Degradation state prediction of rolling bearings using ARX-Laguerre model and genetic algorithms

Taoufik Najeh¹ · Jan Lundberg¹

Received: 23 April 2020 / Accepted: 24 November 2020 / Published online: 10 December 2020
© The Author(s) 2020

Abstract

This study is motivated by the need for a new advanced vibration-based bearing monitoring approach. The ARX-Laguerre model (autoregressive with exogenous) and genetic algorithms (GAs) use collected vibration data to estimate a bearing's remaining useful life (RUL). The concept is based on the actual running conditions of the bearing combined with a new linear ARX-Laguerre representation. The proposed model exploits the vibration and force measurements to reconstruct the Laguerre filter outputs; the dimensionality reduction of the model is subject to an optimal choice of Laguerre poles which is performed using GAs. The paper explains the test rig, data collection, approach, and results. So far and compared to classic methods, the proposed model is effective in tracking the evolution of the bearing's health state and accurately estimates the bearing's RUL. As long as the collected data are relevant to the real health state of the bearing, it is possible to estimate the bearing's lifetime under different operating conditions.

Keywords Vibration analysis · Condition monitoring · RUL · Rolling-element bearings · Through-life engineering · GAs · ARX-Laguerre model

1 Introduction

In many industries, prognostics and health management (PHM) are key tools for condition-based maintenance. The bearing industry, like other industries, uses various approaches to extract health indicators that help in decision-making for maintenance. One common method to determine the remaining useful life is to use the dynamic load capacity and applied load, a method endorsed by standard ISO281:1977 and the modified ISO281:2007. However, in real operating conditions, the bearing can suffer from unexpected circumstances, and the actual operating life could be completely different [1]. Another method is to monitor the condition of the bearing to determine its health state and remaining useful life (RUL). This paper proposes a new model to track the evolution of bearing health using vibration data to more accurately estimate the bearing's RUL. The concept is

based on the actual running conditions of the bearing combined with a new linear ARX-Laguerre representation.

By the end of the eighteenth century, bearing manufacturers and users started to focus on bearing selection and the life of bearings needed for a well-designed machine. In 1896, Stribeck [2] was the first to measure the mechanical fatigue of bearings. A decade later, Goodman [3] adopted the fatigue approach to determine load limits on cylindrical roller bearings. For quite some time, Palmgren's work was the most important in the field of bearing life calculations. In 1947, Palmgren and Lundberg used Palmgren's previous work and the Weibull distribution to develop a modified version of bearing life [4]. Since 1952, all standards have been based on Lundberg and Palmgren's approach [5]. It takes into account many parameters like the contact area and the length of the raceway, the number of stress repetitions, the probability of survival, the internal stress created by the external load, and the stressed volume.

By 1970, however, both manufacturers and users began to admit that bearing life was much better than ISO-standard predictions. In 1971, ASME proposed "Life Adjustment Factors" to minimize the errors in remaining life prediction [6]. But bearing design continued to improve, and bearing normal service life was about six times longer than the

✉ Taoufik Najeh
taoufik.najeh@ltu.se

¹ Division of Operation and Maintenance, Luleå University of Technology, 97187 Luleå, Sweden

predicted lifetime. In 1985, based on Lundberg and Palmgren's theory, Harris et al. [7] added an additional parameter to describe the fatigue strength of bearing material. The new contribution allowed more accurate predictions for the ball and roller bearings. This method still works even in less than optimal operating conditions like the reduction of lubrication or contamination inside the housing. In its last version, international standard ISO 281: 2007 fully supports this theory for bearing-life calculation using the basic following equation:

$$L_{10} = \left(\frac{C}{P} \right)^p \quad (1)$$

where C is the basic dynamic load capacity, P is the applied load, and p is the life equation exponent. The dynamic load capacity is developed based on empirical testing under a constant load that allows the bearing to reach a specific number of revolutions without fatigue. The L_{10} life refers to the expected life of 90% of an ensemble of similar bearings which can be customized with a life adjustment factor for reliability a_1 . The basic equation has since been adjusted and non-linear modifications include the addition of a stress life modification factor, a_{slf} , to combine the effect of the contamination level and lubrication quality of the bearing.

In addition to the C/P technique, there are various online or offline data-driven methods for prognostics and health management using the available observed failure time data and various health indicators [8]. The condition monitoring data can be used directly or indirectly. For example, data on wear or cracks can give a direct estimation of the RUL, while other data, such as vibration data, indirectly describe the health state of the bearing. In the latter case, a failure event is needed as additional information to predict the RUL. Several researchers have proposed methods for RUL. Hasan et al. suggested a technique based on wavelet packet decomposition for bearing prognostics [9]. Guo and colleagues proposed using a recurrent neural network-based health indicator for RUL estimation [10]. Hinch and Tkiout developed an end-to-end deep framework based on convolutional and long short-term memory (LSTM) recurrent units for RUL prediction [11].

More approaches to rolling element bearing RUL estimation are reported in the literature and differ according to the nature of the data and the way they are collected [12–15]. This paper proposes a new perspective in the field of estimating a bearing's lifetime. It uses artificial intelligence to solve the problem of high nonlinearity and to achieve more accurate health predictions. This state-of-the-art research is based on the ARX-Laguerre model and uses genetic algorithms (GAs). Its goal is to provide an accurate estimation of the RUL of bearings using a new signal processing algorithm.

2 Experimental details

Figure 1 is a photograph of the test rig used for the experiment. It has a customized bearing house for the SKF 61900 deep groove ball bearing which is directly coupled to the shaft of 75 kW, three-phase, 1650 rpm motor. This high-powered electrical motor was justified by the idea of extending the test rig to support additional functions related to gearbox fault detection. In the rig's hydraulic system, a cylinder pulls the bearing house to apply a radial load to the tested bearing. All parts are bolted to a large steel bed secured to concrete flooring. The choice of the tested bearing (SKF 61900) was justified by the low load needed during the test; the housing is directly mounted on the shaft, so the radial load applied on the tested bearing must be less than the maximum load supported by the original bearings installed inside the electric motor.

In this experimental set-up, the rotating shaft is directly attached to the bearing. The bearing housing is thus stationary and is connected to a rigid support (the steel bed) using a hydraulic cylinder which both give the radial load and the support. This bearing arrangement is thus in principle, from the load point of view, identical with the bearing housing arrangement used for an instant in machinery equipment. The advantage of the experimental set-up, even though different from the conventional test rigs, is that it is purely considering the main parameters that are affecting the lifetime of the bearing normally, angular speed, radial load in a clearly defined direction, and the lubricant. The measurements will therefore not be disturbed by the support of the bearing, the radial load will be accurately measured, and the measured parameters will be the same as used in the standardized method for bearing lifetime calculation. An example of machines with this type of bearing arrangement can be seen in excavators and other heavy equipment vehicles. Another advantage, with this test rig, just one bearing is considered; with the conventional test rigs, we can have several bearings running simultaneously, and it will be hard to draw a consistent conclusion.

Measurement equipment and software schematics for the test rig are presented in Fig. 2. The PXI National Instruments platform was used for data acquisition, speed control of the electric motor, and load control of the hydraulic pump. The NIPXIe 6361 was used to measure the speed, and because this module has two analog outputs (2.86 MS/s), 24 digital I/Os; it was used as a speed and load controller respectively for the electric motor and the hydraulic pump. The NIPXI 4472B was used for the vibration signal acquisition and temperature measurement. This module had eight channels, each of which has a sample rate of 102.4 kHz.

A triaxial accelerometer (*Brüel-Kjær*) with frequency range (0.25–3000 Hz) was mounted directly on the bearing house using adhesive. To get an accurate measurement of the bearing's strain, a place was reserved as close as possible to the housing for the strain sensor to directly measure the strain

Fig. 1 Test rig

on the tested bearing. *DTE 25* hydraulic oil (*ISOV G46*) was used for lubrication, and the housing was filled to half level. The vibration data, combined with actual running conditions, are used to define the health state of the bearing and predict when it will reach a faulty mode. Failure is defined as a specific level of the root mean square (*RMS*) value which will indicate the presence of cracks on the surface of raceways or rolling elements. The final goal is an accurate assessment of the degradation path from a healthy to a faulty mode to estimate the remaining useful life of a rolling element bearing.

Before beginning the experiment, to acquire a general understanding of the bearing's behavior, several random tests were done for different loads and various threshold values to decide on the selected thresholds. First, a constant load of 1 kN and normal to load-bearing surfaces was used; this load is the maximum load supported by the SKF 61900 deep groove ball bearing. However, we never managed to create defects, even after 20 h of running time, and the *RMS* never exceeded the 1.8 m/s^2 level. Figure 3a confirms the absence of defects; it indicates how much running time is required to

Fig. 2 Measurement equipment and software schematic for the test rig

Fig. 3 Microscopic images of degradation

create a defect under those conditions. Next, we tried a 3-kN load. In this case, the test ended up with a failure in less than 10 h, but a plastic deformation was noted from the first test (see Fig. 3b). It is impossible to get any reasonable results on the lifetime estimation under this plastic deformation.

The problem was how to accelerate the test without overloading the bearing. *Arizona dust* was used to solve the problem; this had an acceptable test duration without changing the failure mechanism, and it was possible to keep the load equal or under 1 kN where degradation of the bearing health could be recorded from the start-up to failure and confirmed with microscopic images, as shown in Fig. 3c and d. Table 1 shows the values of the predefined levels where the threshold RMS levels were varied from 1 to 5 m/s².

There are several kinds of Arizona dust referring to the standard ISO 12103-1. The *ARIZ-KSL* is the hardest type, moreover is not labeled as hazardous to health. For this type of Arizona dust, there are four possible grades of fineness: ultra-fine (A1), fine (A2), medium (A3), and coarse (A4). This study only considered A2 (0.97 to 176 μm) and A3 (0.97 to 284 μm) fine grade. The A1 or A2 grade refers to

the size distribution of particles. As an example, Table 2 represents the distribution of A2 fine dust content in terms of particle size.

Based on several tests performed on the test rig, we end up with the conclusion that the *RMS* is starting with a value usually less than 1 m/s² and almost constant, but suddenly, it monotonically increases. An increase of 10% in the current *RMS* value will be assumed as a triggering event to consider the bearing running in the second phase. A value of 7 m/s² is more or less common for most of the tests when total failure accrues; the time consumed to reach this threshold was significantly different from one run to another. This can be explained by the smoothing process caused by the continuous rotation of balls against the inner race and the outer race.

Anyhow, it is important to consider when a critical vibration level has reached to avoid critical future failure. In this

Table 1 Duration and threshold values for the termination of each test

Run	Load (kN)	Arizona dust	Duration (h)	RMS (m/s ²)	Figure
1	1	No	20	2	3a
2	3	No	11	5	3b
3	1	Yes	14	4	3c
4	0.9	Yes	17	5	3d

Table 2 Size distribution of A2 fine dust

Particles(μm) ≤	%
0.97	4.5–5.5
1.38	8.0–9.5
2.75	21.3–23.3
5.50	39.5–42.5
11.00	57.0–59.5
22.00	73.5–76.0
44.00	89.5–91.5
88.00	97.9–98.9
124.50	99.0–100.0
176.00	100.0

study, the value 7 m/s^2 will be considered the failure threshold of the RUL predicted. Each time the measurements were acquired using a sampling frequency of 25.6 kHz, the measured sample length was 3 s, and the samples were taken once per minute. The purpose of these tests was to create a database that could be used in the bearing life estimation or any other future study connected to prognostic problems. Note that to take into account the inherent randomness of end-of-life of bearings, it is crucial to collect data during all operational scenarios and cover all normal and abnormal behavior states. This can be done using a factorial experimental design.

3 Remaining useful life prediction of bearings

The main goal is to predict the bearing's health state and estimate upcoming degradation as early as possible. The proposed strategy is inspired by the *RMS* measurement versus time (Fig. 4). As Fig. 4 shows, there are always two distinguishable stages in the curve. The first one lasts from the beginning until the defect reaches an almost constant *RMS* level. The second stage is identified by a continuous and ascendant variation of the *RMS* measurement. The *RMS* variations typically show this behavior in all tests; the only differences are the end time of the first phase and the slope in the second phase, both of which change from one bearing to another. In this paper, we focus on the second phase. The bearing lifetime calculation refers to the period after the initial defect occurs. We first determine a critical level at which to start using data; this time is considered the beginning of the failure

mode. We then use the ARX-Laguerre model to predict the *RMS* value at a specific point in time and estimate when the bearing will reach the end of its useful life. In terms of parameter complexity reduction and quality approximation, the ARX-Laguerre with the *RMS* feature shows good performance. Besides, the results confirm the efficiency of the proposed model for the RUL estimation with respect to the running conditions. Given the good results, we propose a possible extension of this work by combining other features. Specifically, expanding the ARX coefficients on two Laguerre bases instead of directly using the ARX model gives an accurate approximation of a complex linear system.

The idea of expanding the ARX model in this way was first proposed by Bouzrara et al. [16]. However, the capability of this model is highly dependent on the poles' calculation of both Laguerre. When we combine the ARX with two Laguerre bases, we end up with a simple representation and a good estimation of the complex system. The new model is called the ARX-Laguerre model. The efficiency of the model is closely linked to the choice of the poles of both Laguerre bases.

Before the lifespan prediction model can be adapted, we start by choosing a reasonable way to experiment with this test rig. It seems that a full factorial experiment design is feasible in our case, i.e., $3 \times 3 \times 2 = 18$ runs. The speed and load factors have three levels, and the contamination size and amount have two. The term level is used when referring to the value of one of the independent parameters (e.g., speed = 1 means 1650 rpm) and the term run when referring to a combination of levels (e.g., load = -1, speed = 1, contamination = 0). The selection of the level takes into account the load capacity of

Fig. 4 RMS measurement

Table 3 Levels of variables and coding identification

Level	Load (kN)	Speed (rpm)	Particle size	Coding	
High	1.03	1650	A3	11	1
Center	0.92	1450	-	00	-
Low	0.76	1250	A1	- 1-1	0

the bearing and the limiting operating condition of the test rig. The factors of the test are given in Table 3. The table shows two three-level factors and one two-level factors.

3.1 The mathematical formulation of the ARX-Laguerre model

To model a discrete-time process where $u(k)$ and $y(k)$ are the input and output, respectively, the ARX model can be expressed as follows [16]:

$$y(k) = \sum_{j=1}^{n_a} h_a(j)y(k-j) + \sum_{j=1}^{n_b} h_b(j)u(k-j) \quad (2)$$

where $\{n_a, n_b\}$ and $\{h_a(j), h_b(j)\}$ are respectively the ARX model orders and parameters. These parameters can be developed on two independent Laguerre bases formed by a set of Laguerre functions as shown in Eqs. (3) and (4):

$$h_a(j) = \sum_{n=0}^{\infty} g_{n,a} l_n^a(j, \xi_a) \quad (3)$$

$$h_b(j) = \sum_{n=0}^{\infty} g_{n,b} l_n^b(j, \xi_b) \quad (4)$$

where $l_n^a(j, \xi_a)$ and $l_n^b(j, \xi_b)$ are the orthonormal functions of Laguerre bases associated with the output and the input, respectively, $\{g_{n,a}, g_{n,b}\}$ are the Fourier coefficients and $\{\xi_a, \xi_b\}$ are the pole defining the orthonormal bases, respectively.

The Z-transform of the ARX-Laguerre model truncated to a finite order N_a and N_b can be represented as:

$$Y(z) = \sum_{n=0}^{N_a-1} g_{n,a} X_{n,a}(z, \xi_a) + \sum_{n=0}^{N_b-1} g_{n,b} X_{n,b}(z, \xi_b) + E(z) \quad (5)$$

$$\text{With : } \begin{cases} X_{n,a}(z, \xi_a) = L_n^a(z) Y(z) \\ X_{n,b}(z, \xi_b) = L_n^b(z) U(z) \end{cases} \quad (6)$$

$$\begin{cases} L_n^a(z) = \frac{\sqrt{1-\xi_a^2}}{z-\xi_a} \left(\frac{1-\xi_a z}{z-\xi_a} \right)^n \\ L_n^b(z) = \frac{\sqrt{1-\xi_b^2}}{z-\xi_b} \left(\frac{1-\xi_b z}{z-\xi_b} \right)^n \end{cases} \quad (n = 0, 1, \dots, N_i-1) \quad (7)$$

where $Y(z), U(z), L_n^a(z), L_n^b(z), X_{n,a}(z, \xi_a), X_{n,b}(z, \xi_b)$, and $E(z)$ are the system output, and input, the Z-transform of the orthonormal functions defining both independent Laguerre bases, and the truncation error and the filtered output and the filtered input respectively by Laguerre functions.

The orthonormal functions ($L_n^i(z)$, $i = a, b$) defining both independent Laguerre bases satisfy the following recurrence:

$$\begin{cases} L_0^i(z) = \frac{\sqrt{1-\xi_i^2}}{z-\xi_i} \\ L_n^i(z) = \frac{1-\xi_i z}{z-\xi_i} L_{n-1}^i(z, \xi_i) \end{cases} \quad (n = 0, 1, \dots, N_i-1) \quad (8)$$

Based on Eq. (8), the filtered input and output $X_{n,a}(z, \xi_a)$, $X_{n,b}(z, \xi_b)$ can be represented as:

$$\begin{cases} X_{0,a}(z, \xi_a) = \frac{\sqrt{1-\xi_a^2}}{z-\xi_a} Y(z) \\ X_{n,a}(z, \xi_a) = \frac{\sqrt{1-\xi_a^2}}{z-\xi_a} X_{n-1,a}(z, \xi_a) \end{cases} \quad (9)$$

$$\begin{cases} X_{0,b}(z, \xi_b) = \frac{\sqrt{1-\xi_b^2}}{z-\xi_b} U(z) \\ X_{n,b}(z, \xi_b) = \frac{\sqrt{1-\xi_b^2}}{z-\xi_b} X_{n-1,b}(z, \xi_b) \end{cases} \quad (10)$$

The ARX-Laguerre filter network based on Eqs. (5), (9), and (10) is illustrated in Fig. 5.

The discrete time-recursive representation of the ARX-Laguerre model can be created from Fig. 5 as:

$$\begin{cases} X_{Na}(k+1) = A_a X_{Na}(k) + b_a y(k+1) \\ X_{Nb}(k+1) = A_b X_{Nb}(k) + b_b y(k+1) \\ y(k) = C^T X(k) + e(k) \end{cases} \quad (11)$$

with:

$$C = [g_{0,a}, \dots, g_{N-1,a}, \quad g_{0,b}, \dots, g_{N-1,b}] \quad (12)$$

and $X(k)$ is defined as follows:

$$X(k) = [X_{Na}(k)^t \quad X_{Nb}(k)^t]^T \quad (13)$$

Fig. 5 ARX-Laguerre filter network

where X_{Na} and X_{Nb} are defined in Eqs. (14) and (15), respectively:

$$X_{Na} = \begin{bmatrix} x_{0,a}(k)^T & X_{Na-1,a}(k)^T \end{bmatrix}^T \quad (14)$$

$$X_{Nb} = \begin{bmatrix} x_{0,b}(k)^T & X_{Nb-1,b}(k)^T \end{bmatrix}^T \quad (15)$$

A_i for $(i = a, b)$ are two square matrices with dimensions N_i given by:

$$\begin{bmatrix} a_{11}^i & 0 & \cdots & 0 \\ a_{12}^i & a_{22}^i & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ a_{(N_i)1}^i & a_{(N_i)2}^i & \cdots & a_{(N_i)(N_i)}^i \end{bmatrix} \quad (16)$$

with:

$$a_{sm}^i = \begin{cases} \xi_i & \text{if } s = m \\ (\xi_i)^{(s-m-1)} (1 - (\xi_i)^2) & \text{if } s = m \\ 0 & \text{if } s = m \end{cases} \quad (m = 1, \dots, N_i) \quad (17)$$

and b_i for $(i = a, b)$ are defined as follows:

$$b_i = \begin{bmatrix} b_1^i & b_2^i & \dots & b_{N_i}^i \end{bmatrix}^T \quad (18)$$

$$\text{with: } b_m^i = (-\xi_a)^{m-1} \sqrt{1 - \xi_i^2} \quad , \quad (m = 1, \dots, N_i) \quad (19)$$

3.2 Laguerre poles optimization based on genetic algorithms

As mentioned, when the ARX coefficients are expanded on two Laguerre bases, the capability of the resulting ARX-Laguerre model is very sensitive to the choice of the poles defining Laguerre bases ξ_a and ξ_b . Bouzrara et al. [17] proposed an iterative algorithm to optimize Laguerre poles based on an analytical solution of coefficients defining the ARX-Laguerre model. To find the optimum values of Laguerre poles, we choose an approach based on genetic algorithms and proposed by Tawfik et al. which is used [18, 19].

The first step is the formulation of the objective function to evaluate any possible values of Laguerre poles by minimizing the normalized mean square error (NMSE) and the normalized mean absolute error (NMAE) as a cumulative error between the real and the predicted output:

$$\text{NMSE}(\xi_a, \xi_b) = \frac{\sum_{k=1}^D [y_{\text{real}}(k) - y_{\text{model}}(k)]^2}{\sum_{k=1}^D [y_{\text{real}}(k)]^2} \quad (20)$$

Fig. 6 Input signal: strain

$$\text{NMAE}(\xi_a, \xi_b) = \frac{\sum_{k=1}^D |y_{\text{real}}(k) - y_{\text{model}}(k)|}{\sum_{k=1}^D [y_{\text{real}}(k)]} \quad (21)$$

where D is the observation number, $y(k)$ is the real output of the system, and y_{model} is the predicted output.

After the fitness function is determined, a population of a set of possible values of ξ_a and ξ_b is randomly generated. It will perform genetic operations, such as evaluation, mutation, crossover, and selection [20, 21]. The optimum Laguerre poles are selected by minimizing the fitness function [20].

After a predefined number of generations, the algorithm ends up with optimal poles defining Laguerre

bases. The following algorithm summarizes the optimization approach:

Selecting a measurement window of input/output ($y_{\text{real}}(k)$, $U(k)$) and the truncating orders (N_a , N_b).

A maximum number of generation G_{max} are predefined

Repeat until the number of generation = G_{max}

Generate N_{ind} population of poles (ξ_a^i, ξ_b^i), $i = 1, \dots, N_{\text{ind}}$

Apply the assessment of each pair of poles using the fitness function

Select a set of poles based on the computed fitness

Apply crossover and mutation

Reinsertion of best poles in the current population with maintaining the size constant

End Repeat

Fig. 7 Output signal: RMS

Table 4 ARX-Laguerre poles (ξ_a , ξ_b) with the NMSE and the NMAE of each test

#Data set	ξ_a	ξ_b	NMSE	NMAE
1	-0.74	0.95	0.0028	0.0013
2	0.23	0.86	0.0013	0.0006
3	-0.86	0.21	0.0070	0.0045
4	-0.4694	0.88	0.0242	0.0090
5	0.45	0.37	0.0185	0.0087
6	0.84	-0.27	0.0702	0.0433
7	0.33	-0.94	0.0046	0.0032
8	0.19	0.35	0.0330	0.0179
9	0.46	0.94	0.0924	0.0067
10	-0.83	0.50	0.0087	0.0056
11	0.42	0.68	0.0764	0.0447
12	0.61	0.83	0.0059	0.0031
13	0.53	0.76	0.0496	0.0244
14	0.80	-0.92	0.0092	0.0059
15	-0.25	0.63	0.0448	0.0377
16	0.67	-0.98	0.2731	0.1355
17	0.79	0.38	0.0624	0.0216
18	0.86	-0.58	0.0837	0.0368

4 Results and discussion

Once all combinations of the full factorial experiment design are accomplished, the ARX-Laguerre model is applied to the experimental data to predict degraded states of the bearing reflected by the *RMS* increase. To build a reliable model with high accuracy, relevant variables covering the behavior of the bearing's health should be collected. Two variables are

considered in our ARX-Laguerre model, the force as the input (Fig. 6) and the *RMS* as the output (Fig. 7). Eighteen sets of data with different running are generated under specific conditions (load, speed...). For each test, a model is built using 40% of the recorded data; the remaining data are used for the validation of the model. We select the truncating orders $N_a = N_b = 6$, and algorithm 1 is used for the optimization of the poles based on GAs.

The bearing degradation can be described by the ARX model; 12 parameters of degradation are estimated using the least-squares method. To validate the proposed model, we use the output of the real *RMS* value and the ARX-Laguerre model output as a predicted value for 18 independent runs of bearings (Table 4). The performance of the model is measured in terms of normalized mean square error (NMSE) and normalized mean absolute error (NMAE), the cumulative error between the measured output $y_m(k)$, and the proposed model output $y_{\text{model}}(k)$. These performance metrics are used as accuracy measures for the optimal identification of Laguerre poles ξ_a and ξ_b , which can guarantee an important reduction of ARX-Laguerre complexity. Several performance metrics (error measures) can be used for the evaluation in the forecasting model validation. In the forecasting literature using the ARX-Laguerre model, the NMSE metric has been the most commonly, suggested metric [16–18]. The results are presented in Figs. 8, 9, 10, and 11 (for runs 1, 4, 8, and 12, respectively). From this plot, we see that for all tests, the ARX-Laguerre model can predict the *RMS* level with enough accuracy to anticipate any failure just on time; thus, total failure of the bearing can be avoided.

The goal of the adopted approach is to predict the unknown output presented as a fault and then to detect the time corresponding to the bearing malfunction. To

Fig. 8 Validation of prediction. Dataset 1

Fig. 9 Validation of prediction.
Dataset 2

Fig. 10 Validation of prediction.
Dataset 3

Fig. 11 Validation of prediction.
Dataset 4

Table 5 Performances of RUL prediction methods

Prediction method	Accuracy (%)
ARMA	96.51
SVM	99.4
Extended Kalman filtering	80
LSTM	45.27

evaluate the efficiency of the proposed method, we study the *RMS* variation compared with other existing methods in the literature, such as *ARMA*, support vector machine (*SVM*), Kalman filtering, and long short-term memory network.

From Table 5, we can conclude the prediction effectiveness based in terms of prediction error for different approaches. For example, Pengfei et al. [22] and based on the built ARMA model, the prediction accuracy is about 96.51%. Using the *SVM* method and a standard accelerated aging platform named PRONOSTIA, Abdenour et al. [23] end up with a prediction accuracy between 99.4 and 98.75%. Rodney et al. [24] have used the same test rig (PRONOSTIA) as [23] but they used a data-driven methodology based on extended Kalman filtering; the average prediction accuracy was about 80%. In the case of a long short-term memory network [25], a prediction accuracy of 45.27 % is obtained.

5 Conclusion

The paper describes how run-to-failure data can be used to build an ARX-Laguerre model as a decision model to monitor the health of bearings. This type of reduced complexity model is subject to the optimal selection of Laguerre poles obtained from input-output measurements and genetic algorithms. It finds that the GA method for ARX-Laguerre pole optimization is more efficient in terms of mean square error, but the approach requires a high computing time compared to other methods (Newton-Raphson's and Bouzrara et al.'s methods). However, the performance of the model is reasonably good, with a small deviation between the predicted and experimental values. No extra hardware is needed except for a classical accelerometer and a load cell. Finally, the proposed method has high accuracy, and the estimated lifetime can be estimated at any point in time using the present running conditions.

Authors' contributions Experimentation: Taoufik Najeh, Jan Lundberg; numerical modeling: Taoufik Najeh; writing (original draft preparation): Taoufik Najeh; writing (review and editing): Taoufik Najeh, Jan Lundberg.

Funding Open access funding provided by Lulea University of Technology.

Availability of data and material The authors confirm that material supporting the findings of this work is available within the article. The collected data of this work are not available within the article.

Compliance with ethical standards

Competing interests The authors declare that they have no competing interests.

Ethical approval The article follows the guidelines of the Committee on Publication Ethics (COPE) and involves no studies on human or animal subjects.

Consent to participate Not applicable. The article involves no studies on humans.

Consent to publish Not applicable. The article involves no studies on humans.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

References

- Harris TA, Kotzalas MN (2007) Fatigue life: basic theory and rating standards. In: Rolling Bearing Analysis, vol ch. 11, 5th edn, pp 195–252
- Stribeck R (1900) Reports from the central laboratory for scientific-technical investigation. ASME Trans 29:420–466
- Goodman J (1912) Roller and ball bearings. Proc Inst Civil Eng 189:82–127
- Lundberg G, Palmgren A (1947) Dynamic capacity of rolling bearings. Generalstabens litografiska anstalts förlag, Sweden, ACTA polytechnica, Mechanical Engineering Series, Ingeniörsvetenskapsakademiens handlingar (1):3
- Lundberg G, Palmgren A (1952) Life formula for rolling bearings. In: Dynamic Capacity of Rolling Bearings. Sweden, ACTA Polytechnica
- Bamberger EN (1970) Effect of materials-metallurgy viewpoint, vol 237. In: Ku PM (ed) NASA Special Publication, Washington, pp 409
- Harris TA, Yu WK (1999) Lundberg-Palmgren fatigue theory: considerations of failure stress and stressed volume. ASME J Tribol 121(1):85–89
- Si X, Wang W, Hu C, Zhou D (2011) Remaining useful life estimation-a review on the statistical data-driven approaches. Eur J Oper Res 121(1):1–14
- Ocka H, Loparo K, Diczieno FM (2007) Online tracking of bearing wear using wavelet packet decomposition and probabilistic modeling: a method for bearing prognostics. J Sound Vib 302(4):951–961

10. Guo L, Li N, Jia F, Lei Y, Lin J (2017) A recurrent neural network-based health indicator for remaining useful life prediction of bearings. *Procedia Comput Sci* 240(C):98–109
11. Hinch AZ, Tkiout M (2018) Rolling element bearing remaining useful life estimation based on a convolutional long-short-term memory network. *Neurocomputing* 127:123–132
12. Qian Y, Yan R, Gao R (2017) A multi-time scale approach to remaining useful life prediction in rolling bearing. *J Mech Syst Signal Process* 83:549–567
13. Zhao M (2018) Bearing remaining useful life estimation based on time-frequency representation and supervised dimensionality reduction. *J Meas* 86:41–55
14. Wang D, Tsui K (2018) Two novel mixed-effects models for prognostics of rolling element bearings. *J Mech Syst Signal Process* 99: 1–13
15. Aye SA, Heyns PS (2017) An integrated Gaussian process regression for prediction of remaining useful life of slow speed bearings based on acoustic emission. *Mech Syst Signal Process* 84(A):485–498
16. Kais B, Tarek G, Jose R, Hassani M (2013) An integrated Gaussian process regression for prediction of remaining useful life of Online identification of the ARX model expansion on Laguerre orthonormal bases with filters on model input and output. *Int J Control* 86(3):369–385
17. Kais B, Tarek G, Jose R, Hassani M (2012) An integrated Gaussian process regression for prediction of remaining useful life of Online identification Decomposition of an ARX model on Laguerre orthonormal bases. *ISA Trans* 51(6):848–860
18. Tawfik N, Abdelkader M, Kais B, Lotfi N, Hassani M (2017) New methods of Laguerre pole optimization for the ARX model expansion on Laguerre bases. *ISA Trans* 70:93–103
19. Tawfik N, Chakib B, Tarek G, Jose R (2017) Input fault detection and estimation using PI observer based on the ARX-Laguerre model. *Int J Adv Manuf Technol* 90(5–8):1317–1336
20. Goldberg DE, KORB B, DEB K (1989) Messy genetic algorithms: motivation, analysis, and first results. *J Complex Syst* 5(3):493–530
21. Kerry G, Sambridge M (1994) Genetic algorithms: a powerful tool for large-scale nonlinear optimization problems. *Comput Geosci* 20(7–8):1229–1236
22. Dang P, Zhang H, Yun X, Ren H (2017) Fault prediction of rolling bearing based on ARMA model. *International Conference on Computer Systems, Electronics, and Control*:725–728
23. Soualhi A, Medjaher K, Zerhouni N (2015) Bearing health monitoring based on Hilbert–Huang transform, support vector machine, and regression. *IEEE Trans Instrum Meas* 64(1):52–62
24. Singleton R, Strangas E, Aviyente S (2015) Extended Kalman filtering for remaining- useful-life estimation of bearings. *IEEE Transactions on Ind Electronics* 62(3):1781–1790
25. Wang F, Liu X, Deng G et al (2019) Remaining life prediction method for rolling bearing based on the long short-term memory network. *Neural Process Lett* 50:2437–2454

Publisher's note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.