUSSION

Results show that all the presented approaches estimate the RUL of ball bearings within error bounds of $\pm 20\%$. However in prognostics, late estimations are usually undesirable since the system may fail before scheduled maintenance. Therefore when computing performance weights of different approaches, a method of penalizing late predictions more than early predictions should be employed. One such method is using the exponential weighting method shown below (Gouriveau et al., 2014) with

$$w = \begin{cases} \exp(-\ln(0.5) \cdot (\frac{\text{Error}}{5})) \text{ if Error} < 0 \\ \exp(\ln(0.5) \cdot (\frac{\text{Error}}{20})) \text{ if Error} \geq 0. \end{cases} \quad (21)$$

The maximum score is 1 for the case when Error = 0. Based on this performance evaluation criteria, the performance of the discussed methods (methods 1-5 in subsections 2.1-2.5) is presented in Table 7. Also in Table 7 is the computation time for each method. The computation time includes time taken to extract relevant features and to estimate the remaining useful life but does not include time for feature selection and algorithm training or parameter identification. This is because during testing or real-time prognostics, the trained model or model parameters depending on the algorithm have already been obtained. Table 7 shows that machine learning algorithms utilizing vibration measurements yield the best performance. In particular, method 4 that involves health state estimation is suitable for systems that undergo through various stages of degradation before failure. This method can further be coupled with diagnosis to identify the fault type, location and size at each health state. This information would be of great importance in selecting the most suitable model to use as well as reducing the maintenance time. However, the method requires much longer computation time compared to the wear-temperature correlation methods as well as the complexity of the algorithms involved, both for feature extraction and for machine learning algorithms. Diagnosis is much more difficult to conduct with temperature measurements.

RUL estimation can be improved by sensor data fusion or ensemble of several methods either through simple mean or weighted mean of the RUL as shown in Eq. (22)

$$\text{RUL}_{ens} = \frac{\sum_{i=1}^{n} w_i \text{RUL}_i}{\sum_{i=1}^{n} w_i}, \quad (22)$$

where RUL_i is the RUL estimated by method i and w_i is the weight of method i, which can be taken as the mean score of each method in Table 7. For the case of simple mean, $w_i = 1$. Table 8 shows the effect of combining all or a number of the methods described using weighted mean and simple mean. All possible combinations of the algorithms were evaluated and a combination of three methods (2-3-4) yielded the best results. This shows that an ensemble of a number of algorithms, especially with data fusion from different sensors yields a more robust prognostic approach. Combination of all temperature-based methods yields predictions within a 10% error bound, with all the results being early predictions.

4. CONCLUSION

Five approaches to prognostics of technical systems have been presented. Three methods are empirical based and utilize temperature measurements for prognosis while two methods are data-driven and utilize vibration measurements for prognosis. The methods have been evaluated on their accuracies to estimate the remaining useful life as well as their suitability for real-time prognostics based on temperature and vi-

Table 7. Performance evaluation of the presented methods

Method	**Method 1**		**Method 2**		**Method 3**		**Method 4**		**Method 5**	
Bearing	w	Time (s)	w	Time (s)	w	Time (s)	w	Time (s)	w	Time (s)
1_4	0.64	1.65	0.64	1.74	0.18	55	0.73	74	0.83	72
1_5	0.30	1.68	0.30	1.85	0.90	111	0.94	160	0.53	158
1_6	0.65	1.68	0.65	1.87	0.41	110	0.51	159	0.31	157
1_7	0.68	1.64	0.68	1.78	0.86	190	0.87	145	0.88	143
mean w	**0.69**		**0.56**		**0.58**		**0.76**		**0.63**	

Table 8. Performance evaluation of ensemble of prognostic methods using weighted mean

Applied Method	**1-2-3-4-5**		**1-2-3**		**2-3-4**	
Bearing	Error (%)	w	Error (%)	w	Error (%)	w
1_4	4.37	0.86	5.27	0.83	3.53	0.88
1_5	2.19	0.93	0.34	0.98	-0.93	0.88
1_6	7.41	0.77	1.56	0.95	-0.16	0.98
1_7	2.72	0.91	2.04	0.93	0.17	0.99
mean		**0.87**		**0.92**		**0.93**

bration measurements. Vibration measurements yield better results and can be used for diagnosis and prognosis simultaneously. However, vibration analysis is computationally intensive and calls for relatively complex data driven algorithms for estimating remaining useful life. In addition, data acquisition and processing requirements for temperature sensors are less complex than those of vibration sensors such as accelerometers. With a multifunctional data acquisition system, it is possible to combine sensor information in order to build a low cost as well as a more robust condition monitoring system. This would give rise to the possibility of reducing the number of accelerometers within the system. A condition monitoring system utilizing a single accelerometer for each bearing and two temperature sensors, one as a reference sensor and the other to track the temperature rise of the bearing should be explored. For a more robust prognostic approach, ensemble of different prognostic approaches and in particular the use of sensor data fusion is necessary. The presented results show that fusion of methods utilizing the different sensor data improves the RUL prediction accuracy significantly. Some remaining issues that can be explored include the possibility of using dynamic weights during ensemble. Since the methods perform differently at different time intervals, an ensemble approach utilizing the higher weights at different estimation time intervals should be explored. Integration of uncertainties such as future loading conditions, uncertainty in measurements and uncertainty in model selection and propagation need to be incorporated in the proposed methods. The possibility of reducing the number of vibration sensors in a condition monitoring system for rotating machinery and having a temperature sensor on each component subjected to wear should also be explored. This way the vibration data can be used both for detecting faults and for prognosis while the temperature sensor can be used in locating the faulty component. The end result would be a robust, low cost condition monitoring system for rotating machinery as well as technical systems with wear related failures.

ACKNOWLEDGMENT

The authors wish to acknowledge the support of the German Academic Exchange Service (DAAD) and the Ministry of Higher Education Science and Technology (MoHEST), Kenya.

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