Vibration Analysis with Application in Predictive Maintenance of Rolling Element Bearings

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***Abstract*—The paper presents the vibration analysis problem with application in predictive maintenance of Rolling Elements Bearings (REB). After an overview of the maintenance approach, the condition monitoring in predictive maintenance is presented. A general view on change detection problem, with application in vibration monitoring, precedes some experimental results obtained in REB operating, for multiple faults and faults which gradually occur, with the conceptual description of the algorithm used. The approach proved to offer more robust detection of faults in REB, able to assure proactive actions in predictive maintenance.**

***Index Terms*—Fault detection and diagnosis; Rolling element bearings; Optimal segmentation; Vibrating signals.**

I. INTRODUCTION

Vibration analysis is one of the most effective tool used to check the health of plant machinery and diagnose the causes. The health of a machine is checked by routine or continuous vibration monitoring, giving an early indication of a possible failure and offering countermeasures to avoid a possible catastrophic event. Every machinery problem generates specific spectrum patterns, which are identified using frequency and phase analysis.

Vibration monitoring problem consists of machines condition and the change rate of its behavior. It can be ascertained by selecting a suitable parameter for deterioration measuring and recording its value for further analysis. This activity is known as condition monitoring. The great part of the defects encountered in the rotating machinery give rise to a distinct vibration pattern, or "vibration signature". Vibration monitoring has the ability to record and identify vibration "signatures" for monitoring rotating machinery. Vibration analysis is applied by using transducers to measure acceleration, velocity or displacement, depending of the frequencies making the object of the analysis. Different mechanical and electrical faults generate vibration "signatures" and careful scrutiny and deep study eliminates different possibilities and concludes to a single fault.

The problem of fault modeling and predictive health monitoring of Rolling Elements Bearings (REB) is one of great interest and made the object of many papers and books. El-Thalji et al. [1] presents such a monitoring procedure that includes detection, diagnosis and prognosis, to extract the features related to the fault occurrence. A general overview of various condition-monitoring and fault diagnosis techniques for REB in current practice is discussed in [2]. The paper of Randall and Antoni [3] offers a tutorial to guide the reader in REB diagnostics using vibrating signal analysis, and presents different case studies. An application of blind source separation method in diagnosis rolling bearing faults is presented in [4]. The study [5] presents a procedure for fault detection of roller bearings using signal processing and optimization techniques.

The matter of monitoring of REB plays a crucial role in the assessment of the overall health state of a rotating machine and is still a challenge. A new approach operating in time domain, using the optimal segmentation of vibration signals [6] occurred during REB operating, is used in the present paper. It offers new possibilities for more robust detection of changes in REB, and assures proactive actions in predictive maintenance.

The paper is organized as follows. Section II has as subject the maintenance approach, while in Section III, we present the condition monitoring problem in predictive maintenance. Section IV offers a general view on change detection problem with application in vibration monitoring. Finally, Section V presents some experimental results obtained in REB operating, for multiple faults and faults which gradually occur, and the conceptual description of the algorithm used.

II. MAINTENANCE APPROACH

Usually, the maintenance is performed as *preventive maintenance*, at fixed time intervals, or as *reactive maintenance*, after the fault occurs. In the last case, it is necessary to perform immediately maintenance actions, while in the *predictive maintenance*, after a warning of a fault occurrence, the problem solving is carried out when necessary, so to avoid disruption of machine operations. A comparison of different maintenance

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types, with disadvantages and advantages, is given in [7]. We present in the following some aspects concerning these approaches, to be taken into account, mainly in predictive maintenance of REB.

A. Reactive Maintenance

This approach refers to machine running until a fault occurs and involves fixing problems only when the fault occurs. It represents the simplest and cheapest approach in terms of maintenance costs; often it implies additional costs, usually due to unplanned downtime. It can be seen as an easy solution to many maintenance strategies.

In rotating machines, REB represent the most critical components, both in terms of initial selection, as well as in how they are maintained. Monitoring the condition of rolling bearings is essential and vibration based monitoring is frequently used to detect an early fault.

B. Preventive Maintenance

The preventive maintenance implies the scheduling of regular machine shutdowns, even if they are not required; this will increase the maintenance costs as some machine components are replaced, when this is not necessarily required. Some risks could appear due to replacing a defective machine part, incorrectly installing or reassembling parts. A frequent result of preventive maintenance consist of the fact that the maintenance is performed when there is nothing wrong in machine operating. Significant costs saving can be obtained by predictive maintenance.

C. Predictive Maintenance

The predictive maintenance refers to the process of monitoring the machine condition as it operates in order to predict which components are likely to fail and when. So, the maintenance can be planned and there is the possibility to change only those components that show failure signs in their operation. The predictive maintenance principle consists of taking additional measurements in order to predict the behavior of machine components that are susceptible of failure, and also to predict when these failures will occur. Usually, these measurements include machine vibration, and machine operating parameters: flow, temperature, pressure, etc.

The continuous monitoring detects, in advance, the onset of component problems, so the maintenance is performed when needed. By this approach, unplanned downtime is reduced, and also the risk of catastrophic failure is reduced. This will increase the efficiency and reduce the costs. By predictive maintenance strategy, applied in rolling bearings, the costs can be cut, giving in advance, a warning of a possible failure, enabling remedial action in advance.

III. Condition Monitoring

Condition monitoring consists of machine monitoring for early signs of failure so that the maintenance activity can be better planned, with reduced down time and costs.

The monitoring of vibration, temperature, voltage or power and oil analysis is frequently the most used. Vibration is the most widely used for its ability to detect and diagnose failure problems, but it offers also a prognosis on the useful life and possible failure mode of the machine. The prognosis is much more difficult to be performed and usually relies on continue monitoring of the fault to estimate the time when the machine will become unusable, taking into account the known experience in similar cases.

Vibration monitoring can be considered the most widely used predictive maintenance technique, and can be applied to a wide area of rotating machines. Machine vibration comes from many sources such as bearings, gears, unbalance, etc., each sources having its own characteristic frequencies, manifesting as a discrete frequency, or as a sum and/or difference frequency. It can generate complex vibration signals, which cause problems in vibration analysis, but some techniques, with a high sensitivity to faults, can reduce the complexity of the analysis. Bearing defects can affect higher frequencies, offering a basis for detecting incipient failure.

Usually, the detection uses the basic form of vibration measurement, where the vibration level is measured on a broadband basis (10-1000 Hz or 10-10000 Hz). The spikiness of the vibration signal, in machines with little vibration other than in the case of the bearings, is highlighted by the Crest Factor, indicating an incipient defect, and the a great value of the energy given by RMS level indicates a severe defect.

These measurements offer limited information, but they can be useful for trend evaluation; increasing vibration level highlights the machine condition deterioration. Also, a comparison of the measurement level with some vibration criteria from literature proves to be useful in practice.

Generally, rolling bearings generate very little vibration in faults absence, and present specific frequencies when a fault occurred. At the beginning of a fault, for a single defect, the vibration signals present a narrow band frequency spectrum. As the malfunction increases, an increase in the characteristic defect frequencies and sidebands can be noticed, with a drop in these amplitudes, broadband noise increasing and considerable vibration at shaft rotational frequency [7]. At very low machine speed, low energy signals are generated by the bearings, difficult to be detected. Also, bearings located within a gearbox are difficult to monitor, because of the high energy at the gear, which can mask the bearing defect frequencies.

IV. Change Detection in Vibration Monitoring

The CD problem is frequently present for continuous monitoring of systems like machinery, structure, process, equipment or plant, using data provided by the sensors. So, it is possible to anticipate the abnormal functioning or these systems, before it occurs and to reduce the maintenance costs. The normal behavior of the system can be described by a parametric model, without using artificial excitation, reducing the speed of the equipment or temporary stop. If such early detections are possible, large changes of the system can be prevented, and the effects of defects, mechanical fatigue, etc., can be quickly anticipated, raising the usability of the system.

The applications in this field make use of theories based on statistics, providing theoretical instruments to solve the early detection problem. Many industrial processes are based on known physical principles, with available analytical models, and for very complicated or unknown models, semi-physical or black-box models can be used. Vibration analysis and surveillance of machinery or industrial equipments represent important cases of detection and diagnosis problems.

The CD problem refers to detection of the change (the alarm) and evaluation of the change (estimation), providing information, in some cases, for diagnosis (source isolation). The performance criterion of a change detection algorithm consists in its ability to correctly detect the changes, with minimum delay and minimum probability of false decisions. So, it must respond to the small changes (sensitivity to changes), without being affected by the disturbances, noise or modeling errors (robustness of the algorithm). The sensitivity and robustness properties are usually in conflict, a good change detection algorithm must perform a compromise between the two aspects.

Two basic approaches in CD are reported as based on quantitative models (using analytical redundancy) and qualitative models, which can be conveniently combined to improve the robustness of the generation of quantitative residuals. In the case of analytical exact models absence, learning models, such as fuzzy and neural models, can be used. Moreover, the neural networks can be used for classification of the residuals, while fuzzy logic is useful for decision making. The methods based on quantitative models are oriented to identification (parameter estimation), observers (state estimation) and parity space. Some heuristics results, obtained from the previous experience, can be used for diagnosing the origins of the failure or change, based on the dispersion of the characteristics.

Almost all CD solutions assume that the monitored system can be described with sufficient precision by a finite-dimensional linear model. In practice, if the system is more complex than the structure described by a finite-dimensional model, the parameter estimates will still converge, but their values can be strongly dependent on the experimental conditions. The algorithms will not be able to separate the changes determined by the external conditions from those occurred by the internal defect of the investigated system, so the classical tests will fail. The problems mentioned above point out the requirement of the robust CD algorithms, able to separate the changes determined by the external conditions from the changes of the internal dynamics of the system.

The first generation of CD algorithms is based on strong hypotheses, or strong assumptions, which are difficult to verify in practice. So, a second generation of solutions were required, insensitive to the uncertainty of the system's dynamics, to the operating environment, and to large noise, statistically unknown. In our opinion, the central problems to be addressed in the CD area refer to robustness, sensitivity and versatility. The lack of robustness of the classical algorithms concerns the failure of the detection, if one or more of the hypotheses assumed during the design are not verified in practice. The sensitivity relates to the ability of the algorithm to detect the change, even if there are small scale incipient changes. Finally, the versatility is linked to the ability of the methods and techniques to solve more CD problems, using the same set of algorithms.

To solve the vibration monitoring problem different techniques have been developed, one can mention: analysis of overall vibration level, frequency spectrum, envelope spectrum, cepstrum analysis, etc. [7]. The success of vibration monitoring, in many practical cases, requires specialized functions and tools. Simple application of CD techniques on original mono- or multivariate vibration signals can assure successful monitoring. Sometimes, it is necessary that some signal pre- or postprocessing procedures to be applied, to emphasize and highlight the characteristics of the vibration signals making the object of the analysis. So, some signal processing techniques can be used in conjunction with CD techniques: independent component analysis (ICA), time-frequency analysis (TFA), energy distribution (ED) evaluation in time-frequency domain. These techniques are implemented in a software toolbox, Matlab VIBROTOOL Toolbox [8], built as a set of programs that compute specific parameters and solve specialized tasks for vibration monitoring. A general approach, making use of these techniques, and a case study having as object the condition monitoring of a rotating machine, an industrial pump, with a progressed pitting in gears, is presented in [9].

The CD problem can be solved by change point estimation (mean change), change detection using one and two model approach, with different distance measures and stoping rules [10], multiple change detection [6], detection and diagnosis of model parameter and noise variance changes [11], for mono- and multivariable vibration signals. Some algorithms, making the object of [12] and [13] in CD, represented the starting points in developing these algorithms. The analysis of the vibration signals behavior reveals that most of the changes that occur are either changes in the mean level, variance, or changes in spectral characteristics.

V. Fault Detection in Rolling Elements Bearings

This section presents some experimental results, obtained in a case study, having as object fault detection in REB, as well as the conceptual description of the algorithm used.

A. Test Data

The experiments performed use a data set from [14], with three faults having different locations: $F1$ (Inner race), $F2$

(Ball) and $F3$ (Outer race), and four sizes of the faults; $F0$ denotes no faults; only the data for the first case (06HH) have been used (see Table I).

TABLE I. 1ST DATA TEST SET (6203 BEARING TYPE).

Fault size	$F0$ Free	$F1$ Inn. Race	$F2$ Ball	$F3$ Outer Race
0.000"	$y_0(t)$	-	-	-
0.007"	-	$y_1(t)$	$y_2(t)$	$y_3(t)$
0.014"	-	$y_4(t)$	$y_5(t)$	$y_6(t)$
0.021"	-	$y_7(t)$	$y_8(t)$	$y_9(t)$
0.028"	-	$y_{10}(t)$	$y_{11}(t)$	-

$y_0(t)$ contains 4,096 samples recorded during normal conditions operating, while $y_i(t)$, $i = 1, \ldots 11$ indicate files/vectors, containing each 4,096 samples, for the cases with faults; the sampling rate was of 12,000 samples/s.

B. Preliminary Analysis

For the signals mentioned above, some statistical features in time domain [2], have been computed, and are given in Table II, offering a general view of the signal characteristics.

TABLE II. STATISTICAL FEATURES OF THE SIGNALS $y_0(t)$, $y_1(t)$, $\ldots$, $y_{11}(t)$ IN TIME DOMAIN.

Signal	RMS	Mean	Var.	Cres. fact.	Skew.	Kurt.
$y_0(t)$	0.999	-0.002	0.998	3.796	-0.094	2.890
$y_1(t)$	0.992	0.007	0.985	5.145	0.124	5.456
$y_2(t)$	1.007	0.021	1.014	3.720	0.003	2.997
$y_3(t)$	0.997	0.016	0.995	5.189	0.088	7.698
$y_4(t)$	0.997	-0.001	0.995	4.016	0.067	4.281
$y_5(t)$	1.013	0.013	1.027	5.299	0.012	7.032
$y_6(t)$	0.987	0.078	0.974	9.747	-0.144	22.505
$y_7(t)$	0.724	0.001	0.525	6.937	-0.066	5.775
$y_8(t)$	0.978	0.046	0.958	3.779	0.023	2.982
$y_9(t)$	1.018	0.011	1.037	6.495	0.315	6.868
$y_{10}(t)$	0.981	0.019	0.963	4.378	0.043	3.457
$y_{11}(t)$	0.955	0.002	0.913	9.992	-0.086	21.255

The signals, making the object of the analysis, are simultaneously characterized in time and frequency domain using their mean localizations and dispersions. So, the averaged time and the time spreading, as well as the averaged frequency and the frequency spreading [15], are given in Table III for signals analyzed.

TABLE III. TIME-FREQUENCY STATISTICAL FEATURES OF THE SIGNALS $y_0(t)$, $y_1(t)$, $\ldots$, $y_{11}(t)$.

Signal	Aver. time	Time spread	Aver. freq.	Freq. spread
$y_0(t)$	2.104e+003	4.251e+003	-8.197e-009	0.287
$y_1(t)$	2.032e+003	4.155e+003	-2.359e-008	0.850
$y_2(t)$	2.026e+003	4.103e+003	-1.035e-006	0.906
$y_3(t)$	2.090e+003	4.167e+003	-2.206e-008	0.969
$y_4(t)$	1.944e+003	4.157e+003	-5.457e-009	0.804
$y_5(t)$	2.082e+003	4.247e+003	-3.880e-008	0.983
$y_6(t)$	1.954e+003	4.099e+003	-1.229e-008	0.920
$y_7(t)$	1.993e+003	4.843e+003	-1.134e-008	0.820
$y_8(t)$	2.057e+003	4.187e+003	-1.800e-007	0.968
$y_9(t)$	2.054e+003	4.273e+003	-1.604e-007	0.857
$y_{10}(t)$	2.006e+003	4.184e+003	-1.435e-007	0.909
$y_{11}(t)$	2.085e+003	4.081e+003	-9.584e-010	0.911

C. Algorithm Description

The model used in the case study is a linear regression model with piecewise constant parameters [6],

$$y_t = \phi_t^T \theta(i) + e_t, \quad E(e_t^2) = R_t, \tag{1}$$

where y_t is the observed signal, $\theta(i)$ is the d-dimensional parameter vector in data stationary segment i, ϕ_t is the regressor. The noise e_t is assumed to be Gaussian with variance R_t. Its important feature is that the jumps divide the vibration signals into a number of independent segments, since the parameter vectors in different segments are independent.

To solve the segmentation problem, all possible segmentation k^n are considered, estimate one linear regression model in each segment, and then choose the particular k^n that minimizes an optimality criteria of the form:

$$\widehat{k^n} = \arg \min_{n \geq 1, 0 < k_1 < \ldots < k_n = N} V(k^n) \tag{2}$$

For the measurements in a i-th segment, $y_{k_{i-1}+1}, \ldots y_{k_i} = y_{k_{i-1}+1}^{k_i}$, results the least square estimate and its covariance matrix:

$$\hat{\theta}(i) = P(i) \sum_{t=k_{i-1}+1}^{k_i} \phi_t R_t^{-1} y_t, \tag{3}$$

$$P(i) = \left(\sum_{t=k_{i-1}+1}^{k_i} \phi_t R_t^{-1} \phi_t^T \right)^{-1}. \tag{4}$$

The following quantities are used in optimal segmentation algorithm:

$$V(i) = \sum_{t=k_{i-1}+1}^{k_i} (y_t - \phi_t^T \hat{\theta}(i))^T R_t^{-1} (y_t - \phi_t^T \hat{\theta}(i)) \tag{5}$$

$$D(i) = -\log \det P(i) \tag{6}$$

$$N(i) = k_i - k_{i-1} \tag{7}$$

where $V(i)$ - the sum of squared residuals, $D(i)$ - $-\log \det$ of the covariance matrix $P(i)$ and $N(i)$ - the number of data in each i segment, and represent sufficient statistics for each segment. The data and quantities used in segmentation k^n, having $n-1$ degrees of freedom are given in Table IV.

TABLE IV. DATA AND QUANTITIES USED IN OPTIMAL SEGMENTATION PROCEDURE.

Data	$y_1, y_2, \ldots, y_{k_1}$	$\ldots$	$y_{k_{n-1}+1}, \ldots, y_{k_n}$
Segment	Segment 1	$\ldots$	Segment n
LS est.	$\hat{\theta}(1), P(1)$	$\ldots$	$\hat{\theta}(n), P(n)$
Statistics	$V(1), D(1), N(1)$	$\ldots$	$V(n), D(n), N(n)$

To solve the optimal segmentation procedure, different types of optimality criteria have been proposed [13]. In the following we will use Maximum A posteriori Probability estimate

(MAP) criterion [6]. The number of segmentations k^n is 2^N (can be a change or no change at each time instant), and this raises problems concerning the dimensionality.

The conceptual description of the MAP estimator [6], [13] for the data and quantities given in Table IV it is presented below, for three different assumptions on noise scaling: (i) known $\lambda(i) = \lambda_0$, (ii) unknown but constant $\lambda(i) = \lambda$ and (iii) unknown and changing $\lambda(i)$, where q is the change probability at each time instants ($0 < q < 1$).

Data: Vibration signal $y_t, \quad t = 1 \ldots N$

Step 1: Examine every possible segmentation, parameterized in the number of jumps n and jump times k^n,separately.

Step 2: For each segmentation, compute the best models in each segment parameterized in the least square estimates $\hat{\theta}(i)$ and their covariance matrices $P(i)$.

Step 3: Compute in each segment:

$$\begin{aligned} V(i) &= \sum_{t=k_{i-1}+1}^{k_i} (y_t - \phi_t^T \hat{\theta}(i))^T R_t^{-1} (y_t - \phi_t^T \hat{\theta}(i)) \\ D(i) &= -\log \det P(i) \\ N(i) &= k_i - k_{i-1} \end{aligned}$$

Step 4: MAP estimate, $\widehat{k^n}$, for the three different assumptions on noise scaling

(i) known $\lambda(i) = \lambda_0$,

$$\widehat{k^n} = \arg\min_{k^n, n} \sum_{i=1}^{n} (D(i) + V(i)) + 2n \log \frac{1-q}{q}$$

(ii) unknown but constant $\lambda(i) = \lambda$,

$$\widehat{k^n} = \arg\min_{k^n, n} \sum_{i=1}^{n} D(i) + (Np - nd - 2) \times \times \log \sum_{i=1}^{n} \frac{V(i)}{Np - nd - 4} + 2n \log \frac{1-q}{q}$$

(iii) unknown and changing $\lambda(i)$,

$$\widehat{k^n} = \arg\min_{k^n, n} \sum_{i=1}^{n} (D(i) + (N(i)p - d - 2) \times \times \log \frac{V(i)}{N(i)p - d - 4}) + 2n \log \frac{1-q}{q}$$

Results : Number n and locations k_i , $k^n = k_1, k_2, \ldots, k_n$

In a practical problem, only one of the equations from **Step 4** is evaluated, according with the assumption on noise scaling of the procedure.

For the exact likelihood evaluation, there are implemented recursive local search techniques and numerical searches based on dynamic programming or Markov Chain Monte Carlo (MCMC) techniques [6], [13].

Starting from the optimal segmentation results, it is possible to analyze the data resulted for each stationary data segment to locate and diagnose the occurred fault or change in the REB: outer race, inner race, bearing cage, ball (roller), according with the frequency area where it has occurred.

D. Multiple Fault Detection

Started from the data given in TABLE I data sequences with multiple faults have been generated, for 3 types of events: inner race faults, ball faults and outer race faults, with different fault size: 0.007", 0.014", 0.021", 0.028", for the first two cases, and 0.007", 0.014", 0.021" for the third case. The following data sets have been used in the analysis, for fault detection:

$$\begin{aligned} s_1(t) &= [y_0(t), y_1(t), y_4(t), y_7(t), y_{10}(t)] \\ s_2(t) &= [y_0(t), y_2(t), y_5(t), y_8(t), y_{11}(t)] \\ s_3(t) &= [y_0(t), y_3(t), y_6(t), y_9(t)] \end{aligned}$$

resulting data sequences of 20480 values for signals $s_1(t), s_2(t)$ and 16384 for signal $s_3(t)$. The real faults instants were 4097, 8193, 12288 and 16384. These data sets offer the possibility to fault detection of a graduate size of fault, for the cases mentioned above.

The experimental results refer to the signals $s_1(t), s_2(t), s_3(t)$ and the segmenting algorithm presented above with unknown and constant noise scaling, and MCMC algorithm, [6], with a value of jump probability, $q = 0.3$ and appropriate design parameters in search scheme, for different model orders, na. The fault instants detected for different model orders na are presented in Table V, Table VI and Table VII for $s_1(t)$, $s_2(t)$ and $s_3(t)$, respectively.

The signal $s_1(t)$, making the object of the analysis, and the estimated multiple fault times for the inner race, $na = 20$ and $q = 0.3$, are presented in Figure 1, while the signal $s_2(t)$ and the estimated multiple fault times for ball, $na = 20$ and $q = 0.3$ are given in Figure 2. The signal $s_3(t)$ and the estimated multiple fault times for the outer race, $na = 60$ and $q = 0.3$ are presented in Figure 3.

TABLE V. FAULT DETECTION IN SIGNAL $s_1(t)$ USING DIFFERENT MODEL ORDER.

Model order	Fault detection instants
$na = 10$	4096, 8687, 9501, 10684, 11322, 11500, 12570, 12627, 12967, 13068, 13961, 14527, 14627, 14777, 15964, 16384.
$na = 15$	4096, 8687, 9502, 10684, 11501, 12570, 14777, 16384.
$na = 20$	4096, 8195, 8687, 11502, 13026, 16384.

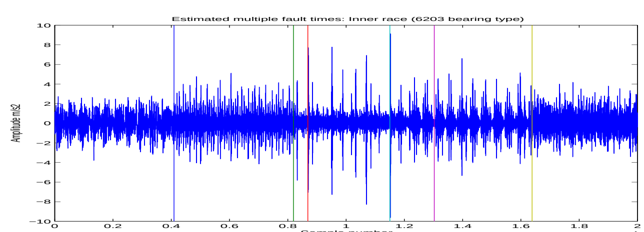

Fig. 1. The signal $s_1(t)$ and estimated multiple fault times for inner race, $na = 20$, $q = 0.3$.

The changes in signals $s_1(t)$, $s_2(t)$ and $s_3(t)$, resulted after data concatenation, are gradual, and the effect may increase, producing new changes in the signal dynamics that can be

TABLE VI. FAULT DETECTION IN SIGNAL $s_2(t)$ USING DIFFERENT MODEL ORDER.

Model order	Fault detection instants
$na = 10$	4096, 8191, 8497, 8614, 9305, 9929, 11946, 16385, 16711, 16901, 18065, 18129.
$na = 15$	4096, 8190, 11946, 16385, 16719, 18108, 18128.
$na = 20$	4096, 8190, 11945, 16385, 16751, 18233.

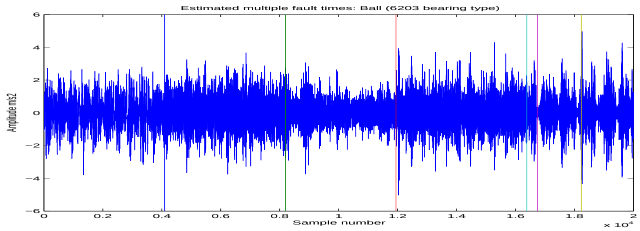

Fig. 2. The signal $s_2(t)$ and estimated multiple fault times for the ball, $na = 20$, $q = 0.3$.

detected by the algorithm. The further deterioration of the rolling element bearing during operating occurs new fault instants, different from 4096, 8192, 12288 and 16384 instants. According with data from Table V, Table VI and Table VII, one can notice that in all the cases the main faults are detected. Also, it can be noted that for the models of high order ($na = 20$, $na = 20$ and $na = 60$, respectively), only the main faults are detected at instants 4096, 8192, 12288 and 16384 or near instants. The models of high order, can increase the robustness of the optimal segmentation algorithm to gradual, or small changes in signal dynamics. Different values of q offer similar results, but a higher order of the model leads to a better fault detection, the model being able to better approximate the signal dynamics.

VI. CONCLUSIONS

The paper presents a vibration analysis approach, with application in predictive maintenance of REB. The experimental results, presented in the case study, have as object detection of the multiple faults, as well as of the faults, which gradually occur, in REB operating. The optimal segmentation method is based on maximum a posteriori probability estimator and need a minimum of design parameters, depending to a great extend of the linear regression model order. The used approach offers new possibilities for more robust detection of changes in vibration signals, and assures proactive actions in predictive maintenance.

TABLE VII. FAULT DETECTION IN SIGNAL $s_3(t)$ USING DIFFERENT MODEL ORDER.

Model order	Fault detection instants
$na = 10$	4096, 4383, 7081, 7170, 7897, 7950, 8192, 12298, 12367, 12480, 12982, 13151, 13260, 13407, 13596, 14042, 14179, 14378, 14489, 14668, 14823, 15169, 15271, 15575, 15605, 16050, 16229.
$na = 15$	4096, 8192, 12296, 12368, 12479, 12669, 12813, 13261, 13455, 13596, 14042, 14173, 14378, 15015, 15164, 15271, 15469, 15605, 16051, 16346.
$na = 20$	4096, 8192, 12293, 12367, 12479, 12669, 12813, 13261, 13460, 13594, 14042, 14189, 14378, 15271, 15473, 15604, 16051.
$na = 60$	4096, 8198, 12287, 12352, 14057.

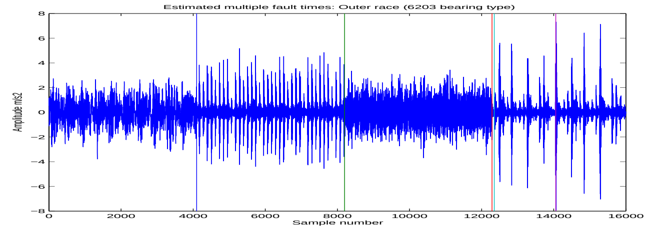

Fig. 3. The signal $s_3(t)$ and estimated multiple fault times for outer race, $na = 60$, $q = 0.3$.

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