A particle filtering approach for temperature based prognostics

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ABSTRACT: Rubber-metal-elements are used in a wide range of applications for vibration and sound isolation. Nowadays it is state of the art to calculate the lifetimes of these elements under mechanical stress prior to their service life. To establish more reliable and safer rubber-metal-elements, continuous monitoring by different sensors can be used. Especially prognostics enable a rise in reliability, availability and safety. To establish these advantages, estimating the remaining useful lifetime of rubber-metal-elements should be realized during its service life based on current information on its condition. Therefore a suitable measure to monitor the condition of the element is necessary. This work focuses on temperature signals. This approach allows including the ambient temperature and thereby involving changing operating conditions. For estimating the RUL of rubber-metal-elements a model-based prognostics approach based on particle filtering is proposed. Its performance is analyzed regarding relevant parameters to enable the best performance for the applied data.

1 INTRODUCTION

1.1 *State of the art and motivation*

Rubber-metal-elements are used in a wide range of applications for sound isolation and in particular for isolating critical components from strong vibrations. Typical applications are trains, trucks and wind turbines. The bearing in focus is displayed in figure 1. It consists of an inner steel ring, a rubber part and an outer steel ring which is slotted. This main part is within the outer hollow cylinder which is used in combination with the inner bolt for generating a prestress on the rubber part. Nowadays, it is state of the art to follow a preventive maintenance strategy handling these bearings. Thereby, the lifetime of the bearing needs to be estimated prior to its service life. Therefore this lifetime is estimated conservatively by the developer based on experience, lifecycle tests and the conditions of the planned application. This calculation is often based on linear damage accumulation theory (Spitz 2012). A preventive maintenance strategy shows some drawbacks regarding optimal utilization of the resource and costs. Moreover, today's industry develops growing expectations concerning efficiency of capabilities and availability. That is why condition monitoring gains more and more importance in the field of maintenance.

Figure 1. Rubber-metal-bearing.

1.2 *Maintenance strategies*

Maintenance can be divided in different strategies according to DIN EN 13306. The oldest strategy is the reactive maintenance. Technical systems were used until failure and needed to be repaired or replaced once they reached their end of lifetime. This procedure leads to a couple of problems concerning costs and time, for example possible high consequential costs due to unplanned downtime. Therefore the preventive maintenance strategy was developed. In that case mechanically lifetimes of technical systems are calculated based on experience, lifecycle tests and fatigue life calculations. However, this maintenance strategy does not enable exploiting the whole lifetime of a single product.

The calculation is a generalized one that bases on assumptions regarding the expected loads over all bearings. Furthermore, safety factors are included in the calculations that ensure with a high degree of certainty that every product is maintained or replaced previously to its end of lifetime. However, this strategy provides no information on the current state of individual bearings which experience individual loads during their lifetime and therefore degrade individually. That is why on the one side, possible early failures could occur and on the other side, bearings are replaced although their lifetimes are not yet exhausted. These disadvantages of the previous named strategies are the reason why the condition based maintenance strategy was developed. This strategy is mainly based on the condition of the product in focus. Using different kind of sensors, information about the condition of the product is acquired and progressed by condition monitoring methods. So, maintenance can be planned optimally based on the condition of the product and, in case of prognostics, additionally on the estimated remaining useful lifetime (RUL), which improves the reliability of the product and leads to an optimized efficiency.

1.3 *Structure of the following sections*

In this work the prognostics method which is used to estimate the RUL of these rubber-metal-bearings is analyzed regarding its performance on temperature data of these bearings. The used method is a particle filter. Due to the fact that different types of particle filters exist (Arulampalam et al. 2002, Jouin et al. 2016), in chapter 2 the used method is presented regarding type correlated differences. Aiming for realizing the best RUL prediction for rubber-metal-bearings, relevant parameters of the method for a performance analysis are identified. Chapter 3 focusses on necessary lifecycle tests and generated data for developing the condition monitoring system. Chapter 4 deals with the analysis of that temperature based prognostics. Two different measured values are implemented and particle filtering performance is analyzed based on varied parameters. In chapter 5 a conclusion and a short outlook are given.

2 PROGNOSTICS METHODS

2.1 *Types of particle filter*

Particle filters are Monte Carlo methods that base on Bayesian probability theory. These filters are model-based methods for state estimation that are appropriate for estimating non-linear behavior. Currently, it is a classical method for model-based predictions of RUL (Jouin et al. 2016). Moreover, particle filters create a probabilistic output which can be used to present uncertainty involved in RUL predictions. Additionally, this method was chosen because a multi model particle filter has been successfully applied to other signals of rubber-metal-elements (Bender et al. 2017b, Bender et al. 2017a, Bender et al. 2017c).

These filters can be divided in different types. The commonly known ones are Auxiliary particle filter, Unscented particle filter, Regularized particle filter, Sequential Importance Sampling (SIS) filter and Sampling Importance Resampling (SIR) filter (Arulampalam et al. 2002). In this work a SIR particle filter is used for estimating the RUL of rubber-metal-bearings due to the named advantages and the SIR related improvement of particle degeneracy. Particle degeneracy is a weakness of the classical SIS filter. The SIR particle filter is a further development of the SIS filter and prevents that degeneracy by resampling. All these Monte Carlo based filters use random samples that are called particles to estimate the state of the monitored product in the form of a distribution. Therefore, the samples' relevance is symbolized by weights. These weights are calculated based on a defined distribution and a comparison of the predicted and the measured values. In the case of degeneracy after little iteration most of the particle weights tend towards zero while only one particle has a bigger weight. That means that only one particle builds the base for the state estimation and the consecutive estimation of the RUL. Nevertheless all particles are still part of the estimation even if their influence on the result tends towards zero. This degeneracy problem can be solved by resampling. Thereby only relevant samples survive which means samples with a higher weight. Those samples build the base for the next prognostics step while the probably irrelevant particles are no longer considered. In that case a smaller variance of samples is used, but the result is more accurate. The RUL prediction is an iterative method. As long as measured data is available the weights can be updated and resampling can be proceeded (Arulampalam et al. 2002, Jouin et al. 2016).

The general structure of a particle filter is given in figure 2. The models are developed based on data for training that is presented in chapter 3. Due to the complex, nonlinear behavior and multiple ways of degradation, no physical model of failure for rubber-metal-elements exists. Therefore empirical parameterized models are implemented. For every dataset these parameters are estimated by using Differential Evolution, a population based optimization algorithm (Elsayed et al. 2012). So, every model is related to one bearing. These models are used within the method for state estimation based on samples. Therefore a multi model version of a SIR particle filter is implemented. The general state equation to estimate the samples is given in Equation 1 (Vachtsevanos 2006, Arulampalam et al. 2002) and the particular state equation in Equation 2.

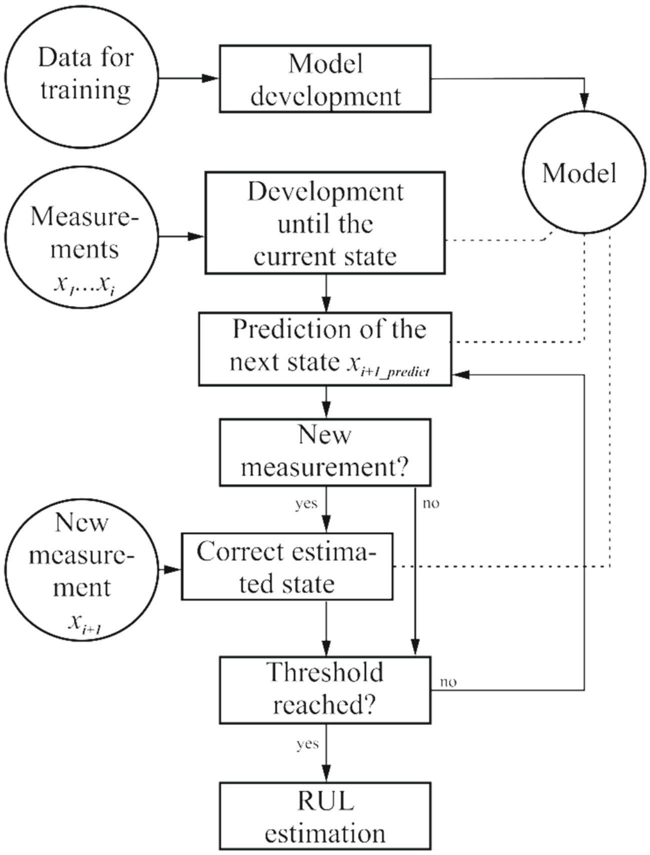

Figure 2. Structure of a particle filter.

$$x_i = f(x_{i-1}, mdl_{i-1}, v_i, t_i); \qquad (1)$$

$$x_i = \frac{x_{i-1} \cdot \left[e^{p_{i-1,1} \cdot \left(\frac{t_i}{p_{i-1,2}} \right)^{p_{i-1,3}}} + e^{\frac{p_{i-1,4}}{p_{i-1,5} \cdot t_i + 1}} \right]}{2} + v_i; \qquad (2)$$

where x_i is state vector at time t_i, mdl_{i-1} is the model with parameters $p_{i-1,1-5}$ and v_i is added noise. The model parameters are chosen based on the weights of the previous state vector. In this version the initial samples or initial states are in each case generated by one of the models and the first measurement. By an appropriate number of samples, model choice is equally distributed for the initial sample generation. Therefore different numbers of samples are evaluated in chapter 4. If new measurements are available, the estimated states can be corrected through resampling. With the aim of estimating the RUL, the prediction step is repeated until a given threshold is reached by the samples.

2.2 *Relevant parameters*

Variable parameters of a particle filter influence the accuracy of prognostics. The parameters to be analyzed are number of simulations, number of samples, the measured values and the resampling strategy.

Accuracy of particle filter strongly depends on the number of particles. That is because it is more likely that a big random sample of a defined distribution is able to show a good representation of that distribution than a smaller random sample. To show the influence of variable number of samples on predictions of RUL, three possible numbers of samples should be compared. In this context the number of simulations is analyzed as well.

The measured values in focus are temperatures acquired in or close to the bearing. It was observed that the temperature of rubber-metal-bearings changes over their lifetime, especially in the end of their lifetime. Due to the fact that bearing temperature is influenced by operating conditions, these conditions should be considered. In chapter 4 measurements based on similar conditions are implemented including similar exciter power, similar frequency and similar bearings. Nevertheless, there is one parameter that cannot be kept constant, the ambient temperature. That is why the ambient temperature is measured as well. The relative temperature ΔT involves both temperatures in the form of a subtraction, ΔT = T (bearing) – T (ambient). In the following chapter both measured values, absolute bearing temperature and relative temperature are presented.

To improve the degeneracy problem, resampling can be involved in the particle filter. Multiple resampling schemes exist (Arulampalam et al. 2002, Ignatious, Lincon 2013), in this work the SIR is implemented. One point of interested in this context is the question when to resample. Two possibilities are compared for the application of rubber-metal-bearings. The first continuous strategy enables resampling in every iteration step which is easy to implement but leads to high computational cost. The other strategy is based on a defined threshold for resampling. In this case resampling is only executed if the condition is fulfilled. The realized threshold is based on the effective sample size N_{eff} which is a measure for degeneracy. The effective sample size cannot be computed exactly, therefore an estimate $\widehat{N}_{eff}$ of N_{eff} is used here, see Equation 3.

$$\hat{N}_{eff} = \frac{1}{\sum_{i=1}^{N_S} \left(\omega_k^i \right)^2} \qquad (3)$$

where ω_k^i is the normalized weight (Arulampalam et al. 2002). A threshold needs to be defined which allows resampling when $\widehat{N}_{eff}$ is smaller than that threshold. This resampling strategy needs less computational time because resampling is not realized in every iteration step.

3 LIFECYCLE TESTS

3.1 *Lifecycle tests*

Testing rubber-metal-elements is a complex task. Due to their nonlinear behavior and wide distributions concerning lifetime characteristics of rubber caused by manufacturing, lifetime estimation is not trivial (Steinweger 2006, Wallmichrath et al. 2009). That is why nowadays preventive maintenance based on prior calculated lifetimes, often using linear damage accumulation, is state of the art in applying rubber-metal-elements.

Due to a lack of real data, lifecycle tests are performed to generate data for prognostics. Here accelerated lifecycle tests with an increased excitation force are realized because of the long lifetime of these bearings. In the suspension system of trains they are used for up to 8 years (Bender et al. 2017b). These lifecycle tests are performed on a vibration analysis system using a hydraulic cylinder as exciter. It enables movements of the outer ring of the bearing, whereas the inner ring is fixed. The rubber between those rings allows a small movement. Under this mechanical stress the characteristics of rubber change over time due to degradation. Finding a suitable measure to monitor a rubber-metal-bearing condition is a challenging task due to non-linear rubber characteristics and many possible impacts on the lifetime of rubber. Moreover, the structure of the elements increases the difficulty of installing a sensor for a suitable and reliable measure. In this work the focus is on temperature, a measure that is used in other applications as well, for example ball bearings (Kimotho, Sextro 2015) or subsystems of wind turbines (Crabtree 2011). The correlated concept for temperature measurements in rubber-metal-bearings is introduced in (Bender et al. 2017c). Based on that work, a prototype of a rubber-metal-bearing was developed that enables temperature measurement inside the bearing. Integrating a sensor inside the rubber presents a weakness and could lead to a shorter useful lifetime. Moreover, (Molls 2013) showed that temperature inside the rubber part of rubber-metal-bearings have deviations of maximum 3 °C compared to temperature measurements at its surface. Therefore, the used thermocouples are placed inside the outer ring of the bearing close to the surface of the rubber. Little pockets are shaped in the metal, in which the thermocouples are bonded. These pockets protect the sensible thermocouples from external influences. Additionally to the absolute temperature of the bearing, the ambient temperature is measured close to the lifecycle tests.

3.2 *Measurement data*

For temperature measurements sheath thermocouples of type K are inserted in the lifecycle tests that are able to monitor the temperature of the bearing. Moreover, they are robust to weather the conditions of the tests and real applications. Data is measured over the whole lifecycle test including data of the failure state. Prior to the prediction, the measured data is preprocessed for generating empirical models. As shown before these models are based on a combination of e-functions which describes the graph of the measurements. The characteristic graphs of the absolute temperature of three bearings are shown in figure 3

In the beginning the absolute temperature of bearings raises strongly, before it fluctuates during the main part of the life of a bearing. Bearing 2 shows a small fall of temperature during that time whereas the temperature of bearing 3 stays almost constant. In the last part all temperature curves rise until the end of lifetime is reached. Analyzing figure 3, it becomes obvious that in addition to their common characteristics these curves differ in aspects such as starting and ending temperature, lifetimes of bearings and the corresponding graph. This has different reasons based on characteristics of the bearing and operating conditions, especially the ambient temperature. That is why the ambient temperature is involved in the second measured value, the relative temperature. The graph of the relative temperature for bearing 3 is depicted in figure 4. In general the curve of the relative temperature shows similar characteristics like absolute temperature of bearings during its lifetime. The significant temperature rise in the beginning and in the end is related to the absolute temperature of the bearing. Due to the fact that the ambient temperature fluctuates more easily than the temperature inside the bearing, the relative temperature fluctuates during the main part of the lifecycle test. Moreover a stop of the test after about 10^6 cycles leads to a falling temperature because of a cooling. After starting the test again the temperature of the bearing raises quickly. Due to the similar graphs, all models of both measured values base on the same state equation, only the parameters differ. All in all, the relative temperatures have a more similar value range than the absolute temperatures of bearing. Therefore the models should fit better and might result in an improved prediction. Both measured values are implemented in the following analysis where the influence of the previously mentioned parameters comes under focus.

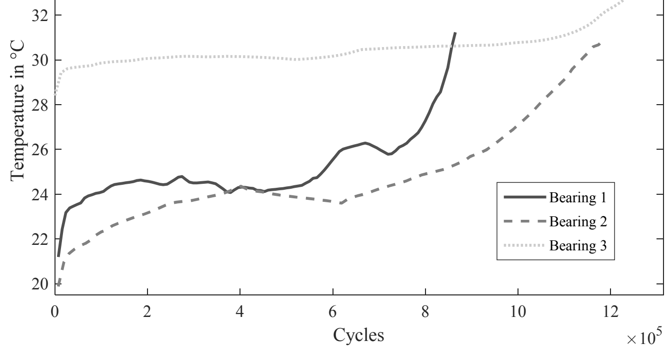

Figure 3. Absolute temperatures of bearings during lifecycle tests.

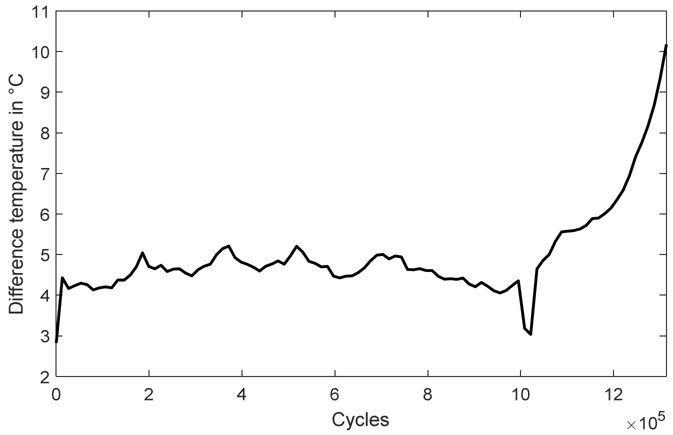

Figure 4. Relative temperature during lifetime of bearing 3.

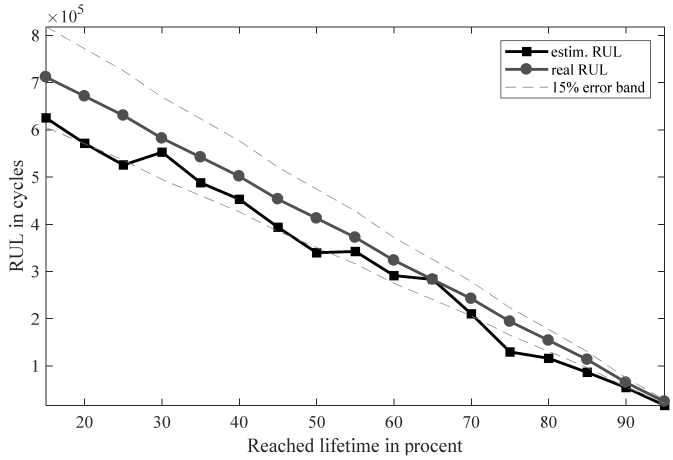

Figure 5. Estimated RUL at different times of bearing 1.

4 ANALYSIS OF PREDICTIONS

4.1 *Test structure*

In this chapter the presented measured values are used for estimating the RUL with the presented SIR particle filter. To find the best performance different parameters shall be implemented and compared. The following tests are evaluated on:

1. Measured values: absolute temperature of bearings and relative temperature
2. Number of simulations
3. Number or samples
4. Resampling strategy including different thresholds

For evaluating the performance a metric based on relative error is used. This metric is calculated analogue to Equation 4.

$$Error = \frac{RUL_{real} - RUL_{estimated}}{RUL_{real}} \cdot 100\% \qquad (4)$$

where RUL_{real} is the current RUL of the element and $RUL_{estimated}$ is the predicted RUL. In this work the RUL is estimated for different times from 15 to 95 % of spent lifetime of the bearings. Thus the error is the mean error calculated as the mean of the RULs from different times. Thereby positive and negative errors compensate each other; therefore the number of negative errors is given in brackets to get an impression of the sign of single RULs. As an example figure 5 depicts the RULs at the mentioned starting times for bearing 1. Illustrated are the real (grey circles) and the estimated RULs (black squares). The dashed lines symbolize an error band of 15 %. Only one error is negative (1 N) which is good. Greater RULs present a too late prediction and thereby a possible unwanted breakdown of the system. The parameters used to generate this result are 100 particles, three simulations, resampling realized in every iteration step and the relative temperature as measured value.

4.2 *Results for bearing temperature*

In this paragraph prognostics base on absolute bearing temperature measurements and the associated models. The first parameter of interest is the number of simulations. Due to the fact that the SIR particle filter is based on probability it is necessary to reach a repeatable result within certain limits. To find a suitable number of simulations three different alternatives between three and 100 simulations are tested and the results are displayed for three test bearings in table 1. The tests are numbered. An ‘a’ is added to the name as a symbol for measured value absolute temperature of bearings.

Table 1 shows that prediction of the RUL of these three test bearings do not lead to the same results regarding the best number of simulations. Each of the bearings shows the best performance for another number of simulations. However, the number of negative errors differs only slightly for each bearing. SIR particle filter are sensitive to outliers (Arulampalam et al. 2002), that is why a high number of simulations is necessary to compensate outliers. To reach valuable results particle based methods need a suitable (minimum) number of samples or particles. Therefore in the previous simulations 100 particles were implemented.

Table 1 Influence of number of simulations on prognostics of absolute temperature of bearings

Test No.	Simulations	Error (bearing 1) in %	Error (bearing 2) in %	Error (bearing 3) in %
1a	3	12.6 (1 N)	-26.0 (17 N)	13.1 (3 N)
2a	10	15.7 (0 N)	-19.1 (17 N)	13.7 (0 N)
3a	100	14.0 (1 N)	-22.6 (17 N)	13.0 (1 N)

For that reason 10 and 100 trails are analyzed again for varying number of samples from 100 to 1000 with the aim of improving the result. The performance metrics for the three test bearings are compared in table 2. Again no consistent results over all bearings exist.

Table 2: Influence of simulations and number of samples for absolute temperature of bearings

Test No.	Simu-la-tions	Number of sam-ples	Error (bearing 1) in %	Error (bearing 2) in %	Error (bearing 3) in %
2a	10	100	15.7 (0 N)	-19.1 (17 N)	13.7 (0 N)
3a	100	100	14.0 (1 N)	-22.6 (17 N)	13.0 (1 N)
4a	10	500	13.3 (0 N)	-24.4 (17 N)	10.1 (1 N)
5a	100	500	13.5 (0 N)	-24.3 (17 N)	10.0 (1 N)
6a	10	1000	13.6 (0 N)	-24.5 (17 N)	9.6 (2 N)
7a	100	1000	13.4 (0 N)	-24.0 (17 N)	9.3 (1 N)

Bearing 3 performs best for 1000 samples, bearing 1 for more than 100 samples and bearing 2 for 100 samples. It indicates that especially bearing 2 leads to unexpected results. Furthermore, only 2 / 3 of the results exhibit a better performance for 100 simulations. This may be related to the small number of models. However, the difference between the results of variable trails decreases with a growing number of samples. To analyze the influence of the number of samples and resampling thresholds on the performance both parameters are varied in the next step for bearing 1. So far a continuous resampling was implemented; in table 3 both resampling strategies are realized. The resampling threshold is in a first step based on the mean effective sample size measured during a continuous resampling strategy. In the following steps it is adapted to the performance metric. The chosen number of simulations is ten.

Table 3: Influence of number of samples and resampling strategy (bearing 1) for absolute temperature of bearings

Test No.	Number of samples	Resampling threshold	Error in %
2a	100	-	15,7 (0 N)
8a	100	40	13.3 (1 N)
9a	100	42	13.1 (2 N)
10a	100	45	15.7 (0 N)
11a	100	50	12.0 (2 N)
6a	1000	-	13.6 (0 N)
12a	1000	390	13.8 (0 N)
13a	1000	400	14.5 (0 N)
14a	1000	405	14.1 (0 N)
15a	1000	410	13.4 (0 N)
16a	1000	412	15.5 (0 N)

Table 3 underlines that a threshold based resampling strategy is able to improve the performance for both number of samples. While for 100 particles a threshold of around 50 leads to the best performance, for 1000 particles a threshold of 410 is the best. A threshold based resampling strategy can balance worse performance metrics based on a smaller number of simulations. As table 3 shows, a parameter combination of 10 simulations, 1000 samples and a threshold of 410 (test 15a) leads to a similar result like a parameter combination of 100 simulations, 1000 samples and a continuous resampling strategy (test 7a). In the context of online prognostics this could be a great advantage, since less simulations and a threshold based resampling strategy need less computational cost. However, the error is smaller for 100 samples, but more sensitive to unwanted negative prediction errors.

4.2.1 *Results for a further position of measurement*

Molls suggested that the rubber temperature inside the rubber changes quite similar to the surface temperature (Molls 2013). The measurements in this work show similar temperature behavior between the bearing temperature and the temperature measured at the bolt of a bearing. In figure 6 these two temperatures are visualized for bearing 3.

This leads to the possibility of testing the method and the models, based on those of absolute temperature of bearings, by new bearings whose bolt temperatures are known. The used parameters are 100 particles, 10 simulations and a resampling threshold of 50 effective samples. The resulting errors are 12.6 % (0 N) for bearing I and 4.0 % (8 N) for bearing II. Figure 7 depicts the result of bearing I. The errors are within a 15 % error band or just below it. The estimated RULs of bearing II fluctuate stronger as the large number of negative errors shows, while the mean error of 4.0 % seems to be good.

These two tests show that temperature measurements close to the rubber-metal-element that have similar characteristics could be used for estimating RULs in the case of missing bearings' temperatures.

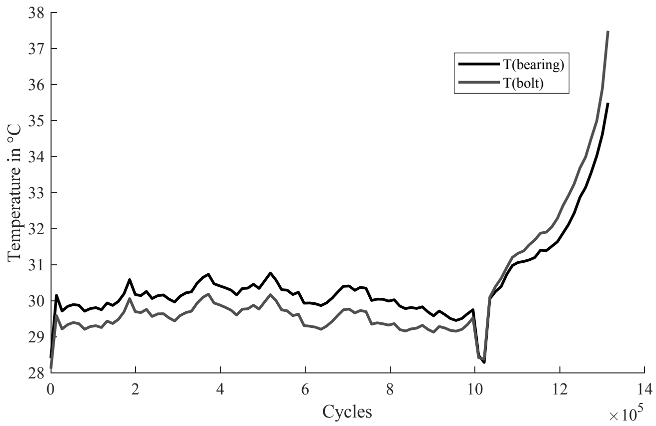

Figure 6. Absolute temperature of bearing and bolt temperature

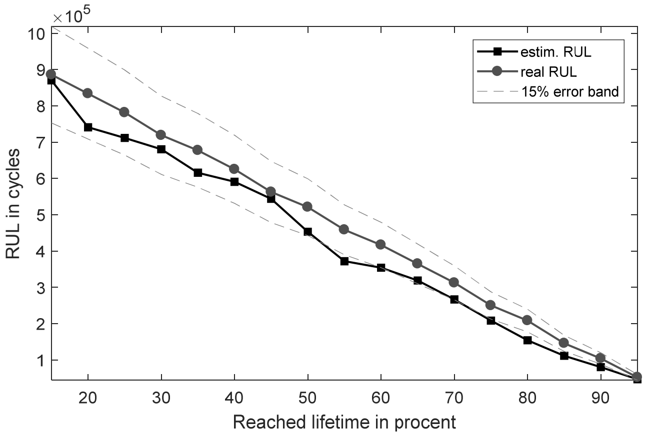

Figure 7. Estimated RULs for bolt temperature of new bearing.

4.3 *Results for relative temperature*

In this paragraph predictions based on the relative temperature are evaluated. Because of the former results and the similarities between the two measured values, this evaluation is based only on bearing 1. The implemented models base on relative temperatures measurements. The structure of this analysis is similar to the one in chapter 4.2, the parameters simulations, number of samples and resampling strategy are varied and the performance metric is evaluated. In table 4 the influence of the number of simulations on the performance of bearing 1 is shown for 100 particles. The names of the numbered tests for this measured value contain an added 'b'. The error falls with increasing number of simulations. The number of negative errors is small and nearly constant as before. The best result is based on 100 simulations that is why the predictions shown in table 5 include 100 simulations.

Table 4 Influence of simulations (bearing 1) for the relative temperature

Test No.	Simulations	Error in %
1b	3	15.4 (1 N)
2b	10	12.7 (0 N)
3b	100	12.4 (0 N)

Table 5: Influence of number of samples (bearing 1) for the relative temperature

Test No.	Number of samples	Error in %
3b	100	12.4 (0 N)
4b	500	12.2 (0 N)
5b	1000	12.0 (0 N)

Table 5 depicts an improved estimation of the RUL for an increasing number of samples. The best performance of 12.0 % is predicted for 1000 particles. The former good result with less simulations and a threshold based resampling ($error_{15a}$) should be examined in the next step for the relative temperature. Table 6 shows the results for varying resampling strategies and thresholds based on 10 simulations and 100 or 1000 samples. Similar to table 3 table 6 presents possible performance improvements based on suitable thresholds. Due to the small differences regarding the performance metric of different number of samples, the best performance for 100 and 1000 samples were evaluated. An error of 12.3 % was achieved for a threshold of 45 using 100 samples. The best threshold of 400 enables an error of 11.8 % using 1000 samples. Comparing the threshold based results of 1000 particles and 10 simulations (test 9b) to the one of continuous resampling with 100 simulations (test 5b), the threshold based resampling slightly improves the former results. It can be concluded that a threshold based resampling can lead to an improvement of the performance of the SIR particle filter. At least a saving of computational time is realized.

Table 6: Influence of resampling strategy (bearing 1) for the relative temperature

Test No.	Number of samples	Resampling threshold	Error in %
6b	1000	-	12.5 (0 N)
7b	1000	390	12.5 (0 N)
8b	1000	395	12.0 (0 N)
9b	1000	400	11.8 (0 N)
10b	1000	405	11.9 (0 N)
11b	100	45	12.3 (0 N)

4.4 *Comparison of the results*

In this part of chapter 4 the results of the two measured values are compared. Regarding the number of simulations, 100 simulations are less outlier prone and therefore lead usually to the best results. Comparing the errors, the measured value relative temperature enables better performance regarding the number of simulations. While the smallest error related to absolute temperature of bearing 1 is 14.0 %, an error of 12.4 % is related to the relative temperature of bearing 1. The errors are in most cases reduced by an increased number of samples. Once again the relative temperature performs better than the absolute temperature of bearings ($error_{5b} = 12.0$ %, $error_{4a}$ (bearing 1) = 13.3 %). In the end the analysis of different resampling strategies emphasis that a threshold based resampling with a suitable threshold leads to a similar good performance with a smaller number of simulations. Moreover, in the case of the relative temperature the performance is slightly improved ($error_{5b} = 12.0$ %, $error_{9b} = 11.8$ %).

All in all estimating RUL for rubber-metal-bearings is possible based on temperature measurements and SIR particle filter for almost constant conditions. In reality applied bearings experience variable changing conditions, e. g. changing excitation. If the operation conditions are changed to a great extent, the similarity between the measurements will not be given. Therefore, implementing or adapting models for different excitation forces seems to be necessary.

5 CONCULSIONS

In this paper a temperature based estimation of the RUL of rubber-metal-bearings is introduced. To evaluate and improve the performance of the SIR particle filter number of simulations, number of samples and resampling strategy are analyzed. The predictions base on two different measured values, absolute temperature of bearings and relative temperature that includes the ambient temperature and absolute temperature of bearings. Predictions based on relative temperature show a better performance than those based on absolute temperature. The reason lies in bigger differences between temperature curves that lead to more variance in the results compared to predictions based on relative temperature. Regarding the parameter, on average 10 to 100 trials and 1000 particles are a good choice for this application. Moreover, both predictions can be improved by a threshold based resampling strategy. It can be concluded that even if rubber-metal-bearings show nonlinear behavior and slightly changing characteristics a threshold based resampling in combination with a suitable threshold enables a relative good RUL estimation based on temperature measurements.

Open questions are related to the threshold of the previous predictions. In this work the end of lifetime is defined by the last measurement. Therefore a threshold needs to be estimated that marks the end of lifetime. Moreover, finding thresholds for effective resampling can be optimized.

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