On the detection of rolling contact fatigue in large bearings using roller embedded sensors

Stephan BAGGERÖHR[1]

[1]SKF, RTD Diagnostics and Pronostics, 3992 AE Houten, The Netherlands
stephan.baggerohr@skf.com

Abstract

Sensor Roller (SR) system is a prototype technology, developed by SKF, that uses sensors embedded in bearing rollers to collect data on load, roller accelerations & rotation speed, and temperature. This data is then transmitted wirelessly to operations and maintenance staff, allowing them to monitor the state and performance of machinery in real time. The system is currently being used in customer pilots for design validation and is being tested in various types and sizes of bearings. There is a desire to further analyse the data collected to improve the performance and reliability of new bearings. Towards this approach, a study was conducted to determine if SR can be used to detect surface damage. Early detection of damage is important to prevent problems such as increased friction, decreased efficiency, and, therefore, reduced lifespan of the machinery. Gathering the data for this study involved artificially damaging an SKF Nautilus bearing raceway and testing it at the SKF Sven Wingquist Test Centre (SWTC), where the testing rigs are designed to reproduce all the loads that this bearing may experience in operation. The Nautilus bearing, mainly used as a main shaft bearing for offshore wind turbines, has an outside diameter of up to four meters and a weight of up to 14 tonnes, and an expected bearing life of more than 20 years. A testing protocol of various machine speeds and loads was initiated with the SR. The damage detection algorithm is comprised of mapping multiple records of data around the bearing race by performing signal processing techniques on the SR data. The results of the study show that it is possible to detect damage on a bearing raceway using a SR.

1 Introduction

The Sensor Roller (SR) employs sensors embedded within its bearing rollers to gather data on load, roller rotational speed, acceleration, and bearing temperature, as shown in Figure 1. This data is then wirelessly transmitted to the operations and maintenance teams, enabling real-time monitoring of machine status and performance. This system has been incorporated into pilot tests with customers for design validation, with evaluations being conducted on various types and sizes of bearings. The present study seeks to evaluate the feasibility of using SR for detecting surface damage on bearings, a task critically important for avoiding increased friction, diminished efficiency, and a shortened lifespan of machinery [1].

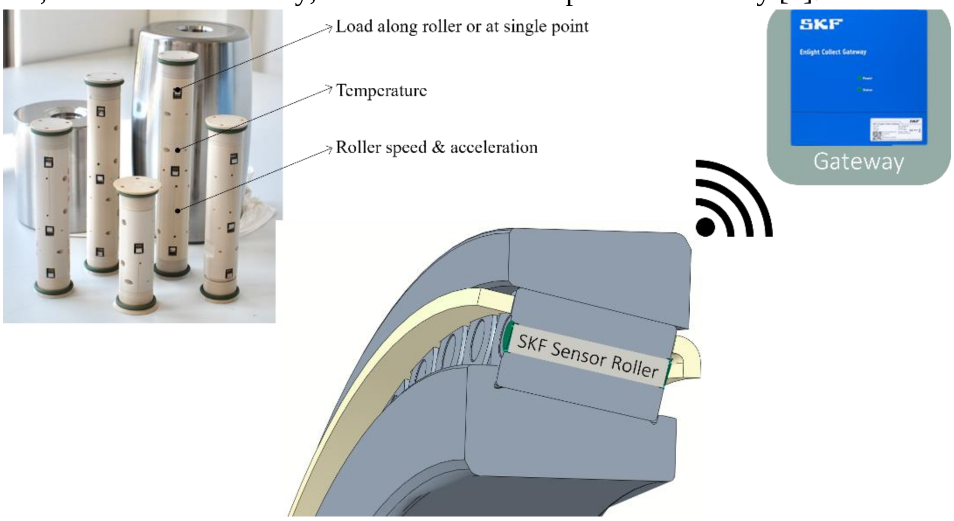


Figure 1: Embedded within each SR are either one, two or three displacement sensors used to calculate load, a six-dimensional sensor capturing both speed and acceleration data, and a temperature sensor. The SR then wirelessly transfers the data to a gateway for further processing.

While the need for early damage detection in bearings is universally recognized, significant challenges exist that limit the effectiveness of the current prototype methodologies. Two such limitations pertain to the SR orientation relative to the surface damage and the SR prototype sample rate and packet transfer limitations.

During rotation, the SR measures the displacement of the bore of the roller as it is squeezed between the inner and outer ring. An example of the SR displacement recording is shown in Figure 2. The radial load is then derived from the SR displacement recording and a calibrated transfer function. The maximum displacement occurs when the SR is in line with the contact of the raceway. This makes the orientation of the SR in relation to surface damage a critical factor in the ability to detect surface damage, also shown in Figure 2. If the SR is not optimally positioned relative to the damage site, the sensitivity of surface damage can be significantly compromised.

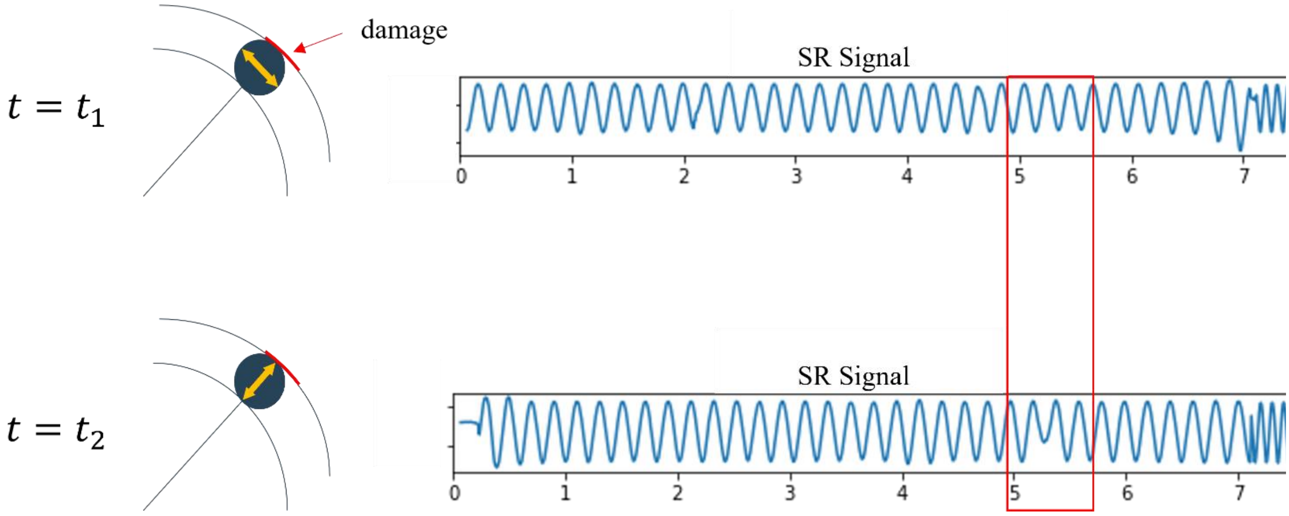


Figure 2: The measurement orientation of the SR relative to the surface damage can significantly influence the resulting calculated load signal, causing it to vary depending on the position of the sensor.

Furthermore, due to the hardware limitations of the current SR prototype, the length of one continuous recording might not span a full rotation. Therefore, multiple measurements have to be combined to achieve a comprehensive view of the bearing.

Addressing these challenges, the present study explores the potential of SR in the early detection of surface damage in bearings. By leveraging the sensor technology and data analysis methods, this study seeks to overcome these issues and deliver a solution that improves machinery performance.

2 Methods

2.1 Data collection

The data used in this study was gathered by damaging a SKF Nautilus bearing raceway to mimic realistic defects and conducting subsequent tests at the SKF Sven Wingquist Test Centre (SWTC). Primarily utilized as a main shaft bearing for offshore wind turbines, the bearing boasts an outside diameter of up to four meters, weighs as much as 14 tonnes, and has an anticipated bearing life of over 20 years. Figure 3 showcases a Nautilus bearing at the SWTC test centre, situated in the testing rig employed for this experiment. This test rig is designed to simulate loads from various applications as well as simulating more extreme loads for accelerated life testing of bearings. The bearing consists of two sides, upwind and downwind. Each side was fitted with a SR with one load sensor placed in the centre of the roller.

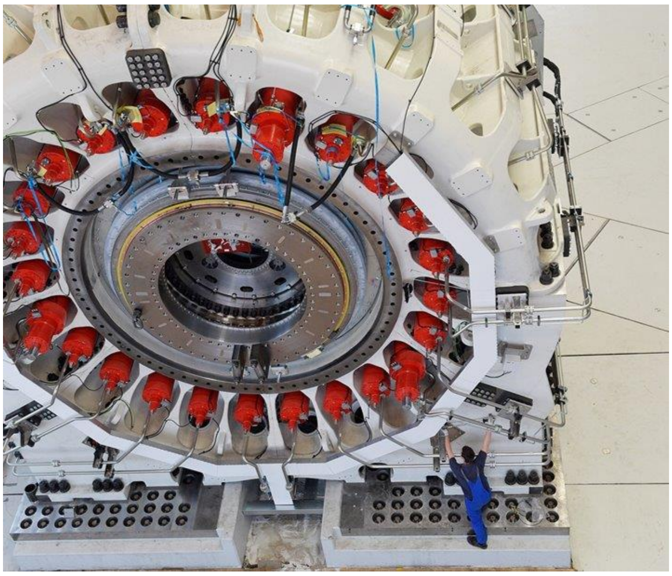


Figure 3: A Nautilus bearing positioned within the test rig at the SWTC.

A testing protocol was designed to emulate some of the speeds and loads that a bearing might encounter. The intent of this testing procedure was to comprehend how the SR responds to various types and degrees of surface damage. Although the speed and SR sample rate are important to ensure good spatial resolution around the bearing raceway, their effects were not actively studied in this work. By the conclusion of the test campaign, the two SR systems on the upwind and downwind side yielded a total 431 recordings, with a sample length of 1080 each, for each of the sensor types.

The induced surface damage to the bearing is depicted in Figure 4. Damage was inflicted on both the upwind and downwind rows of the bearing. The damage varied in size, as illustrated in Figure 4, and was distributed at 60-degree intervals around the bearing. Some damage, such as D4 in Fig 4, was deliberately made off-centre from the raceway. In total, 12 damaged zones were created.

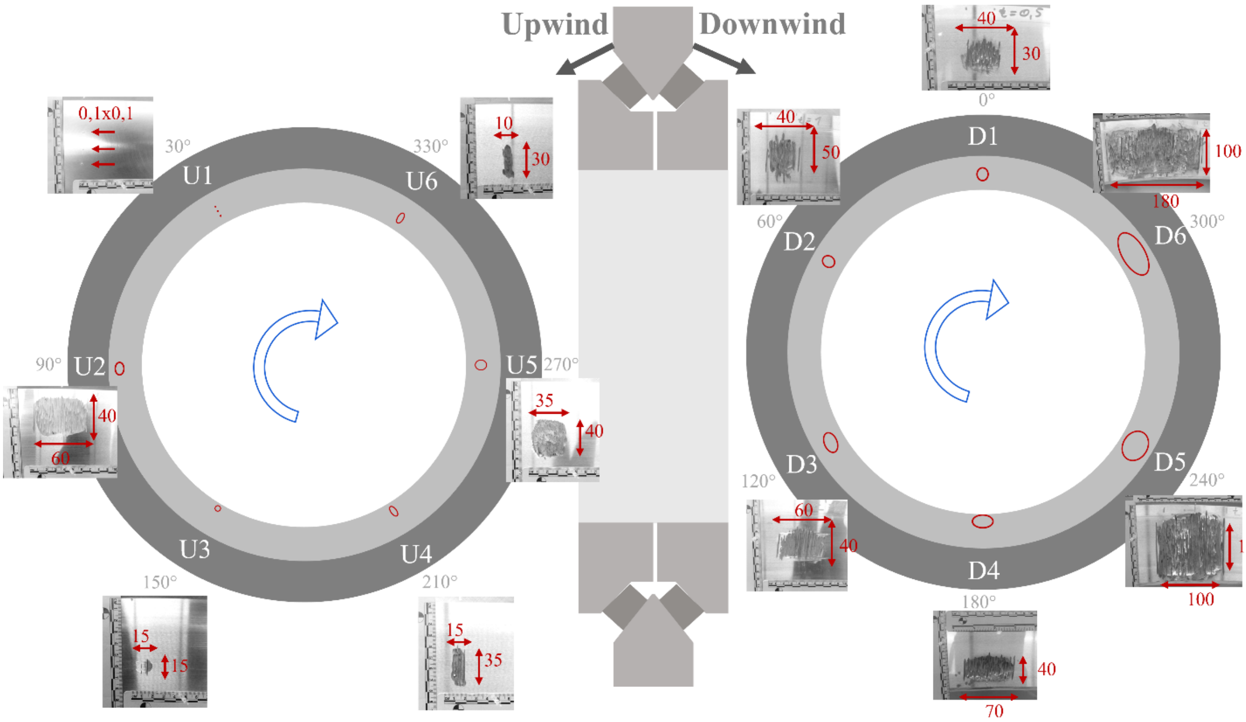


Figure 4: The image depicts the artificially induced surface damage inflicted on the upwind and downwind rows. The values in red give a rough estimate of the size of the surface damage.

2.2 Cage Location

The damage detection algorithm employed in this study involves mapping multiple data records around the bearing raceway, using a cage phase estimation. This cage estimation comprises several steps as shown in Figure 5:

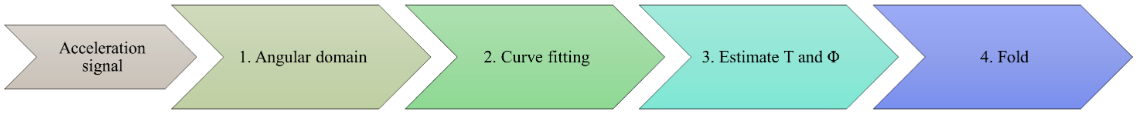


Figure 5: Steps used to estimate the bearing cage phase. The phase is used to map the load signal to locate the surface damage.

1. **Convert Signal to Angular Domain**: First convert the roller radial acceleration signal from the time domain into the bearing cage order domain. See Fig 6a. This process aligns the sensor data with the angular position of the bearing cage independent of shaft speed, providing a more accurate representation of the SR location relative to the rotation of the shaft.
2. **Fit Sinusoid to Ordered Signal**: After the conversion, the ordered signal is fitted to a sinusoidal using Equation 1, as shown in Fig 6b for one recording. The contact angle and tri-axial accelerometer on the SR are leveraged to indicate the cage position. The sinusoidal fit also helps to normalize the data and reduce the impact of roller slip and the surface damage.

$$y = A\sin(2\pi(bx + c)) \tag{1}$$

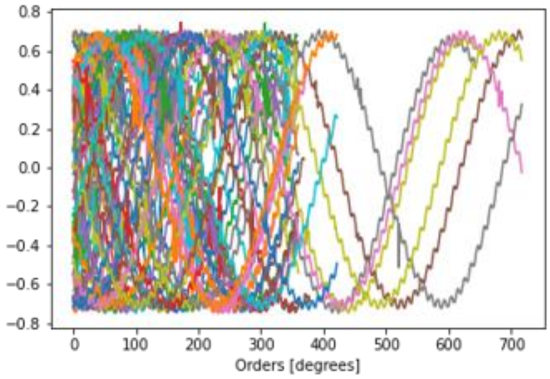
3. **Calculate Initial Phase and Period**: The next step involves calculating the initial phase and period from the parameters fitted to the sinusoid. The initial phase and period are calculated as

$$T = {}^{1}/_{b},\ \phi = {}^{-c}/_{b} \tag{2}$$

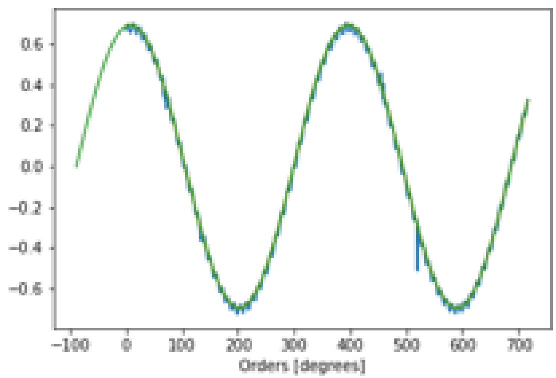
4. **Fold Order Series**: The final step is to wrap the order series to better highlight repeating patterns in the data. This is shown in Fig 6c. The folding process can be mathematically described by Equation 3:

$$P \;=\; (order - \phi)/T - [(order - \phi)/T] \tag{3}$$

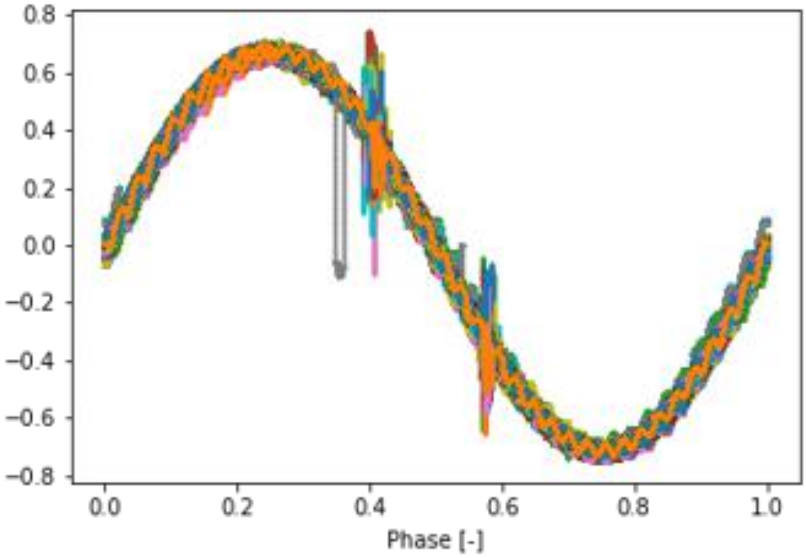
In Equation 3, $[.]$ denotes the floor function. The output, P, of Equation 3 is the estimated phase of the bearing cage. This phase estimation is further used to align the load data from the SR as described in the following section.



(a)



(b)



(c)

Figure 6: (a) All SR acceleration recordings from the downwind side, post speed-normalization of the time axis into the order axis, following Step 1 in Figure 5. (b) An example of curve fitting a single acceleration signal recording from (a). (c) All SR acceleration records after folding the signal into a single shaft order. Note the presence of damage-induced peaks. Figures (a) and (c) contain identical data.

2.3 Damage detection

The damage detection algorithm employed in this study involves mapping multiple data records around the bearing raceway, using the estimated cage phase. This was accomplished by applying signal processing techniques to the SR load signal, used to emphasize the underlying effect of the surface damage. The steps involved are as follows:

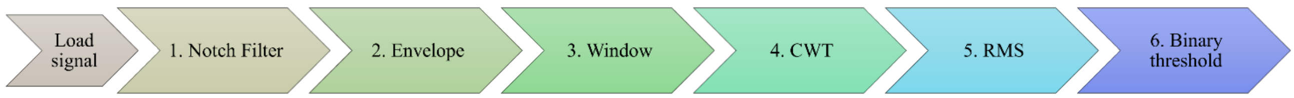


Figure 7:Steps used to process the SR load signal to detect surface damage.

1. **Notch Filter**: A notch filter is applied to remove 2X the fundamental roller spin frequency from the deflection derived load signal.
2. **Envelope**: An envelope technique is employed to extract the amplitude modulation of the filtered signal, which can indicate the presence of surface damage.
3. **Window:** A windowing function is used to focus on smaller sections of the signal. This step reduces the effect of incomplete shaft rotations at the start and end of the recording window.
4. **Continuous Wavelet Transform (CWT)**: The windowed signal is then processed using the Continuous Wavelet Transform (CWT), using a Morlet base function.
5. **Root Mean Square (RMS)**: The RMS value of the wavelet coefficients are then calculated. This step helps to quantify the magnitude of load variations, which could indicate the presence of damage.
6. **Binary Threshold**: Finally, a binary thresholding technique is applied to the RMS values. This process simplifies the final output of the algorithm, making it easier to identify instances of damage (represented as '1') and non-damage (represented as '0').

3 Results and discussion

It is important to note that within the confines of the current experimental setup, the actual phase could not be independently verified. The reported phase should be interpreted as an estimation rather than a precise measurement.

Regarding damage detection, the algorithm displayed a significant degree of sensitivity and precision. As depicted in Figure 8, the algorithm could detect damage as minor as 0.1 mm. This level of detection capability implies the possibility of early intervention, even in instances of minimal surface damage. It is also noteworthy that the algorithm maintained its damage detection capabilities even when the damage wasn't perfectly centred on the bearing raceway. However, under such conditions, the accuracy of pinpointing the exact damage location was somewhat compromised. This underscores a critical area for future refinement and improvement of the process.

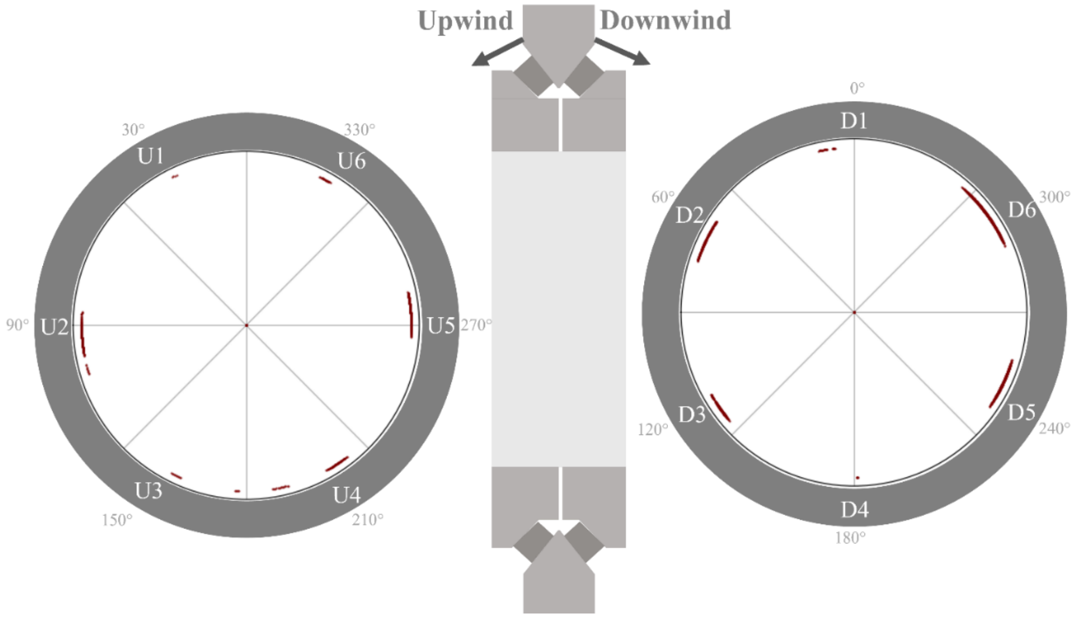


Figure 8: This image presents the result of the signal processing steps outlined in Figure 7. Here, the binary signal is mapped to the bearing location using the estimated cage phase. The red lines denote areas of damage.

4 Conclusion

The results suggest that the SR system has considerable potential for the early detection of surface damage in bearings. The implications of these findings are substantial, as early damage detection can forestall complications such as increased friction, decreased efficiency, and a consequent reduction in machinery lifespan. Particularly in scenarios involving lower speeds, where detecting surface damage using acceleration-based signals presents significant challenges.

Despite these promising results, further research is needed to improve the sensitivity and specificity of the SR system for damage detection. Future studies should consider different bearing types, a variety of damage models, and diverse operating conditions to ensure the generalizability of the findings.

References

[1] G. E. Morales-Espejel & A. Gabelli, *The Progression of Surface Rolling Contact Fatigue Damage of Rolling Bearings with Artificial Dents*, Tribology Transactions, 2015 February, 58:3, 418-431, DOI: 10.1080/10402004.2014.983251.