# A Reliable Technique for Remaining Useful Life (RUL) Estimation of Rolling Element Bearings using Dynamic Regression Models

Wasim Ahmad, Sheraz Ali Khan, M M Manjurul Islam, and Jong-Myon Kim[1]

*University of Ulsan, Ulsan, 44610, South Korea*

*{wasimahmad.qc, sherazalik, m.m.manjurul, jongmyon.kim}@gmail.com*

## ABSTRACT

Induction motors most often fail due to faults in the rolling element bearings. Sudden failures in a system result in long unscheduled downtimes, which cause huge economic losses. Prediction of imminent failures and estimation of the remaining useful life (RUL) of a bearing is essential for scheduling prior maintenance and avoiding abrupt shutdowns of critical systems. This paper presents a hybrid prognostics technique for rolling element bearings that utilizes dynamic regression models, which are updated recursively, to estimate the evolving trend in a bearing's health indicator. These models are then used to predict the future value of the bearing health indicator and estimate the RUL of the bearing. The proposed algorithm is tested on the bearing prognostics data from the Center for Intelligent Maintenance Systems (IMS). Experimental results demonstrate excellent prognostic performance and bearing's RUL estimates within the specified tolerance bounds by effectively determining the time to start prediction (TSP) and dynamically calibrating the models to adopt to the evolving behavior of the bearing health indicator.

## 1. INTRODUCTION

Induction motors fail due to faults in their various components. The most fault prone component in induction motors is the rolling element bearing, which accounts for more than 50% of the total failures (Thorsen and Dalva, 1999). Unexpected plant shutdown due to a failed bearing can incur huge economic losses. Hence, bearing failure has been widely investigated (Leite *et al.*, 2015; Kang *et al.*, 2016; Khan and Kim, 2016b; a).

In literature, data-driven and model-based prognostic techniques are very popular. In the data-driven approach, degradation behavior of the machine is learned from measured data, and techniques such as fuzzy logic, neural networks and Kalman filters are used to estimate the remaining useful life (RUL) of bearings (Soualhi *et al.*, 2014; Lim and Mba, 2015; Singleton *et al.*, 2015). On the contrary, model based methods estimate the RUL by using a mathematical model that is developed using the physics of the system. Researchers have proposed approaches such as the Paris model, logistic regression model and exponential models (Li *et al.*, 2015). Model based methods cannot be generalized to complex systems, whereas data-driven techniques work well for complex systems and can detect deterioration through changes in the condition monitoring data. Data-driven techniques rely on historical data, which is not always available for new systems. In this work, a hybrid prognostics technique is applied on the prognostic data provided by the Center for Intelligent Maintenance Systems (IMS) (J. Lee, 2007).

The proposed hybrid technique achieves good prognostic performance by harnessing currently available vibration data and dynamic regression models. It presents new methods to overcome certain challenges, i.e., determining the time to start prediction (TSP), estimating the future state of the system by predicting future values of the health indicator, resolving unusual errors in data, and setting an appropriate failure threshold to terminate the estimation process. The TSP, which is the instant of time at which the estimation process is triggered, is determined using an Alarm Bound Technique (ABT), whereas, dynamic regression models (DRM) are used to predict the future values of the heath indicator. The root mean square (RMS) of the vibration acceleration signal is used as a bearing's health indicator, as it is positively correlated with its degradation.

## 2. Test Data Description

This study uses the run-to-failure test data of IMS, University of Cincinnati, which is collected from four double row Rexnord ZA-2115 bearings, installed on a shaft that is coupled with an AC motor using rub belts. The shaft is driven

[1] Corresponding author.

at a constant speed of 2000 revolutions per minute (RPM). All the bearings are force lubricated and under a radial load of 6000 lb. The vibration acceleration of bearings is measured using high sensitivity Quartz integrated circuit piezoelectric (ICP) accelerometers, and the data is captured using a National Instruments data acquisition card 6062E (NI DAQ) at a sampling frequency of 20 KHz.

## 3. The Proposed Methodology

### 3.1. TSP Detection using Alarm Bound Technique

In the proposed method, RMS value of the bearing's vibration acceleration is used as its health indicator. For a healthy bearing, it usually remains flat. However, it starts to increase linearly when a bearing develops an incipient defect; the RMS value grows exponentially when the bearing enters a state of severe degradation. The proposed approach uses a window of the *n* most recent RMS samples to determine the current state of a bearing's health and starts predicting the RUL if the TSP is detected. The schematic diagram of the proposed approach is given in Figure 1.

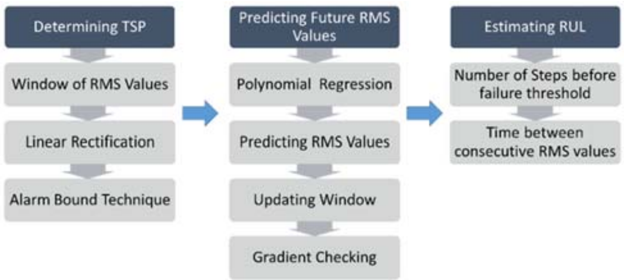


Figure 1. The schematic diagram that depicts complete process of the proposed prognostics approach

First, using the linear rectification technique, random variations are smoothed out from a window of *n* most recent RMS samples. Random fluctuations in the form of sudden downfall in values of the health indicator are rectified in a way if the current value of health indicator $Val_t$ at time $t$ is less than its value $Val_{t-1}$ at time $t-1$. Then the current value is replaced by an estimated value using equation 1.1, where $Val_{t-1}$ represents the previous value while $\eta$ represents the average cumulative rise in all values from the past. This technique ensures that the health indicator is a monotonically non-decreasing function. Afterwards, the TSP is determined using the ABT. The ABT triggers the estimation process if the $n^{th}$ value in the RMS window exceeds the 10% confidence bound, drawn about the first value in the RMS window. The $(n+1)^{th}$ RMS value is estimated by using a linear regression model fitted over the window of *n* RMS values.

$$Est\_Val_t = Val_{t-1} + \eta \tag{1}$$

### 3.2. RUL Estimation using Dynamic Regression Models

The process of estimating a bearing's RUL is triggered once the TSP is detected. The dynamic regression models (DRM) based approach assumes a quadratic degradation behavior. The parameters of this quadratic model are determined using a window of *n* RMS values. The model is used to predict the $(n+1)^{th}$ RMS sample. The estimated RMS values are shown in Figure 2. The window of RMS values is dynamically updated by including the newly predicted RMS values and removing the oldest values to maintain a constant window size. Using the updated window, the parameters of the quadratic model are calculated, and the regression model is updated to reflect the evolving changes in the health indicator. The process is repeated until the predicted value reaches the failure threshold. The failure threshold is determined dynamically by using a gradient based thresholding technique, which develops a linear regression model after every new prediction of the future RMS value. Red markers at the end of estimated RMS paths represents the failure threshold. As the determination of thresholds is based on gradient values, therefore these thresholds varies with the variation in slopes.

The gradient of the obtained linear regression model is checked against a pre-specified gradient value. The RUL at a particular time is calculated by taking into account the number of predicted RMS values before the failure threshold is reached, and the time duration between every two RMS values.

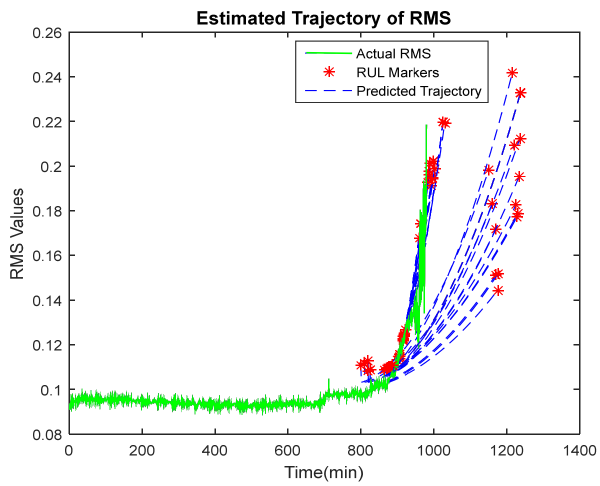


Figure 2. Estimated RMS trajectories at different instants in operational time. End points of the estimated paths represents the failure threshold.

## 4. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed approach offers a new method for the detection of TSP. The algorithm takes a window of *n* RMS values *(n= 75)* as input. It first applies the linear rectification technique and then determines the TSP. Once the TSP is detected, the RUL estimation process starts as discussed earlier. The dynamic regression models attempt to estimate the future RMS values that is shown in Figure 2. RUL values from different points during operational life of bearings is computed based on the estimated RMS paths. The estimates for RUL of the bearing at different time indices are shown in Figure 3. It can be clearly observed that the RUL predicted by the proposed method is very close to the actual RUL values calculated using the actual data.

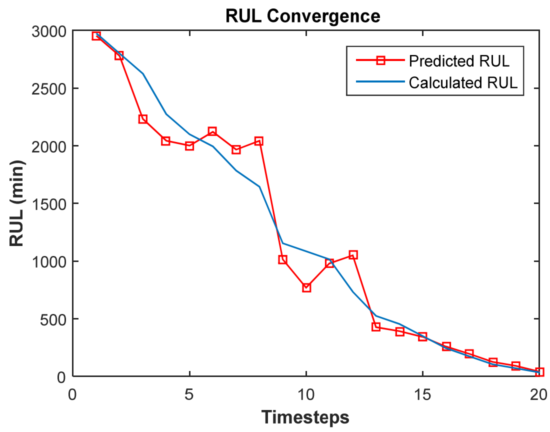


Figure 3. Convergence of RUL estimates predicted the proposed approach.

## 5. CONCLUSION

In this paper, different techniques have been proposed to address different challenges in bearing prognostics, i.e. detection of TSP, handling random errors in data and determination of failure threshold. The TSP is determined using ABT while dynamic regression models are used to estimate the RUL of the bearing. The ABT is effective in correctly determining the TSP, which is evident from the accuracy of the RUL estimates at different stages during the run-to-failure test, especially, when the bearing hasn't entered the severe degradation state and is far away from its end of life. The proposed methodology computes RUL values on the basis of estimated RMS values and the time it takes to reach the failure threshold. It achieves good performance in terms of TSP detection and the estimation of final RUL values.

## ACKNOWLEDGEMENT

This work was supported by the Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry & Energy (MOTIE) of the Republic of Korea (Grant Nos. 20162220100050 and 20161120100350), in part by the Leading Human Resource Training Program of the Regional Neo industry through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT, and Future Planning (Grant No. NRF-2016H1D5A1910564), in part by Business for Cooperative R&D between Industry, Academia, and Research Institute funded Korea Small and Medium Business Administration in 2016 (Grant Nos. C0395147 and S2381631), in part by Basic Research Program through the NRF funded by the Ministry of Education (Grant No. 2016R1D1A3B03931927).

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**Wasim Ahmad** received the B.S. degree in Information and Communication System Engineering from National University of Sciences and Technology (NUST), School of Electrical Engineering and Computer Science (SEECS), Pakistan, in 2012. He is currently doing his Master's degree in Computer Engineering and working as a Graduate Research Assistant at Embedded Ubiquitous Computing Systems Laboratory, Department of Electrical and Computer Engineering, University of Ulsan, South Korea. His research interests include Machine Learning (ML), Data Analytics and Digital Signal Processing (DSP). Currently he is involved in carrying out research on Prognosis of industrial machines using ML algorithms and DSP techniques.

**Sheraz Ali Khan** received BS in Computer Information Systems Engineering from University of Engineering and Technology Peshawar, Pakistan, in 2004, and an MS in Nuclear Engineering from Pakistan Institute of Engineering and Applied Sciences, Islamabad. He is an Assistant Professor at the Institute of Mechatronics Engineering, University of Engineering & Technology, Peshawar, Pakistan. Currently, he is working towards his PhD as a graduate research assistant in the Embedded Ubiquitous Computing Systems Lab at the University of Ulsan, Ulsan, South Korea. His research interests include designing systems on a chip, fault diagnosis and prognostics and health management of rotary machines using signal processing and machine learning techniques.

**M M Manjurul Islam** received a B.Sc. in Computer Science and Engineering from Rajshahi University of Engineering and Technology (RUET), Bangladesh, in 2007. He is currently doing his Ph.D. in Computer Engineering from University of Ulsan, South Korea. His current research interests include data-driven fault diagnosis, prognosis and health management using signal processing, artificial intelligence techniques, and high-performance computing. He has published several journals, book chapters, and technical articles in condition monitoring and fault diagnosis and prognosis.

**Jong-Myon Kim** (M'05) received a BS in Electrical Engineering from Myongji University in Yongin, Korea, in 1995, and MS in Electrical and Computer Engineering from the University of Florida in Gainesville in 2000, and a PhD in Electrical and Computer Engineering from the Georgia Institute of Technology in Atlanta in 2005. He is a Professor of IT convergence at the University of Ulsan, Korea. His research interests include multi-media processing, digital watermarking, multimedia specific processor architecture, parallel processing, and embedded systems. He is a member of IEEE and the IEEE Computer Society.