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Bearing Degradation Prognosis Using Structural Break Classifier

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1. Introduction

Real time engineering applications are full of diversity. This diversity is due to presence of non linarites and randomness in the systems which results in uncertain future state. In engineering systems, when reliability is under discussion than concept of Condition Based Maintenance poses its limitations of forecasting the future health. Specially, when there is an induced nonlinearity (defect), which has to evolve with time (degradation), CBM diagnostics capability can ascertain its present severity; however, how much it will deteriorate in future, needs to be assessed through advance tools; this prediction of future state is termed as Prognosis.

Prognosis is a medical term derived from Greek language pro & gnosis with a literal meaning 'forecast of the likely outcome of a situation'. Prognosis has been widely applied in medical sciences & finance sector and enormous literature is available on the subject. Taking lead from aforementioned fields, researchers directed their efforts to apply prognostics concept in engineering applications.

Machinery health prognosis is broadly driven by (i) physical model of machine/component (ii) data driven models (iii) Hybrid (combination of i& ii). Suitability of each method for prognostics application has adequately been deliberated in [1]. Prognostic on the basis of physical models is theoretically fine but its practical manifestation in real time environment is difficult, as machinery life is governed by various known and unknown effects, while on the other hand, prognosis using data driven models, carries better practical manifestation in real life.

Condition monitoring data provides a comprehensive understanding of machinery condition under prevailing operating conditions. This data while providing various condition indications of machinery can be manipulated using different tools for prognosis [2–3]. Fig. 1 shows the statistics of approaches being used in prognosis [1].

Data driven methods are broadly divided into two approaches i.e. Artificial Intelligence (AI) and Statistical approaches. AI approach has its unique computational power; however, it requires an extensive expertise [2]; however, AI approaches are hard to be explain because of the lack of transparency, thus these techniques are always named as ''black boxes" [1]. In contrast, statistical models being not dependent of physical laws provide a more flexible framework in dealing with machinery health data. Statistical RUL prediction models are constructed by fitting available observations into random coefficient models or stochastic process models under a probabilistic method [1], [4]. Random variances are generally introduced into model parameters to describe the uncertainties caused by different kinds of variability sources, such as the temporal variability, unit-to-unit variability and measurement variability [5].

Therefore, the statistical model-based approaches are effective in describing the uncertainty of the degradation process and its influence on RUL prediction [1]. This paper discusses application of Structural Break Classifier model with Autoregressive component in order to effectively predict the nonlinear and random behavior of failure propagation in Roller element bearing (REBs). Validation of the proposed model is conducted using standard statistical tests vis-à-vis experimental data.

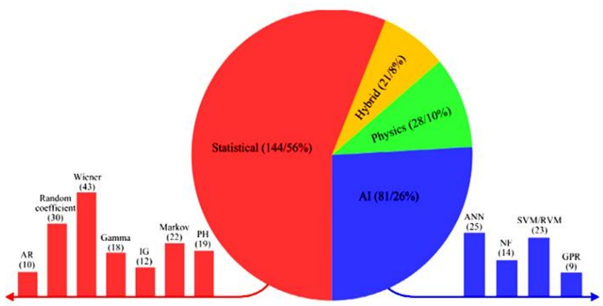


Fig. 1 Machinery health prognosis approaches

2. Bearings prognosis

Bearings are the most critical component of machinery and determinant of machinery health [2] and under continuous deterioration being the loaded part of any machine. Bearing failure statistics shows that most of the failures in case of bearings are not age related [6] and generally do not follow well known bath tub curve [7]. Hence, it is imperative to predict the potential failure point in bearings to ascertain its P-F curve. Most of the condition monitoring tools like Vibration analysis, oil analysis, acoustic emission, and ultrasonic analysis focuses on detecting this potential failure point specially in case of bearings.

This situation is more complex specially when a degradation phenomenon is accelerated near end of life in which the randomness and various non linarites act as catalyst. When the bearing will start exhibiting the deterioration symptoms, an effect called 'butterfly effect' shows that how tiny differences between the initial conditions which apply to any dynamic system lead to dramatic difference after the passage of time.

This may explain why minute variations between the initial conditions of two rolling element bearings can lead to huge differences between the ages at which they fail [7]. Degradation of bearing by wiener process is adequately discussed in [8] alongwith its future trend prediction. Similarly, a comprehensive review [9–12] enumerate in detail the bearing prognosis process with details of research conducted in each prognosis step. Hence, there is a need to explore more reliable and easier prognostic methods in the domain of bearing health prognosis.

3. Experimentation

The bearing datasets were measured during experimentation conducted Bearing failure test rig shown in Fig. 2. Accelerated testing concept was adopted to collect bearing failure data with an induced nonlinearity (i.e. defect) under random conditions. Experimentation was more focused on acquiring the trend after induction of defect till the achievement of failure threshold to estimate remaining useful life i.e. P-F interval.

Test rig is a simple arrangement driven by a two Hp variable speed induction motor. A customized designed shaft is then supported by two bearings. The test bearing SKF-6209 subjected to various radial and axial loading conditions, under modified housing follows the support bearings. A screw type loading mechanism is installed for static load in radial direction and axial loading was kept random using modal exciter. Data was collected using CSI 2130 vibration analyzer.

Fig. 2 Bearing test rig setup

The experimental conditions at various loadings with different bearing defects are listed in Table 1.

Table 1

Experimental Conditions

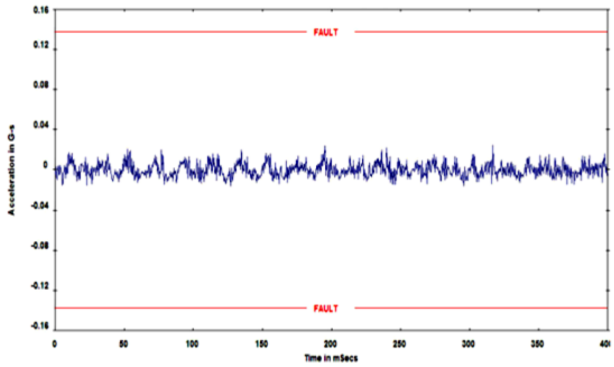
S. No.	Radial loading	Groove width (μm)	Groove depth (μm)
1	30 N	38	12
2	45 N	38	12
3	60 N	38	12

Various researchers have utilized rms, kurtosis and skewness etc. for feature extraction and further development of prognostic models [11] which are proven feature extraction approaches; however, in these methodologies the contribution of particular defect may be shadowed in overall spectral energy; hence true picture of specific defect propagation may not be ascertained. For our study we localize our approach to the peak values of Outer Race Defect frequency (BPFO) to follow propagation of outer race defect to forecast bearing health.

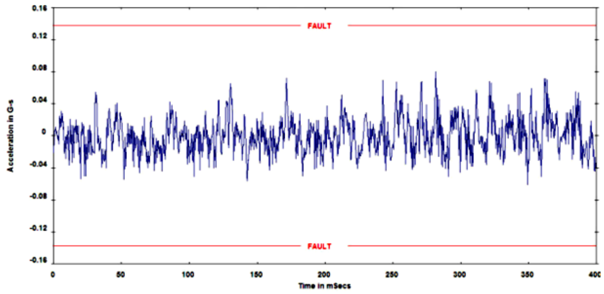
4. Spectral analysis

An outer race defect was discovered in test bearing 6209 at 45 N radial load along with variable axial loading. The change of vibration trend was categorized in three stages. In the first stage, vibration levels were stable and no defect frequencies were observed. After the defect was induced defects frequencies were noted with rise in vibration levels. After further test runs the rise in vibration trend again lowered and stabilizes for some hours and in some cases remain fluctuating due 'healing' effect [13], the nature of the propagating process of the damage.

The signal exhibits strong impulse periodicity because of the impacts generated by a mature outer race defect. To pick these short duration impulses caused due metal to metal contact, we employed PeakVue methodology. However, the vibration signal acquired on the later stages of failure, the periodic impulses are shadowed in noise energy caused due propagated defect across the bearing outer race. The spectral results of 6209 bearing at 45 N loading at various stages are shown in Figs. 3, a–c for reference. Damaged bearings are illustrated in Fig.4.



a



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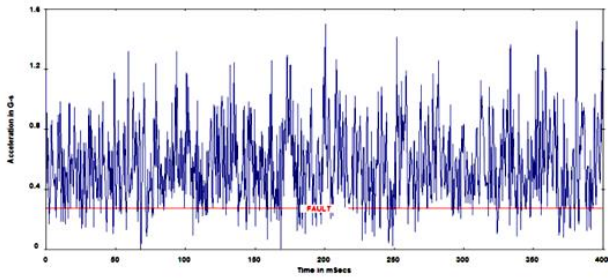


c

Fig. 3 Time waveform spectra: a – no defect, b – defect at initial stage, c – defect at final stages

5. Statistical inference

Upon feature extraction, the structural breakpoint model was applied to estimate statistical features. Features extracted statistically were than utilized for generation of suitable model; which was further validated for its parsimony using various statistical tests. After model validation, bearing degradation was forecasted.

Fig. 4 Damaged bearing

6. Model and method

The model developed by [14] and further modified by [15] for structural breaks in small samples is utilized. Consider standard multiple linear regression models with T periods and m potential breaks (producing m +1 regimes) that can be represented by:

$$y_t = \varphi'_t\,\alpha + \theta_t{}'\,\delta_j + \varepsilon_t t = T_{j-1} + 1, \ldots\ldots T_j\,, \tag{1}$$

where: y_t represents dependent variable, $\varphi'_t \& \theta_t$ are covariate vectors with corresponding coefficients $\alpha \,\&\, \delta_j$ respectively, whereas ε_t is the disturbance. Initially, Eq. (1) allows for joint estimation of regression coefficients by utilizing the term $\varphi_t^{'}\alpha$ along with the determination of structural changes which are captured by $\theta_t^{'}\delta_j$. Later on, this equation signifies fractional structural transform where entire coefficients were estimated with regards to changes in the model with ε_t ~ iid $(0, \sigma_\varepsilon^2)$.

There were two approaches to locate the break in the model by utilizing Eq. (1) (a) Primarily technique of global sum of square residuals (SSR) minimizing break approach is applied in which every partition m is attained such that it minimizes the SSR i.e. at break position (T_j), for j = 1,2,…m are determined to reduce as Eq. (2):

$$\sum_j^{m+1}\sum_{t=T_{j-1+1}}^{T_j}\left(y_t - \varphi'_t\,\alpha - \delta_j\theta'_t\right)^2. \tag{2}$$

Secondly, sequential technique is utilized to determine breaks starting with the single break that minimizes the SSR. For each segment its break is determined which minimize the SSR. The second break is the partition with the minimum SSR between the two and similarly the process is conducted for computation of further breaks sequentially.

7. Testing

Test statistics for multiple segments consists of generalization of test for single structural change case which is shown to be robust to serial correlation and heterogeneity of the residuals under the null [16]. Descriptions of various tests will be discussed in coming sub sections.

7.1. Fixed against zero number of breaks

In this case, one desires to test the null hypothesis of no breaks against the alternative of a known number of breaks k. To test this F-ratio between the unrestricted standard sum of errors (SSE) for null hypothesis and restricted SSE for alternative hypothesis is measured. Simply stated it is the conventional test of the null $\delta_1 = \delta_{k+1}$ against the alternative $\delta_j \neq \delta_{j+1}$ for some j, where 'δ' is the vector of coefficients attached to the covariate θ in the pure structural change model.

For the global minimized breaks, this test is called as Sup $F(0, m)$. In this case an asymptotically equivalent simple variance-covariance matrix for δ is computed to overcome the problem of estimating δ in the presence of autocorrelation and heteroscedasticity in residuals. However, in case of smaller time series, this simpler approach cause power distortion.

7.2. Unknown against Zero number of breaks

In this case, the number of breaks is unknown, and hence, standard F-statistic approach only not suffice for testing of the existence of breaks. In this regard, variations of the Sup F (0, m) test, called double maximum tests is used which is defined as Eq. (3):

$$D_{max} = max_{n=1,2,\ldots\ldots m}\left(a_n\, sup\, F(0,n)\right), \tag{3}$$

where: $a_n = 1 \forall_n = 1,2,\ldots\ldots m$.

D_{max} = test statistics for any number of breaks in each segment In general a_n can be function of the asymptotic critical values for Sup $F(0, n)$ which makes the marginal p-value equal across the value of n, in such case D_{max} statistics is called WD_{max} (i.e. weighted double maximum statistics) test or it may be unweighted double maximum statistics (i.e UD_{max}). Notably the D_{max} statistics depend on the Sup $F(0, m)$, finite sample variation in the estimation of the variance-covariance matrix for δ will too affect the size & power of estimated statistics of break segments or it may employ the unweighted or weighted double maximum statistics.

7.3. l versus l + 1 breaks

Similar to the $F(0, m)$ ratio, the $F(l + 1 \mid l)$ ratio is also related to the 'unrestricted' SSE (for l breaks), to the 'restricted' SSE (for l + 1 breaks). Calculating the $F(l + 1 \mid l)$ ratio is equivalent to estimating l + 1 tests of the null of zero breaks against the alternative of a single break. The test decides in favor of the null whenever the sum of SSE for the optimal l + 2 partitions (or l + 1 breaks) is sufficiently larger than that for l + 1 partitions (or l breaks). However, the critical values of the statistic under the null l + 1 depend on sample-specific factors, such as the break size and the properties of the residual. An alternative approach uses the sup $F(0,1)$ (testing for the presence of one significant break) in each of the partitions. If the null of 0 breaks rejected against the alternative of one break in at least one of the l + 1 partitions, then it establishes that l+1 breaks are statistically significant.

7.4. Criteria for finding the number of breaks

The number of significant breaks can be found using Bayesian Information Criterion (BIC) and the modified Schwarz criterion (SC). The elementary steps will include testing for the existence of one break via the Sup $F(0,1)$ and subsequently to test for the presence of $l + 1$ breaks, via the $F(l + 1 \mid l)$ ratio, till null is not rejected. The variance-covariance of δ set in these tests, is not sensitive to heteroskedasticity and auto-correlation [14], unlike the information criteria-based approaches. However, this approach pose limitation in calculation of breaks when there are multiple existence of breaks vis-à-vis regimes are switching. Using D_{max} stats, regime switching problem can be tackled but for larger number of break identification problem still persist.

8. Application

Above method is applied to historical bearing health data y_t measure through vibration signals by utilizing signal processing techniques. The time plot of the data depicted in Fig. 5 illustrate real time structural break in the health parameters.

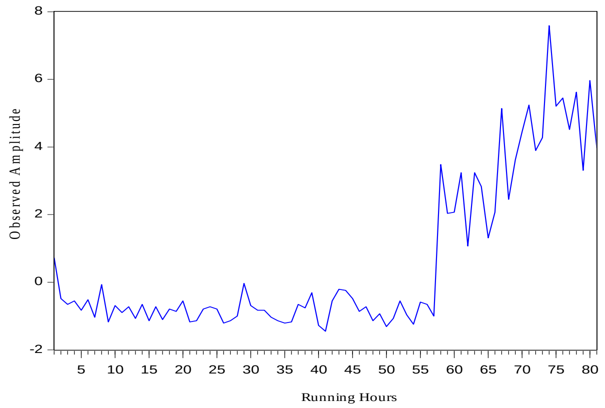


Fig. 5 Real time instability in the health parameter

To examine structural changes in mean during running hours we construct a constant fit to bearing health parameter. This change in structure of model is observed on the basis of sum of squared residuals (SSR). Fig. 6 illustrates the constant fit to the health variation progression from run to its failure.

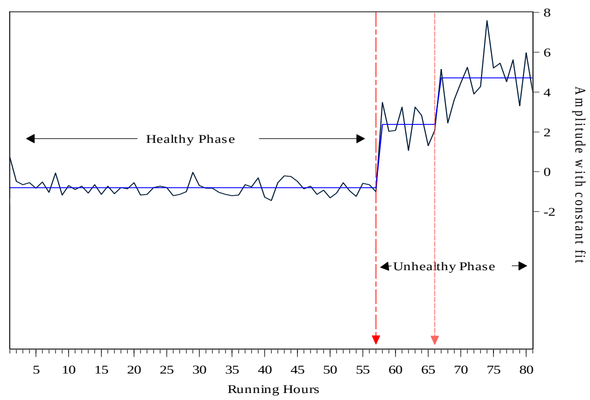


Fig. 6 Constant fit to health degradation of bearing

The fluctuation process has breaks around 58 and 67 hours which surpass the margins and hence indicates a clear structural shift at these hours. The similar conclusion emerges from tests based on F-statistics or on the basis of unweighted / weighted double maximum statistics as displayed in Ttable-2 & 3 respectively.

Table 2

Sequential test statistics for significant breaks

Breaks	F-statistics	Scaled F-statistics	Weighted F-statistics	Critical Values
1	201.14	201.14	201.14	9.63
2	205.29	205.29	225.17	8.77
3	161.99	161.99	198.73	7.84
UDmax Statistics = 205.29		UDmax Critical value = 10.17		
WDmax Statistics = 225.17		WDmax Critical value = 10.91		

Table 3

Estimated breaks in running hours

Break	Estimated Break Running Hours
1	58
2	58, 67
3	58, 67,74

Therefore, three-segment model appears fairly instinctive for these data. Thus, we estimate three-segment breakpoint model with y_t regressed on its lag y_{t-4} with a constant. The evaluation is done by utilizing Bai-Perron chronological breakpoint methodology, with an utmost of 3 breaks, 5% trimming, and a test size of 0.05. Coefficient covariances for the tests and approximation are worked out by utilizing HAC standard errors & covariance technique without modification in degree of freedom. Constructed model equations for each segment is represented as Eqs. (4, 5 & 6).

For healthy segment if $5 \le t \le 57$:

$$y_t = -0.81 + 0.04\, y_{t-4} + \varepsilon_t , \tag{4}$$

t-stat :-10.43 0.41; p-value: 0.00 0.06.

For degradation segment if $58 \le t \le 66$:

$$y_t = 2.62 - 0.27\, y_{t-4} + \varepsilon_t , \tag{5}$$

t-stat : 12.52 0.06; p-value : 0.00 0.00.

For critical segment if $67 \le t \le 81$:

$$y_t = 3.25 + 0.36\, y_{t-4} + \varepsilon_t , \tag{6}$$

t-stat : 8.34 3.35; p-value : 0.00 0.00.

where: $\varepsilon_t \sim$ iid $N(0,1)$ &estimated coefficient of determination is 0.93.

9. Stability of model

Stability of the constructed model is tested on the basis of the departure of serial correlation and heterogeneity of the residuals under the null.

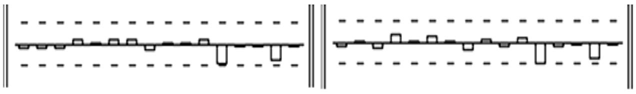
(i) Serial correlation in the error terms is estimated by utilizing serial correlation LM test under the null hypothesis of the test that there is no successive association in the residuals up to the particular order. The test statistics of the model is depicted in Table 4.

The plot of autocorrelation function (ACF) & partial autocorrelation function (PACF) as shown in Fig. 7 lies within 95% confidence bounds indicating iid in error sequence.

Table 4

Serial correlation LM statistics

F-statistic	0.671	Prob. Value $F(2,69)$	0.514
Observed*$R2$	1.471	Prob. Value $\chi^2(2)$	0.479



a b

Fig. 7 Correlation Functions of error term with 95% confidence bond: a-ACF plot, b- PACF plot

The serial correlation LM test along with ACF and PACF plot results reveals that serial correlation in the residuals not exists.

(ii) It is customary to ensure for heteroscedasticity in error terms as of the cause that we want to check if the model thus constructed is incapable to explain some pattern in the response variable that ultimately shows up in the residuals. This would result in an inefficient and unstable model that could yield unreliable forecast afterward. To ensure it Breush-Pagan-Godfery test of heteroskedasticity is utilized whose estimated test statistics is listed in table 5 which is robust to heterogeneity of the residuals under the null.

Since the error terms are neither serially correlated nor heteroskedastics which signify that coefficients are statistically significant and estimated fit is very tight with these.

Table 5

Test output confirms error are homoskedastic

F-statistic	3.391	Prob. $F(5,70)$	0.008
Obs*R-squared	14.821	Prob. Chi-Square (5)	0.211
Scaled explained SS	43.671	Prob. Chi-Square(5)	0.000

10. Results & discussion

The estimated three segments represent the bearing degradation trend. It divides life time of the machinery bearing into three stages. By using these health stages, the remaining useful life is forecasted with the investigation of degradation tendency and a pre-determine failure threshold. The actual & fitted three stage constructed model graph is represented Fig. 8.

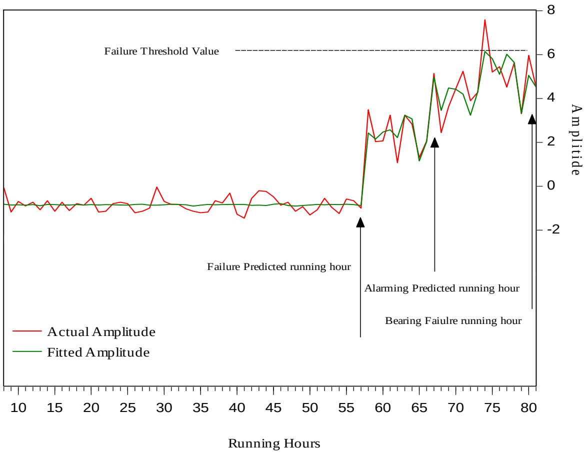


Fig. 8 Actual & fitted constructed model within forecasted running hours and failure threshold

It depicts a classical case of P-F curve for bearing degradation. Uptil 55th hour the trend of bearing health features was stable until a potential failure point was achieved at around 60th hour, where, there is a structural jump. Upon identification of potential failure point (a nonlinearity), the degradation is highly nonlinear with fluctuating values and a rising trend.

The functional failure as per actual health data (experimental data) of bearing is achieved at around 75th hour, where a preset threshold value of 6 is achieved after elapsing 15 hours after identification of potential failure.

However, the fitted graph has taken a slight longer and reached preset threshold at around 78th hour; 03 more hours than actual, after elapsing 18 hours upon identification of potential failure. Such difference in actual and fitted values is catered while calculating uncertainties and errors. It can be seen that developed model has effectively match the actual values in the presence of strong nonlinearities and random conditions.

After the estimation and validation of the constructed model, we utilized this three segment structural break model to predict the bearing failure threshold value by employing out of sample dynamic forecast with stochastic simulation of 1000 repetition. The forecasted statistics along with graph are displayed in Table 6 and Fig.9 respectively.

Table-6

Forecasted Statistics

Forecast Test	Statistics
RMSE	0.04829
MAE	0.03423
MAPE	0.342
Theil Inequality Coefficient	0.098
Theil U2 Coefficient	0.307

The forecast statistics & displayed graph strengthen the constructed model for bearing health parameters. Besides the predicted breakdown threshold value reaches to 6.4 with maximum 84 hours.

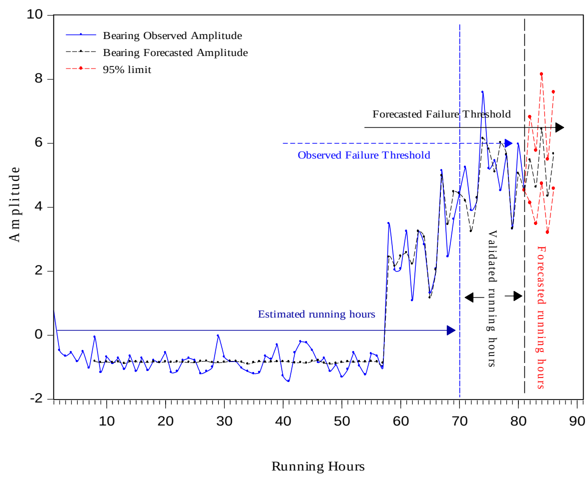


Fig. 9 Forecasted plot with observed & forecasted threshold

11. Conclusion

In this study initially maximum break in bearing health parameter were established by utilizing constant fit technique and then by means of the estimated segments, structural break model has been developed. The projected model expresses the bearing health equation for each segment with regard to different operational hour. The stability of the model has been attained by utilizing error analysis. Lastly, constructed model has been utilized to forecast the bearing failure threshold value. In this regard necessary forecast statistics and graph were work out which authenticate the power of constructed model. In this study the forecasted bearing threshold value note down to be is around 6.4 which achieved at maximum 84 operational hour.

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BEARING DEGRADATION PROGNOSIS USING STRUCTURAL BREAK CLASSIFIER

S u m m a r y

Prognostics based on machine condition monitoring data are one of the key elements of modern maintenance philosophies. Machinery health prognosis follows a sequential methodology inclusive of various processes ranging from data acquisition till remaining useful life estimation. Every step depicts distinct statistical features, which are helpful in estimating health state of a machine. In this investigation, bearing vibration data has been analyzed by utilizing the technique of structural break point regression. Constructed model is also employed to observe degradation of bearing in different regimes to estimate remaining useful life.

Keywords: bearings, failure threshold forecast, prognosis, structural breaks.

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