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# Bearing failure diagnosis and prognostics modeling in plants for industrial purpose

Henry Ogbemudia Omoregbee[1*], Bright Aghogho Edward[2] and Mabel Usunobun Olanipekun[3]

*Correspondence:
omoregbeeho@gmail.com

[1] Mechanical Engineering Department, University of Lagos, Lagos, Nigeria
[2] Department of Mechanical Engineering, Federal University of Petroleum Resources Effurun, Effurun 23401, Nigeria
[3] Department of Electrical Engineering, Pretoria, Tshwane University of Technology, Gauteng 27, South Africa

## Abstract

When condition-based maintenance (CBM) is combined with proper decision support systems, it leads to enhanced utilization of resources and increased productivity which tends towards business efficiency. The forecasting of the future condition, the remaining operating life, or probability of stable system behavior, based on data from acquired condition monitoring is referred to as prognosis which is an important part of the CBM process. Despite auto-regression integrated moving average (ARIMA) time series modeling, being long established and dating back to the 1960s, it has surged through new advances over the years and is now recognized as a major forecasting technique. Its application is therefore investigated here in the context of the FEMTO–ST Institute (Franche-Comté Électronique Mécanique Thermique et Optique-Sciences et Technologies) bearing dataset. The work discussed in this article uses a time series approach which contributes to modeling and forecasting the remaining useful life (RUL) of bearings in plants, thereby helping to prevent catastrophic failure before it occurs. The motivation for this paper lies in the approach used in structuring the ARIMA models, thereby adding value in its application by first ensuring the stationarity of the time series signal by using the Dickey-Fuller Test, which then makes forecasting easy and accurate. The result obtained here using ARIMA is compared to the results obtained in the literature where neural network regression (NNR) was used as part of the FEMTO competition. We checked by contrasting our observations with the NNR observations obtained as well as the experimental results from the National Aeronautics and Space Administration (NASA)

**Keywords:** ARIMA model, Artificial intelligence (AI), Condition-based maintenance (CBM), Dickey-Fuller Test, Forecasting, Naive model, Time series analysis

## Introduction

Condition base monitoring (CBM) is commonly used for assessing the operating states and health of rotating devices. Growth in the sophistication of modern machines has led to advancements in CBM technology to improve and enhance product performance and lower downtimes. Such new and complex instruments often immerse in natural noise vibration and acoustic emission signals, making it impossible to detect any fault. Removing sensitive signaling characteristics from faults often attracts considerable attention to identify and recognize faults in rotating systems. It is especially true for low-speed machinery under varying load and temperature conditions.

In many industrial applications especially in many materials processing environments, such as draglines in the mining industry and large rolling mills, the conditions above applies. Control methods for stationary systems are inadequate to efficiently detect and diagnose faults under these conditions because of its higher sensitivity to detect at low-energy response due to the low-speed. The use of acoustic emission transducers is a better option than using accelerometers for analyzing data generated under these conditions.

Early-fault features include transient signals that occur regularly at a characteristic frequency. Such signals are observed to be very low for most cases and often, with high background noise with rotating rotor frequency interference and having its harmonics over a wide frequency spectrum. There is also signal attenuation and distortion between the sensor which collects the fault signal and weak fault source, especially if the sensor is not properly placed with respect to the fault location [1]. In [1], something similar was done using different approach where bearing fault was detected for a bearing with an initial seeded fault running under the influence of a variable load (acting from the radial and axial direction) but this time the speed was at low speed compared to this present work which is at higher speed. The close relation in the model employed in the journal published by [1] and that presently considered in this article, is with one of the decision tool called log-likelihood which is common in both. While the log-likelihood was used with Bayesian algorithm for decision making in [1] for considering faults initiated at low speed and variable load conditions, ARIMA with log-likelihood in combination with Akaike Information Criteria (AIC) and Bayesian information criterion (BIC) or Schwarz criterion (also SBC, SBIC) was used for the decision making in this article while considering high speed at variable load condition.

Due to the strong stochastic characteristics of the fault propagation process by [2], the future propagation pattern of a particular fault during its early stages was difficult to predict effectively despite the fact that a large number of features was extracted to characterize the AE data. It has been shown by [3, 4], that several features are efficient only for a specific fault in a particular propagation process.

Specific maintenance strategies are introduced to avoid or mitigate rotating machinery failures, and these can be either preventive or corrective maintenance strategies. The proactive maintenance approach has the benefit of ensuring that components are replaced before system failure, while corrective maintenance is typically done following system failure in order to return the asset to full operating condition. The former leads to high maintenance performance and low machine downtime losses in many critical applications [5].

Today, the market is receiving considerable attention from the introduction of so many forecasting devices. One of such method that we find here is the integrated moving average (ARIMA) for auto regression. ARIMA models' implementation is well-established and dates back to the 1960s. Initially its usage in prognostics was limited, but it has surged again over the years through advances in the technology and is today recognized as a major forecasting technique. Due to its capabilities for accurate prediction using past values, time series–based forecasting has gained wide practical application. The method requires stationary data, expert criteria, model diagnostics checking, correlation graphs analysis, etc. [6–8] used ARIMA to forecast a food company's demand by considering the question of the supply chain and how they could predict demand using four output criteria: the Schwarz Bayesian criterion, the Akaike criterion, the optimal probability, and the standard error obtained from the algorithm [7]. Used an ARIMA model for forecasting global solar radiation on a daily and monthly basis. They concluded that when it comes to weather forecasting ARIMA does better than ANN. Due to the easy computational method, simplicity and accuracy in prediction and low data input requirement, they also used a time series forecasting technique in their research. They concluded that for many time series, the prediction method can provide a fast and standard way of generating forecasts in a single step.

Other predicting models include the seasonal auto-regressive moving average (SARIMA), artificial neural network (ANN), fuzzy logic etc. [7] used SARIMA in their aforementioned study for the forecasting of regular monthly solar radiation in Seoul based on data provided by the Korean Meteorological Authority for hourly solar radiation. Many applications, including time series forecasting use artificial neural networks as in [8]. Another forecasting technique is fuzzy logic which mimics human classification capabilities by using multivariate criteria instead of the classical binary logic used in computational environments. Other methods for prediction include support vector regression (SVR) as was used by the winner of the FEMTO competition in comparison with other methods and neural network regression (NNR).

ARIMA-related autoregressive (AR) models are said to be suitable for analyzing mutation signals with: consistency, periodicity when seasonality is present and energy accumulation that is very different from the erratic, non-linear, and non-stationary fault signals in rotating machinery. Recent developments in AR applications now make them suitable for nonlinear and nonstationary week signals [9] and hence its application in this work as will be later seen. The method applied was consider within the scope of predictive maintenance and condition-based maintenance. As with the case of virtually all data obtained from plants bearing, we find that we are more-often dealing with non-linear, non-stationary data which negates their use with ARIMA models. This work helps to correct the notion of directly applying models to data especially when dealing with time series data without applying and ensuring first that for all ARIMA models the data needed ought first to be stationary. With the approach applied, ARIMA AIC-Akaike's Information Criterion (AIC) was aimed at making the close fit estimation for the measure in-order to find the best model of the target data.

This paper comprises the following structure, "Methods" section offers a summary of the time series signals and the model time series forecasts. "Experiment" and "Results and discussion" sections respectively present the experimental procedure as well as results and discussions. The "Conclusion" section concludes the paper.

## Methods

When a signal is recorded over a sequence of regular time intervals it is known as a time series signal. Also, it can be interpreted as a sequence of plotted (or indexed) data points in time order. The data are often taken sequentially in time at equally spaced instants in succession. Box-Jenkins methodology which also includes, other time series techniques such as ARIMA requires the series to be stationary, meaning that the mean and covariance remain constant regardless of the instant time being considered. With non-stationary series, differentiation processes require that the series' first be transformed to a stationary sequence.

Analysis of time series comprise analyzing time series data for the extraction of meaningful statistical values and other characteristics from the data. Predicting potential values by using equations is referred to as forecasting with respect to past observed values. The type of analysis where the evaluation of more than one independent time series, tends to influence the current parameter of another time series when regression analysis is used is not "analysis of time series," since much concentration is on finding the similarity in values of several dependent series or single time series at different points in time. This research lay emphasis on a different form of forecasting method called ARIMA modeling.

ARIMA, is used to predict future values by predicting algorithm-based idea, that the knowledge in the past time series values might be alone. Dataset is also unchangeable for the entire time span. Predicting the series' potential values would take the next step in predicting whatever one would want to take.

If the technique of forecasting assumes that the next predicted point is equal to the last observed point it is called a naive process. From the root mean square error (RMSE) value, and from the graphs, we can infer that high variability datasets are not suitable for naive processes.

**Algorithm 1:** Pseudo code of the proposed algorithm

```
Result: ARIMA Results
Initialization;
while Input Data exist do
    Test for Stationary;
    if non-stationary then
        Instruction1;

        Differentiate

        Instruction2;

        Determine the "p"
        Auto-regression and the
        "q" moving average

    else
        Instructions3;

        Determine the "p"
        Auto-regression and
        the "q" moving average

    end
end
```

Figure 1 below shows the flow chart representation of the pseudo code algorithm 1 as presented above. From these we first reiterate the fitness of the input data once it is available by performing the Dickey-Fuller Test to ensure that the analysis to be carried out on the data obtained in determining induced fault present in plants bearing and also

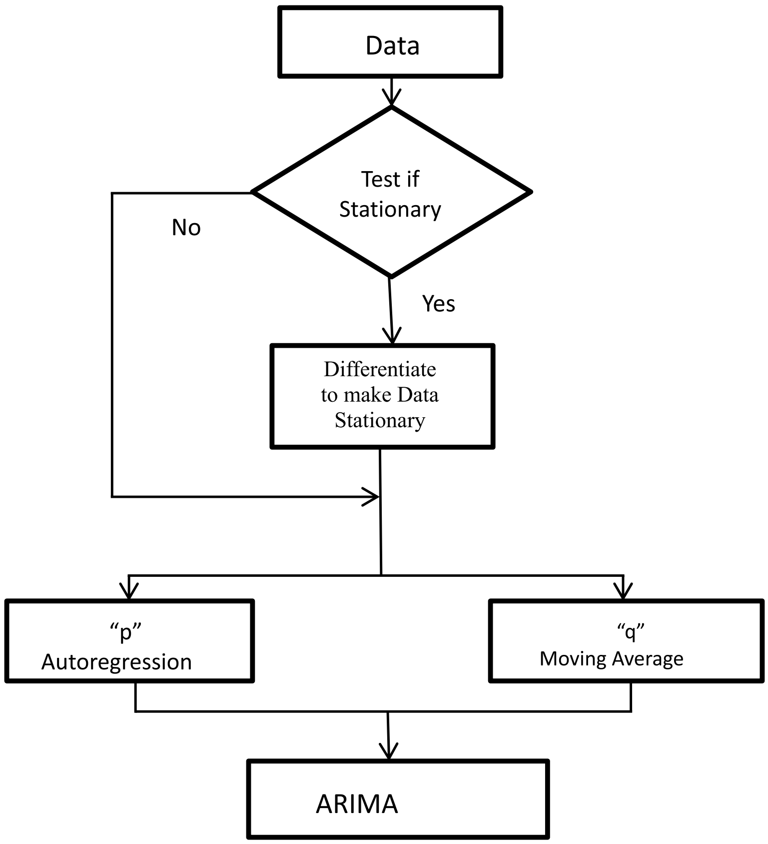


**Fig. 1** Flow chat for the pseudocode proposed algorithm

in the determination the RUL of the bearings present are correct. In a situation where the data fitness is not okay (perhaps if the data is found to be non-stationary), then from the algorithm it is needed to perform a differentiation on the data (known as empirical mode decomposition) in the bid of making the data relevant for use. This method helps to identify modal information in the time-domain signals by breaking down the complex non-linear, non-stationary dataset into smaller parts that can be more manageable. Other data fitness test methods are also essential at this stage such as the *F*-test and normality test; however, in this paper we only stressed our observation on the Dickey-Fuller Test. Having achieved our goal at this stage we can then proceed to determine the auto-regression '*p*' and the moving average '*q*' of the residual data or the data depending on the test state of the data as ARIMA models which are dependent on the *P*, *d*, and *q* factors which refers respectively to the order of the model's autoregressive, and the moving average parts.

In considering forecasting of time series, past collected data are analyzed to construct an efficient mathematical algorithm while, the series data generation processes are been captured [10–13]. A continuous sequence of data points is a time series is typically measured over successive times, and is thus not ultimately determined in nature, i.e., it cannot be guaranteed with conviction for future prediction.

In general, a time series of the nature $\{x(t),\ t = 0,1,2,\ \ldots,\}$ follows a certain probability model, thus defining the random variable $x_t$ as a joint distribution. Using a function *f* with a fixed size $M$ as an input time window to reflect close event of the time series, the frequentist approach for considering future values $\hat{x}(t+1)$) is involved.

$$x(t) = [x(t), x(t-\tau), \ldots\ldots, x(t-(M-1)\tau)] \quad (1)$$

$$\hat{x}(t+\tau) = f(x(t)) \quad (2)$$

where $x(t)$ the time series data, used to construct the model is for $0 \leq t \leq 1$. Ongoing research on forecasting such is a single-step-ahead, and is based on the outcome which shows that under several hypotheses, accurate estimate is possible for $x(t+\tau)$. According to Eq. (2) $M \geq 2d+1$ generates the stationary attractor measurable extent in time series. In this method, past memory is retained which is able to adapt to the time frame. Multi-step forecasting $\{x(t), x(t-\tau), \ldots\ldots, x(t-n\tau), \ldots,\}$ seems good for $\hat{x}(t+h\tau)$ approximation, with the number of steps head being $h$.

Having an in-depth knowledge of the improved ARIMA model and rightfully applying the needed features is very vital hence the approach adopted in this research which makes it unique. More often data are often used the way they are obtained without thoroughly understanding the features of the data one is working with. For the ARIMA model to be effective there is the need in ascertaining if the data is non-linear, non-stationary, or stationary and with ARIMA application for the purpose of diagnosing and predicting, a time series stationary data is needful.

Making the time series stationary is the first step to take in other to build an ARIMA model. This is because in ARIMA, the term 'auto regressive' means that a model of linear regression is used which lags as predictors. It is also known that linear regression models work best when the predictors are independent of each other and are not correlated. The most common approach to make a series stationary is by differencing it. This is deducting the onset value from the previous value. A difference which is more than one can be needed and this is dependent on the nature of the sequence [14–19].

The least number in differencing steps is the estimate $d$, which is of need in making the series stationary. Where $d=0$, the time series is stationary already. The least number of differentiation steps $d$, is the value needed to make the sequence stationary.

For the words $'p'$ and $'q'$ in the model; $'p'$ refers to the 'auto regressive' (AR) sequence number of lags $Y$ needed as predictors and $'q'$ stands for the word 'moving average' (MA). This tells us about the amount of lagged forecast errors that is needed in the ARIMA model.

For the 'lags of $Y_t$', $Y_t$ is a function which is referred to as a pure auto regressive (AR only) model, i.e., $Y_t$ is dependent on only its own lags.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p} + \epsilon_1 \quad (3)$$

where $Y_{t-1}$ is the first lag of the series, $\beta_1$ is the model-calculated lag1 coefficient and α is also the model-calculated intercept term.

Likewise, if $Y_t$ depends only on lagged forecast errors, it is called a pure moving average model (MA only).

$$Y_t = \alpha + \epsilon_t + \varnothing_1\epsilon_{t-1} + \varnothing_2\epsilon_{t-2} + .. + \varnothing_q\epsilon_{t-q} \tag{4}$$

On occasion where the terms of error are the respective lags errors of the autoregressive algorithm, the $\epsilon_t$ and $\epsilon_{t-1}$ errors are the errors in the following equations:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_0 Y_0 + \epsilon_t \tag{5}$$

$$Y_{t-1} = \beta_1 Y_{t-2} + \beta_2 Y_{t-3} + .. + \beta_0 Y_0 + \epsilon_{t-1} \tag{6}$$

Where the time series can be differenced by at least once in order to make it stationary with a combination of the terms AR and MA, we can assume an ARIMA model such that the equation becomes:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + .. + \beta_p Y_{t-p}\epsilon_1 + \varnothing_1\epsilon_{t-1} + \varnothing_2\epsilon_{t-2} + .. + \varnothing_q\epsilon_{t-q} \tag{7}$$

Therefore, this tends to render the time series to become stationary if finite differentiation is applied to the data points in a non-stationary ARIMA model. The ARIMA($p$, $d$, $q$) mathematical formulation using lag polynomials is provided below [20–23]:

$$\varphi(L)(1-L)^d y_t = \theta(L)\varepsilon_t \tag{8}$$

i.e.

$$\left[1 - \sum_{i=1}^{p} \varphi_i L^i\right](1-L)^d y_t = \left[1 + \sum_{j=1}^{q} \theta_j L^j\right]\varepsilon_t \tag{9}$$

where $L$ are denoted as lag operator

$P$, $d$, and $q$ are always integers which are greater than or equal to zero, which refers respectively to the order of the model's autoregressive, and the moving average parts. $d$ is an integer which related to the level of differentiation, and often when $d = 1$ it is sufficient in most cases. With $d = 0$ it reduces the model to an ARMA(pq) model. An ARIMA(p,0,0) model refers only to an AR(p) model while an ARIMA(0,0,q) refers to a MA(q) model, where an ARIMA(0,1,0) is provided the p and q equals zero, i.e., $y_t = y_{t-1} + \varepsilon_t$ is a special case been referred to as a Random Walk model, [6, 15, 24, 25]. This is commonly used for data that are not stationary, such as the economic and stock price series.

The Augmented Dickey Fuller (ADF) form is used in this work, and it is obtained in the python software from the 'StatsModels' module for testing the stationarity of the series. The ADF test's for null hypothesis, tells us if the time series is non-stationary. Therefore, if the test's $p$ value is less than the (0.05) point of significance, it is right to reject the null hypothesis and conclude that the time series is stationary indeed.

Another interpretation of a Dickey-Fuller Test: Is a stationary screening statistical test. The null hypothesis result for the test tells us that the test results consist of a test statistics (TS) and if some important values for difference confidence levels is present, the TS can be decided to be non-stationary.

For the 'test statistic' to be less than the 'Critical Value', the null hypothesis can be dismissed and the series said to be stationary.

From the work flow chart for this work it is expected that data gathered or collected from machineries or plants should first be tested to ensure the nature of the data (if found to be stationary or non-stationary). If found to be stationary, there is the need to determine the autoregressive value '*p*' and the moving average value '*q*'. After these have been determined, the ARIMA model can then be applied to determine local faults in the system and also to make predictions to when faults are likely to occur. But where the test proves to be non-stationary then there is the need to differentiate so as to make it stationary before the process of determining faults or prognostics continues.

## Experiment

PRONOSTIA is a study rig system [5, 26] mainly used to inspect and validate bearing failure detection, diagnosis and prognosis. The platform was designed and developed by AS2 M team from the FEMTO-ST Institute.

The PRONOSTIA aims at providing experimental evidence in real time thereby, characterizing the ball bearings degradation during their working life (till complete failure is experienced). This platform produced data is special in the sense that it corresponds to normal degraded bearings, the test rig allows one to perform bearings degradation in just a couple of hours. The defects are not planted artificially on the bearings, and each damaged bearing is said to comprise all forms of defects (balls, rings and cages). Constant operating conditions which include the given data for each experiment conducted at the PRONOSTIA test rig provides data relating to bearings that are deteriorated at unfavorable operating conditions.

The test rig platform consists of three parts: a deterioration generating part (with applied radial force to the checked bearing) of rotating components, and a part of measurement.

The rotating motor which transmits the spinning motion through a gearbox has a power equal to 250 W, allowing it to produce a speed of the secondary shaft while maintaining its rated torque at a speed of less than 2000 rpm, thus enabling the maximum speed of the motor to reach 2830 rpm.

The radial force diminishes the bearing life by limiting the bearing's average dynamic charge to 4000 N. The vibration sensors used are two small accelerometers, which are placed 90° apart. The first is positioned along the horizontal axis, why the second, is placed along the vertical axis.

Continuous calculation of the applied radial force to the bearing, the torque applied to the bearing, and the rotational velocity of the shaft at which the test bearing is mounted defines the operating conditions. The three operational steps are acquired at a frequency of 100 Hz. Acceleration measurements are given at 25.6 kHz.

## Results and discussion

Figure 2 shows some typical vibration signals which were obtained from the test rig in the horizontal and vertical directions. The normal degradation experienced in the bearing is shown in Supplementary Figure 2 together with the vibration raw signal from an experiment. It reveals that at about $2.75 \times 10^6$ on the $x$ axis the bearing began to show an increase in amplitude in the vertical responses. Tests were recorded from the experiment performed to avoid damaging the entire test bed (and for safety reasons). As the vibration signal amplitude tend to exceed 20 g peak-to-peak, the recording were stopped.

For three different loads, data collected

-For conditions of operation in first case is: 4000 N at 1800 rpm;

-Conditions of operation in second case is: 4200 N at1650 rpm;

-And conditions of operation in third case is: 5000 N at 1500 rpm.

The FEMTO prognostics competition participants were asked to exactly estimate the (RUL) of 11 remaining bearings (see Table 1) after 6 run-to-failure datasets were given to create a prognostic model. All those tests involves the generation of vibration signals. Condition data for the 11 test bearings were shortened for the RULs to be estimated by the participants.

The first activity involved the extraction of traits/features from the vibration signal. Six features each were removed from every signal of vertical and horizontal vibration. The Supplementary Table 1 provides the arrangement of data in ASCII form in the experimental folders provided.

The accelerometer type DYTRAN 3035B with a range of 50 g and 100 mV/g sensitivity was used. Three traits/features were extracted through a crossing of a higher order. The accumulated energy of the signal and the vibration signal peak were additional two features. It eliminated all 15 characteristics.

They were smoothed with an average movable filter for Noise Measurements. Following smoothing, feature normalization was performed to put the features within the same scale thereby, reducing bias due to wide dynamic range features.

We were given from an experimental result the remaining useful life from an experiment which was relatively close to their actual finding and assumed to be the actual, as shown in Table 4. With the formula below, the percentage error on experiment $i$ is described:

$$\%Er_i = 100 \times \frac{ActRUL_i - R\hat{U}L_i}{ActRUL_i} \tag{5}$$

In other to begin the run towards determining the estimated remaining useful life of the bearing sets given, we first had to check if the datasets were stationary or non-stationary. Using the Dickey-Fuller Test for data sample of reading on sample Casefolder1_1 as given in section 4.0, the result is given in Table 2.

The Dickey-Fuller Test for the test data sample of reading on sample Casefolder2_4 result is given in Table 2. The test says we should reject the null hypothesis and take the series to be stationary if the "$p$ value" result is lower than the meaning level or if the "test statistics" are lower compare to the "critical value". The above shows that the ADF Statistics for the four sections of distinct group considered for the time series data are

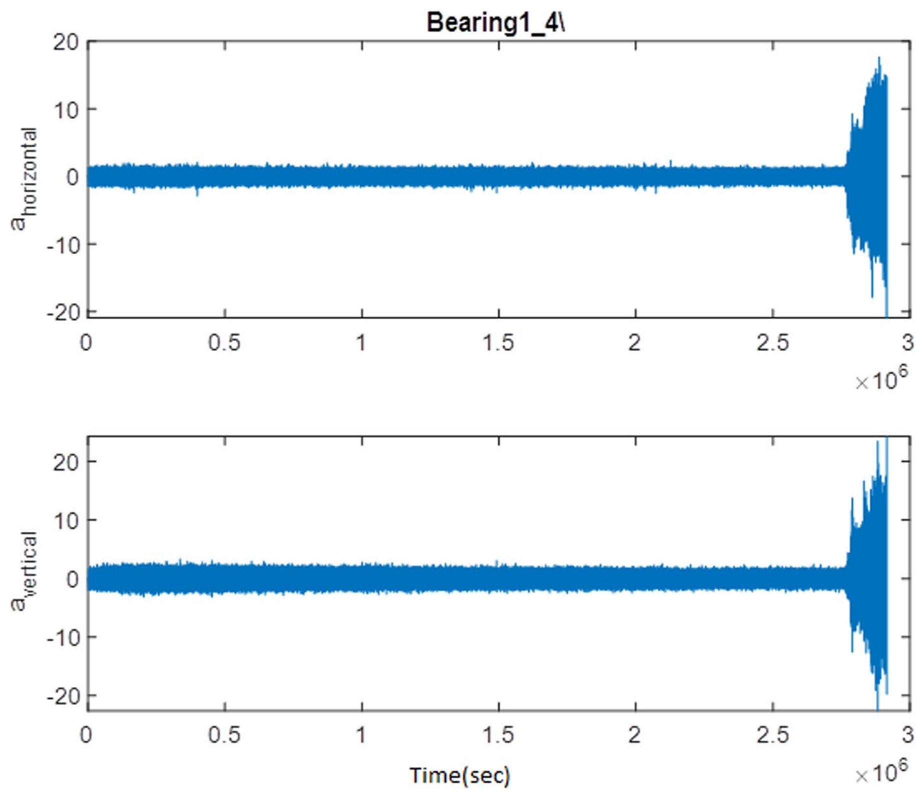


**Fig. 2** Vibration signal of bearing dataset 1_4

less than the values obtained at 99%, 95%, and 90% confidence interval, so we can confidently say that the series is stationary and hence there is no need for differencing it. Note that, the 99%, 95%, and the 90% confidence interval represents the 1%, 5%, and 10% critical values respectively. In most cases, it is sufficient from the second itemized point obtained from Eq. 9 that normally $d = 1$. So, $d = 1$ was used for the simulation carried out. We could only obtain from the autocorrelation function (acf) and the partial autocorrelation function (pacf) respectively, the evaluate values for $p$ and $q$ required for the simulation. To obtain the $p$ and $q$ value, the autocorrelated and partial-autocorrelated values are read from where the initial vertical lines in the plots which crosses the zero-amplitude line. From the Fig. 3 below, these are approximately 1.75 in both plots. The $p$ and $q$ values obtained which must be integer values can then be approximated to $p = 2$ and $q = 2$. This shows how correlated the time series is with its past value.

The dependent variable (Dep. Variable) relative to other variables are the columns D.E+F of the data set as shown in Table 3. Since the critical values for the four sections of the Casefolder1_1 dataset are all the same the first fraction section of the time series was evaluated and the result is given in Table 3 below

For a data sample of 399 data points the log likelihood was found to be − 294.415. The standard deviation of innovation was obtained to be 0.502. And for a data sample of 1000 data points which was the convergence point for the series, the log-likelihood was found to be − 711.502 see Supplementary Table 6. The Hannan-Quinn Information Criterion (HQIC) just like the Akaike Information Critera (AIC) and Bayesian

**Table 1** Datasets of 2012 PHM prognostic challenge

| Datasets | Bearing casefolder for various cases | | |
|---|---|---|---|
| | Case 1 | Case 2 | Case 3 |
| Learning set | Casefolder 1_1 | Casefolder 2_1 | Casefolder 3_1 |
| | Casefolder 1_2 | Casefolder 2_2 | Casefolder 3_2 |
| Test set | Casefolder 1_3 | Casefolder 2_3 | Casefolder 3_3 |
| | Casefolder 1_4 | Casefolder 2_4 | |
| | Casefolder 1_5 | Casefolder 2_5 | |
| | Casefolder 1_6 | Casefolder 2_6 | |
| | Casefolder 1_7 | Casefolder 2_7 | |

**Table 2** Dickey-Fuller test result on data set of Bearing1_1 Learning set sample

| Results of Dickey-Fuller Test: | | | | |
|---|---|---|---|---|
| | Distinct group_1 | Distinct group_2 | Distinct group_3 | Distinct group_4 |
| ADF Statistic: | − 7.228501 | − 10.692968 | − 14.680130 | − 8.267771 |
| *p* value: | 0.000000 | 0.000000 | 0.000000 | 0.000000 |
| Critical Values: | | | | |
| 1%: | − 3.4317 | 3.4317 | − 3.4317 | − 3.4317 |
| 5%: | − 2.8621 | − 2.8621 | 2.8621 | − 2.8621 |
| 10%: | − 2.5671 | − 2.5671 | − 2.5671 | − 2.5671 |

information criterion (BIC) or Schwarz criterion (also SBC, SBIC) which is a criterion for model selection among a finite set of models are measures that mix the likelihood with the number of parameters and data points and these are often used for decision making in the ARIMA model. It was observed that after the bearing was allowed to run to failure just before the amplitude crosses the 20 g peak-to-peak, cracks were found to have been initiated in the inner race of the ball bearing which is both dependent on the load and the speed of rotation of the bearing.

Figure 4 below shows the plot for both the original and the differenced of the original data set. A difference of one, is least needed so as not to make the model an ARIMA$(p, q)$ model thereby reducing the model to an ARMA model.

Figure 5 shows the plot of the residual, the density and the relative plots of both the original and the predicted time series. When a series is differenced, the resulting

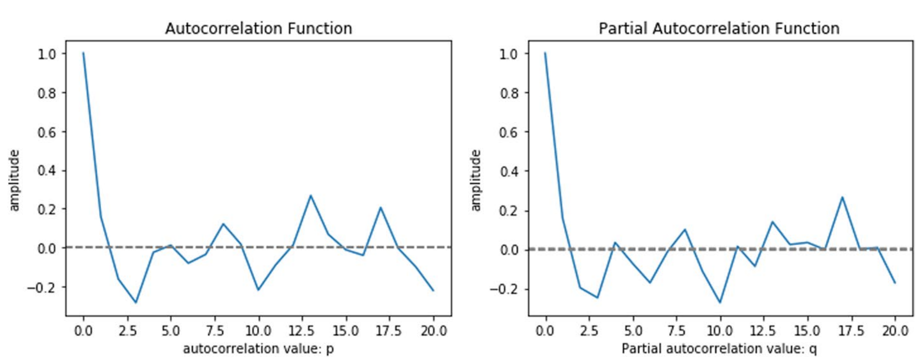


**Fig. 3** The acf and pacf plots

**Table 3** ARIMA model result for 399 sample data points of dataset Bearing1_1 (Github: https://github.com/gmonaci/ARIMA)

| **ARIMA model results** | | | | | | |
|---|---|---|---|---|---|---|
| Dep. variable: | D.E+F | | No. observations: | | 399 | |
| Model: | ARIMA(2, 1, 2) | | Log likelihood | | − 294.415 | |
| Method: | css-mle | | S.D. of innovations | | 0.502 | |
| Date: | Sat, 24 Sept 2022 | | AIC | | 600.831 | |
| Time: | 22:05:14 | | BIC | | 624.765 | |
| Sample: | 1 | | HQIC | | 610.310 | |
| | Coef | Std err | *z* | *p*>\|z\| | [0.025] | [0.975] |
| const | − 0.0005 | 0.000 | − 3.156 | 0.002 | − 0.001 | − 0.000 |
| ar.L1.D.E+F | 0.7042 | 0.110 | 6.429 | 0.000 | 0.490 | 0.919 |
| ar.L2.D.E+F | − 0.4968 | 0.044 | − 11.347 | 0.000 | − 0.583 | − 0.411 |
| am.L1.D.E+F | − 1.4168 | 0.133 | − 10.675 | 0.000 | − 1.677 | − 1.157 |
| am.L2.D.E+F | 0.4169 | 0.132 | 3.149 | 0.002 | 0.157 | 0.676 |
| Roots | | | | | | |
| | Real | | Imaginary | Modulus | Frequency | |
| AR.1 | 0.7088 | | − 1.2291j | 1.4188 | − 0.1667 | |
| AR.2 | 0.7088 | | + 1.2291j | 1.4188 | 0.1667 | |
| MA.1 | 1.0002 | | + 0.0000j | 1.0002 | 0.0000 | |
| MA.2 | 2.3984 | | + 0.0000j | 2.3984 | 0.0000 | |

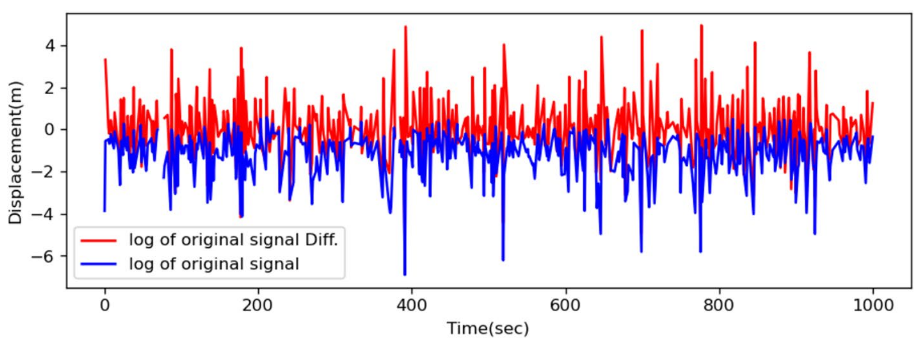


**Fig. 4** Plot of bearing 1_1 original time series and its differenced version

series is the residual. In our work, our series was differenced once hence the residual is plotted in Fig. 5. The plots are used to better understand the distribution of errors beyond summary statistics. The density plot in Fig. 5 is used to better understand the distribution of residual errors.

The$\hat{RUL}_i$ for the datasets were obtained from the simulation done and the percentage error was obtained and is shown in Table 4. In Table 5, the actual prediction from experiment was given. The percent error on experiment *i* was defined by the following formula:

$$\%Er_i = 100 \times \frac{ActRUL_i - \hat{RUL}_i}{ActRUL_i} \tag{10}$$

The percentage error obtained from equation 10 is shown in Table 5.

Equation 11 defines how the score of accuracy of a RUL is estimated for the experiments this was provided by FEMTO for use:

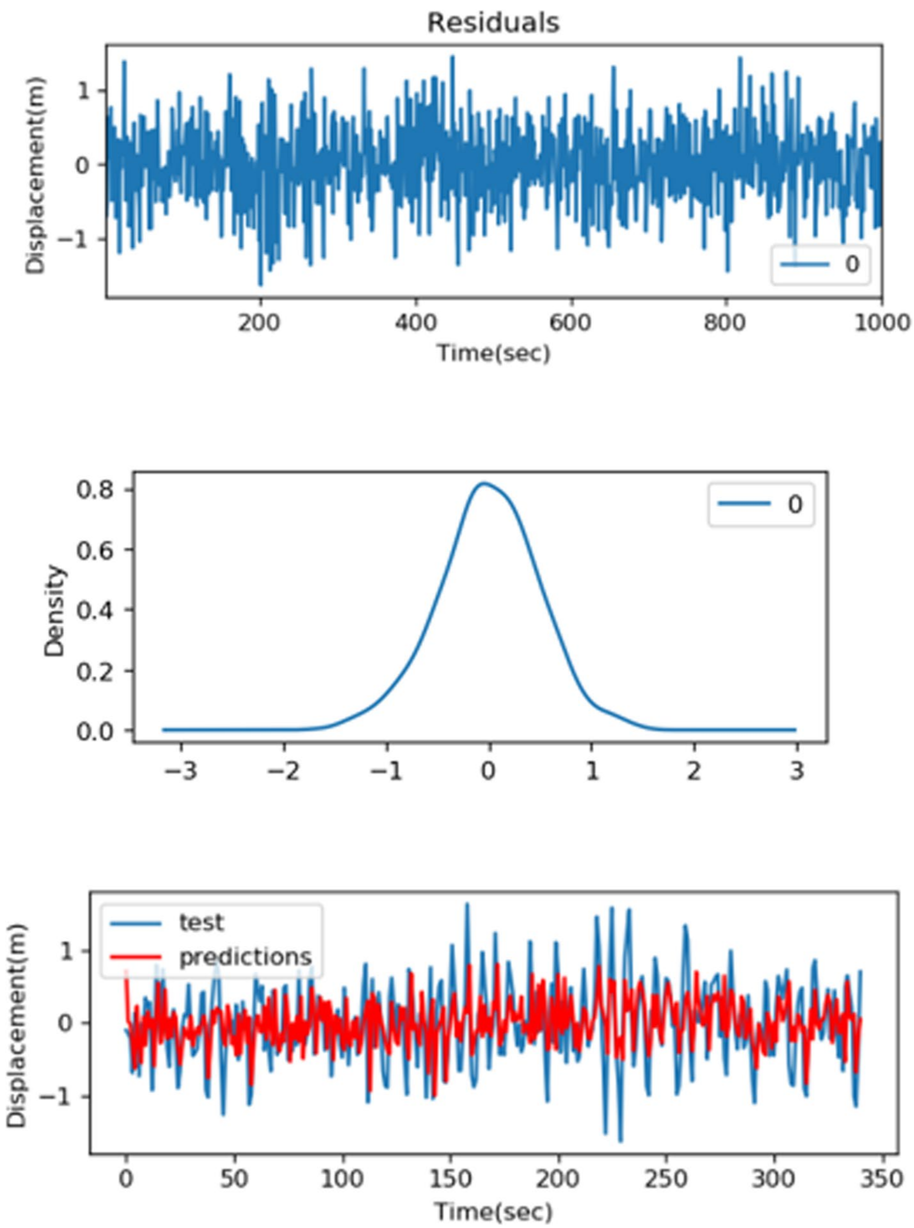


**Fig. 5** The residual, density, and prediction plot of dataset time series for Casefolder1_1

$$A_i = \begin{cases} \exp^{-\ln(0.5).\left(\frac{Er_i}{5}\right)} & if\, Er_i \leq 0 \\ \exp^{+\ln(0.5).\left(\frac{Er_i}{20}\right)} & if\, Er_i > 0 \end{cases} \tag{11}$$

The final score is been defined as the mean of all experiment score and is given in the following formula:

$$\text{Score} = \frac{1}{11}\sum_{i=1}^{11}(A_i) \tag{12}$$

**Table 4** The $\hat{RUL}_i$ estimated result obtained

| Test case set | $\hat{RUL}_i$ ARIMA model |
|---|---|
| Casefolder 1_3 | 1921.017 |
| Casefolder 1_4 | 557.523 |
| Casefolder 1_5 | 313.794 |
| Casefolder 1_6 | 335102.941 |
| Casefolder 1_7 | 823706.674 |
| Casefolder 2_3 | 362126.657 |
| Casefolder 2_4 | 449051.755 |
| Casefolder 2_5 | 1927467 |
| Casefolder 2_6 | 70557.654 |
| Casefolder 2_7 | 110317.264 |
| Casefolder 3_3 | 72211.349 |

**Table 5** Percentage error and score of accuracy

| Test case set | $\%Er_i$ | Score of accuracy |
|---|---|---|
| Casefolder 1_3 | 66.47 | 6.647 |
| Casefolder 1_4 | − 64.46 | 6.446 |
| Casefolder 1_5 | 80.51 | 2.0128 |
| Casefolder 1_6 | − 22852.26 | 2285.226 |
| Casefolder 1_7 | − 10781.20 | 1078.120 |
| Casefolder 2_3 | − 4709.12 | 470.912 |
| Casefolder 2_4 | − 32205.88 | 3220.588 |
| Casefolder 2_5 | − 62277.57 | 6227.757 |
| Casefolder 2_6 | − 5369.59 | 536.959 |
| Casefolder 2_7 | − 18920.22 | 1892.022 |
| Casefolder 3_3 | − 8706.26 | 870.626 |

We thus have that the predicted score for the ARIMA model is within 1508.847 and 2263.2705 s before the failure. That of the FEMTO winner is within the range of 3600 and 25,200 s. Why there was large disparity in the results obtained from the other different models that applied in the competition [15, 26] where judgment was drawn for the first (to be the closest to the predictable prediction obtained experimentally), second and third position. The result obtained from the ARIMA model was at closer range to that of the first position compared to that of other that used various other models, this helps to show the superiority of the ARIMA model for this case consideration (under high speed and variable load condition) especially for predicting purpose.

## Conclusions

Presented in this work is a fulfilled expectation method used for forecasting the RUL of large time series dataset like the NASA dataset. First, we ascertained that the NASA dataset time series was a stationary one by using the Dickey-Fuller Test. The model was successfully trained on observation data from the PRONOSTIA test bed, which was based on the data collected from the test set and used to predict outcomes that were efficient in ensuring validity of the model.

The ARIMA model was compared to that of another literature where the Neural Network regression NNR was used which was for that of the winner of the FEMTO competition and the result obtained here looks promising giving a satisfactory result from judgment that makes this work special to the other methods in use today. It has been proven that ARIMA can comprise of the most important feature of sensory signals. The developed method applied here can be considered within the scope of predictive maintenance and condition-based maintenance. This approach applied aims at making the ARIMA AIC-Akaike's Information Criterion close fit estimation for the measure to find the best model of the target data.

Hence, it is evident that from the predicted accuracy when compared to past results obtained, we could rightly say that ARIMA predicts well. Finally, it is possible to extend this method to other physical components other than bearings as long as the data obtained from the time series are stationary and the tracking data reflecting the component's degradation behavior is available.

**Abbreviations**

| | |
|---|---|
| CBM | Condition base monitoring |
| ARIMA | Auto regression integrated moving average |
| FEMTO | Franche-Comté Électronique Mécanique Thermique et Optique |
| RUL | Remaining useful life |
| NNR | Neural network regression |
| NASA | National Aeronautics and Space Administration |
| AIC | Akaike Information Criteria |
| BIC | Bayesian Information Criterion |
| AE | Acoustic emission |
| ANN | Artificial neural network |
| SARIMA | Seasonal auto-regressive integrated moving average |
| SVR | Support vector regression |
| RMSE | Root mean square error |
| AR | Auto-regression |
| MA | Moving average |
| ARMA | Auto regression moving average |
| TS | Test statistic |
| ACF | Auto-correlation function |
| PACF | Partial auto-correlation function |
| HQIC | Hannan-Quinn Information Criterion |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s44147-023-00183-y.

**Additional file 1: Table 1.** Datasets of 2012 PHM Prognostic Challenge.

**Additional file 2: Figure 2.**

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**Authors' contributions**

HOO did the study idea, analysis, and also provided scientific content to the manuscript preparation and revision. BAE did the drafting of the manuscript. MUO prepared the paper and revisions to submission. However, all authors reviewed the results and approved the final version of the manuscript.

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**Availability of data and materials**
The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request

## Declarations

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

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## Publisher's Note