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TOWARDS A PREDICTIVE MAINTENANCE BASED ON ULTRASONIC GUIDED WAVES NON-DESTRUCTIVE TESTING TECHNIQUE: A CASE STUDY

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ABSTRACT: This paper concerns the predictive maintenance (PM), which is in increasing use in many fields. It proposes the use of a non-destructive testing technique, namely ultrasonic guided waves, in order to reinforce the PM of a given installation. To achieve PM, various sensors are required to collect data, which are needed as inputs of predictive models. These sensors are employed to monitor the health (said also in other words degradation) of the installation to be maintained in operation. In this study two models based on EDM-ARIMA and neural network are built and applied on data collected on a tube via the ultrasonic guided waves. Residual useful life of the structure is provided in different cases.

KEYWORDS: Predictive maintenance, Ultrasonic Guided Waves, Prognostic, Residual Useful Life, ARIMA, EMD, Neural Network, Non-destructive testing.

1 INTRODUCTION

The rise of digitalization and industry 4.0 promises an optimization of industrial production based on data. Numerous players in industrial analytics guarantee to effectively tackle issues just by gathering and analyzing data. Lately, more and more data is acquired and more and more analytical tools become available [1].

Nowadays, mastering the operation of industrial systems represents a big challenge for maintenance operators, since these systems are more and more complex with technological development. Therefore, many companies are now implementing predictive maintenance strategies which is a proactive approach that aims to anticipate faults and breakdowns of an industrial system, based on monitoring modules, diagnosis, prognosis and decision support in the form of an intervention calendar.

In terms of predictive maintenance, the last stage of the Structural Health Monitoring (SHM) process, which is the prognostics, is used to anticipate the evolution of the defect or degradation in the future. A SHM system is defined as an integrated part of the structure to be monitored and should ideally be able to detect, locate and evaluate damage in the structure, estimate its severity and monitor its evolution with time. The utilization of SHM will result in (i) diminished basic load by changing design principles; (ii) decreased maintenance expenses; and (iii) expanded accessibility, however it is recognized at the same time that SHM technologies will be presented only if they have direct financial advantages. Major design aspects that govern any SHM system are (i) changes of the monitored physical properties due to damage; (ii) transducer–structure interaction to reliably measure the expected

changes with the required resolution; and (iii) signal processing and analysis tools to extract the required information on structural integrity [2].

Prognostics essentially attempt to anticipate how much time remains before a fault or failure will happen, giving the current state of the asset. In other words, prognostics are based on predicting the residual useful life (RUL) of a system based on condition monitoring of the asset and subsequent analysis of the information and data collected for a given task occurrence. In many situations, the complexity of the systems observed does not allow to derive robust and precise prognosis models. However, historical data that capture the life signal behavior of measured signals or extracted features from the incipient fault stage to equipment failure are often available. In such cases, data-driven methods that model how such signals and features evolve can be utilized to generate predictions of RUL.

Data collection of physical factors (temperature, vibration, etc.) can be achieved using vibration analysis, thermography etc. [3].

In the present work, data were collected using Ultrasonic Guided Wave (UGW). UGW are mechanical waves, at frequencies over the scope of human perceptible frequencies that propagate along a stretched structure while guided by its limits [4], its use to the field of preventive maintenance is in persistent increment. Today, UGW is assuming a significant economic position, particularly in the fields where the wellbeing of people is of higher significance than financial cost (i.e.: aeronautics, trains ...). They have been generally used to assess the trustworthiness of engineering structures, because they are capable to spread over significant separations and fantastic affectability to the nearness of deformities in the proliferation way [5]. Furthermore, they contain rich information

regarding the mechanical properties along their path of propagation and possess high sensitivity to changes in material and geometric in homogeneities due to damage. UGW is applied as an active as well as passive monitoring techniques [6], where the latter is comparable to an autonomous acoustic emission measurement system. But the majority of GW SHM systems in development use active transducers to excite specific stress wave modes to interrogate the component.

The prognostics rely on the approach of projection methods, which projects the current level of degradation in the future. It's essentially about a time series prediction problem. Many approaches are proposed for time series forecasting like: Artificial Neural Network (ANN), exponential smoothing model (ETS), Auto Regressive Integrated Moving Average (ARIMA), machine learning, Support vector Regression (SVR), etc. [7, 8, 9, 10].

In this study, we focus on two approaches. The first one is a hybrid approach called Empirical Mode Decomposition-ARIMA (EMD-ARIMA), since EMD is suitable for nonlinear non-stationary data [11, 12]. EMD is used to decompose the original data into components in order to reduce the difficulty to realize the high-precision predictions, and ARIMA predicts components respectively [13]. The second one is a statistical approach, mainly used in machine learning, called Auto-Regressive Neural Networks (ARNNET). Its concept is inspired from the biological neural network of the central nervous system. Neural Networks are better used to estimate functions based on a huge volume of training data. These are capable of modelling complex and non-linear functions [23].

The remainder of the paper is organized as follows. The next section provides some basic theoretical aspects of EMD-ARIMA and ARNNET. Section 3 describes the datasets used in the study and discusses the methodology used in the time series modeling and forecasting. The results obtained in this study are presented in section 4.

2 MATHEMATICAL MODEL

2.1 EMD-ARIMA Models

In this section we will discuss a hybrid EMD-ARIMA method of prediction. The computational framework of this method is given in Figure 1. As shown in Figure 1, the method consists in: (a) using the EMD to decompose the original time data into components with different features (sub-layers); (b) applying ARIMA models to each sub-layer and adopt the built models to forecast and (c) summarize the predictions of the sub-layers to get the final prediction for the original data [13].

2.1.1 EMD

EMD is an adaptive time series decomposition technique based on Hilbert-Huang transformation (HHT), which is suitable for nonlinear non-stationary data [11]. EMD can decompose the original data into a series of components

with different frequencies, namely, intrinsic mode function (IMF) [12] using the equation as follows:

$$X(t) = \sum_{i=1}^n C_i(t) + R(t) \quad (1)$$

Where $\{C_i(t)\}$, ($i=1\dots n$) is the IMFs in different decompositions, $\{R(t)\}$ is the residue and n is the number of IMF's. The computational steps of the EMD are given as follows:

Step 1: Identify all the local extrema (maxima and minima) of series $\{X(t)\}$.

Step 2: Connect all the local maxima by a cubic spline to generate its upper envelop $\{X_{up}(t)\}$, and all the local minima to obtain the lower envelop $\{X_{low}(t)\}$.

Step 3: Calculate the mean envelop $\{M(t)\}$ as follows:

$$M(t) = \frac{[X_{up}(t) + X_{low}(t)]}{2} \quad (2)$$

Step 4: Extract the details as follows:

$$Z(t) = X(t) - M(t) \quad (3)$$

Step 5: Check whether $\{Z(t)\}$ is an IMF: (a) if it is then set $C(t)=Z(t)$ and set $X(t)=R(t)=X(t)-C(t)$; (b) if not, replace $\{X(t)\}$ with $\{Z(t)\}$ then repeat the steps 2-4 until the termination criterion is satisfied. The equation of the termination condition can be represented as follows:

$$\sum_{t=1}^m \frac{[Z_{j-1}(t) - Z_j(t)]^2}{[Z_{j-1}(t)]^2} \leq \delta \quad (4)$$

($j=1, 2, \dots, t=1, 2, \dots, m$)

Where "m" is the number of the data points, "δ" is the terminated parameter, and "j" is the time of iterative calculation.

Step 6: Repeat steps 1-5 until all IMFs are found [13].

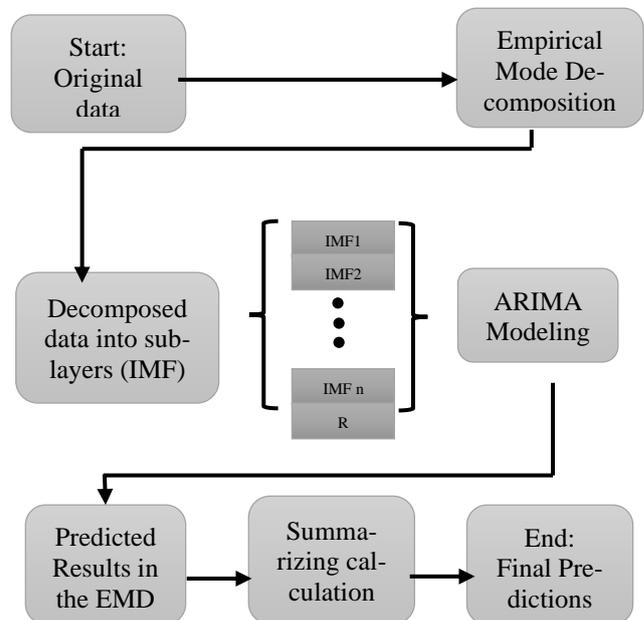


Figure 1. Framework of EMD-ARIMA models.

2.1.2 ARIMA

Once all IMFs are found, we apply ARIMA model to each IMF to fit the time series. An ARIMA model uses autoregressive moving average (ARMA) model to fit stationary time series. When the time series are non-stationary, they must be converted into stationary series by difference transformation before using ARMA for modeling. This is what "I" in ARIMA refers to; integrated. The difference transformation can be divided into the order difference transformation and the periodic difference transformation. The first-order difference transformation is:

$$\nabla Y_t = Y_t - Y_{t-1} = (1 - B)Y_t \quad (5)$$

where, ∇ is the difference operator, Y_t value, B is the back-shift operator.

Occasionally, the differenced data won't appear to be stationary and it is necessary to difference the data a second time to obtain a stationary series, and the second-order difference transformation is:

$$\nabla^2 Y_t = \nabla Y_t - \nabla Y_{t-1} = Y_t - 2Y_{t-1} + Y_{t-2} \quad (6)$$

The periodic difference transformation is as follow:

$$\nabla_s Y_t = Y_t - Y_{t-s} \quad (7)$$

where, ∇_s is the periodic difference operator and s is the number of periods.

When the differentiated series is stationary, we can use ARIMA model and it can be formulated as follows [14]:

$$\varphi(B)(1 - B)^d Y_t = \theta(B)e_t \quad (8)$$

Where, $\varphi(B) = 1 - \varphi_1 B - \dots - \varphi_p B^p$, $\theta(B) = 1 - \theta_1 B - \dots - \theta_q B^q$, $\varphi_i (i=1..p)$ and $\theta_i (i=1..q)$ are the model parameters that are estimated using the autocorrelation function (ACF) and the partial autocorrelation function (PACF); a_t is the error; p and q are the autoregressive and the moving average order, respectively and d is the order of differentiation [15].

2.2 Auto-Regressive Neural Networks

In this section we will introduce the Auto-Regressive Neural Network model. It is a network of multiple nodes working in parallel as shown in Figure 2. The inputs are combined through a linear function defined by :

$$z_j = g \left(\sum_i y_i w_{ij} - \beta_j \right) \quad (9)$$

Where z_j is the output of the j^{th} node, y_i is the i^{th} input, β_j is the bias of the j^{th} node, w_{ij} is the i^{th} weight in the j^{th} node.

The result of the combination is then passed through the non-linear sigmoid activation function $g()$ which transforms the input to the node to an output which in turn acts

as an input for the nodes in the next layer. The activation function is given by [16, 17] :

$$g(x) = \frac{1}{1 + e^{-x}} \quad (10)$$

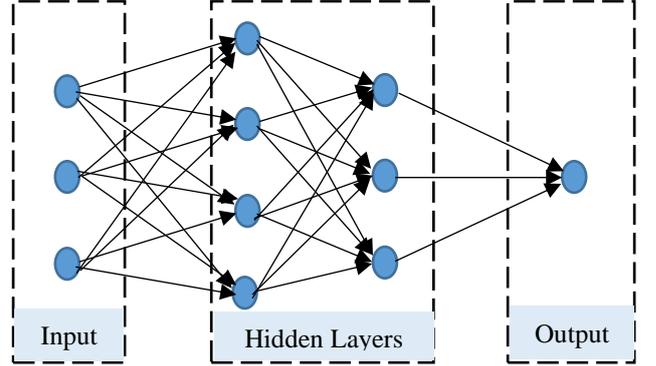


Figure 2. Neural Network architecture of three input nodes, two hidden layers and one node output layer.

3 DATA SET AND METHODOLOGY

3.1 Data set

Our study aims to predict the RUL of tubular structures in order to schedule predictive maintenance, so we are brought to predict the evolution of the degradation indicator (DI) over time. The datasets used in this study are two time series of the degradation indicator for two mode of propagation of UGW in pipes which are torsional and flexural. The dataset contains 1059 observations for each the torsional and flexural modes. This degradation indicator was established over the collected UGW signals basing on singular value decomposition of the matrix of reference signals acquired from the pipe. The time series' plot of the datasets is shown in Figure 3.

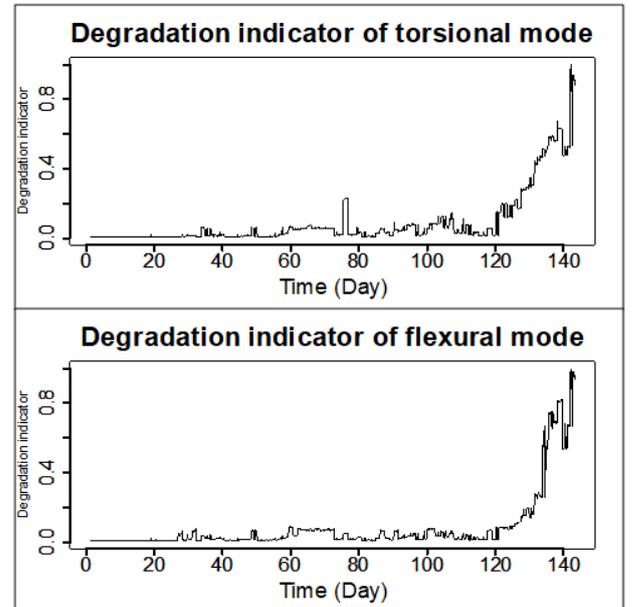


Figure 3. Degradation indicator for torsional and flexural mode. Each signal is normalized by its maxima.

3.2 Methodology

3.2.1 EMD-ARIMA

Mainly, ARIMA's forecasting task is selecting the appropriate model order, which is the value of p, d and q. In this study, the following steps are used to identify the model used for the prediction:

Step 1: As explained in section 2, we adopt the Empirical Mode Decomposition (EMD) to decompose the degradation indicator samples into Intrinsic Mode Functions (IMFs). Figure 4 is an example of data decomposition into IMFs.

Step 2: In the step of model identification, all of the decomposed degradation indicator has their stationarity checked to decide the "d" value in ARIMA (p, d, q). If an IMF has been found non-stationary, a difference will be executed for this IMF. In this study, in order to check the stationarity of time series we compare the p-values of the series by applying the Augmented Dickey Fuller test (ADF Test). If the p-value, using the function is lower than 0.05, means the time series is stationary and vice versa [18, 19].

Step 3: We compute and examine the Autocorrelation function (ACF) and partial autocorrelation function (PACF) of each IMF to decide whether to include an Auto-Regressive (AR) component or Mobile Average (MA) one or both [20].

Step 4: In order to obtain the model and predict the data for each IMF, we split the data into two parts, which are training data and validation data. For the torsional mode, we consider the first 910 data as training data. The remaining data is used as validation data. On the other side, for the flexural mode, we consider the first 950 data as training data and the other 109 data as validation data. For prediction accuracy, the Root Mean Squared Error (RMSE) is introduced to appraise and compare the different simulation results. The RMSE is calculated using the following equation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (x_{n+i} - \hat{x}_n(i))^2}{N}} \quad (11)$$

Where N denotes the length of the validation data, x_{n+i} denotes the i-th actual value of validation data, $\hat{x}_n(i)$ denotes the i-th forecast. It is worth noting that, p, q and d may be also selected via an information criterion such as the Akaike information criterion (AIC) calculated as follow [21]:

$$AIC = -2 \log(L) + 2k \quad (12)$$

Where L is the likelihood of the model and k is the total number of parameters and initial states that have been estimated. This criterion is used to measure the goodness of fit and determine the choice of optimal lags in the model. A negative value of AIC means that the model is well built [22].

Step 5: Once the model is chosen for each IMF, we sum all the forecasted data using ARIMA and compare it to the actual values of the validation data.

Step 6: We set a threshold of the degradation indicator and determine at what time the forecasted values reach it.

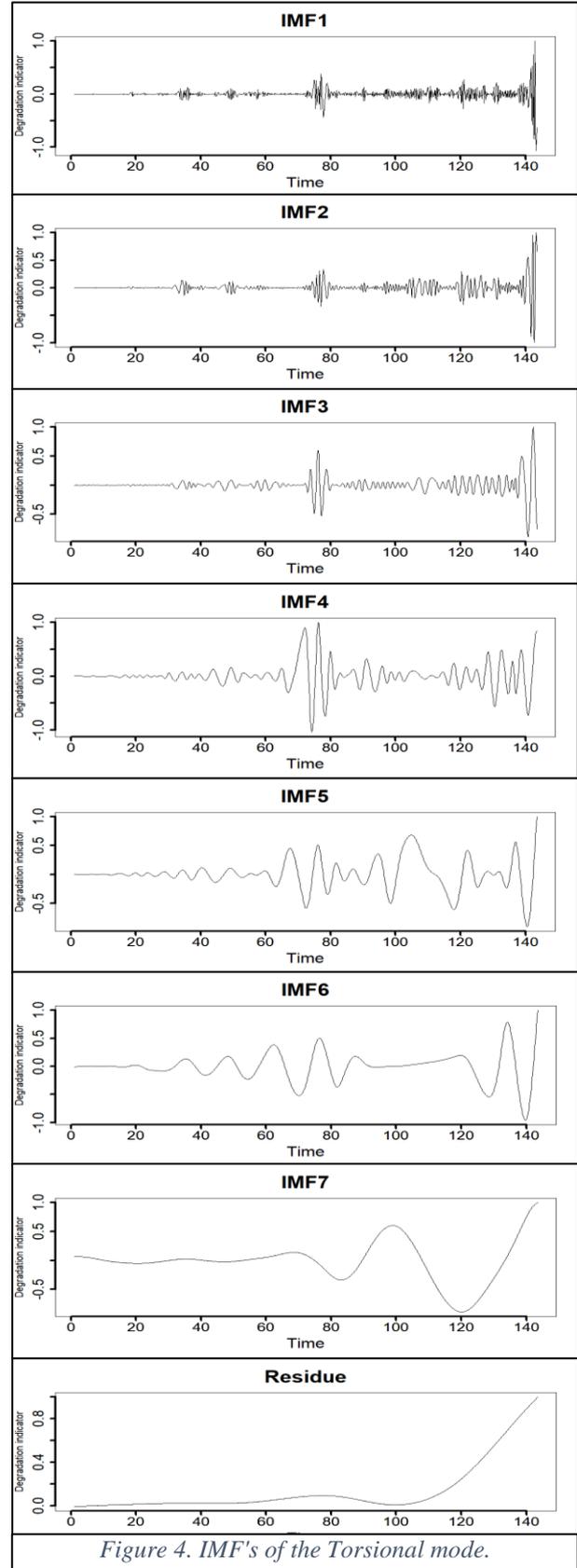


Figure 4. IMF's of the Torsional mode.

3.2.2 ARNNET

The effective execution of a Neural Network is reliant on proper training of the network with large training sets. In the process of training, the algorithm learns to adjust the weights and bias associated with each connection. In this paper we consider the notation NNAR (p, k) to indicate that in the model there are p lagged inputs and k nodes in the hidden layer [23-24]. The steps followed to build the neural network model are the following:

Step 1: Determine the order of auto-regression (p) for the dataset. In Figure 5, PACF plot is drawn for the dataset. The abscissa represents the lags and the ordinate represents the partial autocorrelation values for the corresponding lags. We search for the last significant spike. In our case, the value of p is 19 and 25 consecutively for Torsional and Flexural data.

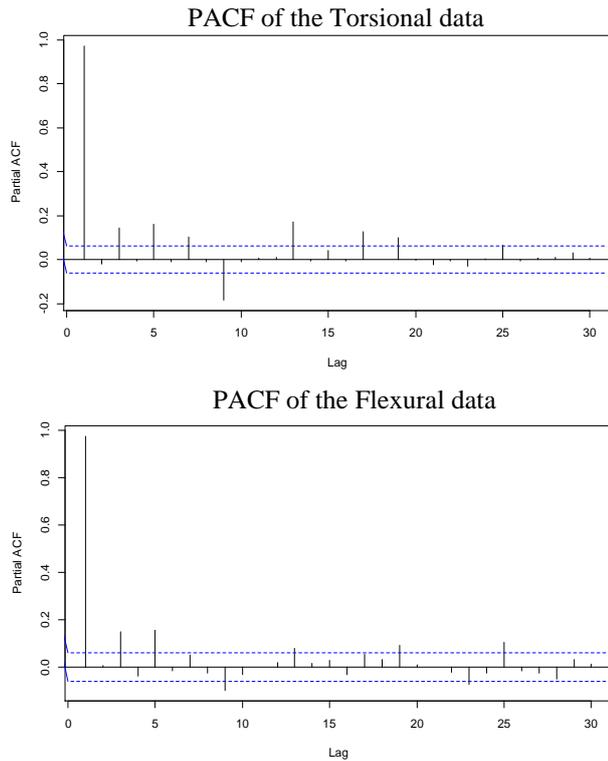


Figure 5. PACF of the Torsional and Flexural data.

Step 2: Data has been partitioned into training and validation data. We used the same partition as the one used for EMD-ARIMA method.

Step 3: Build the ARNNET of the data using the function “nnetar” in R.

Step 4: We set a threshold of the degradation indicator and determine at what time the forecasted values reach it.

4 RESULTS AND DISCUSSION

The results of the EMD of the original degradation indicator for the torsional mode is given in Figure 4. From

Figure 4, it can be seen that the time series have been converted successfully seven IMFs and a residue for the torsional mode. Concerning the flexural mode, the time series was decomposed into eight IMFs and a residue.

The accuracy of some of the estimated results of the tested ARIMA models applied for each IMF prediction as well as their AIC is given in Table 1 and 2. The model with minimum AIC is often the best model for forecasting.

	ARIMA (p, d, q) tested	RMSE	AIC
IMF1	(3, 1, 5)	0.1648	-3354.84
	(2, 1, 4)	0.1652	-3318.13
IMF2	(5, 0, 3)	0.2045	-6185.22
	(4, 0, 4)	0.2044	-6181.75
	(3, 0, 2)	0.2046	-6124.40
IMF3	(4, 0, 3)	0.1024	-11171.84
	(2, 0, 3)	0.1053	-11034.45
	(5, 0, 3)	0.1026	-11138.53
IMF4	(1, 0, 0)	0.153	-6404.08
	(1, 0, 1)	0.1529	-7832.49
IMF5	(0, 0, 0)	0.2122	-2610.2
IMF6	(0, 0, 0)	0.1546	-2820.86
	(0, 0, 1)	0.1537	-4272.69
	(0, 0, 2)	0.1529	-5718.21
IMF7	(0, 0, 0)	0.1741	-2200.24
	(0, 0, 1)	0.1734	-3654.94
IMF8	(0, 2, 0)	0.0878	-18515.45
	(0, 2, 1)	0.086	-19971.26
	(1, 2, 3)	0.06364	-29918
Residue	(0, 2, 0)	0.0108	-19635.96
	(0, 2, 1)	0.0103	-21090.74
	(0, 2, 2)	0.01	-22538.74

Table1. Accuracies and AIC of some tested models for the flexural mode.

	ARIMA(p, d, q) tested	RMSE	AIC
IMF1	(5,0,1)	0.4753	-415.88
	(5,0,4)	0.4748	-420.67
	(5,0,3)	0.4757	-413.04
IMF2	(4,0,1)	0.7661	-2974.21
	(4,0,4)	0.7644	-2999.13
	(5,0,2)	0.7655	-2973.64
IMF3	(1,0,0)	0.5028	-2594.40
	(2,0,0)	0.4659	-6076.33
	(1,0,1)	0.5032	-3993.48
IMF4	(1,0,0)	0.2522	-4287.03
	(3,0,0)	0.2374	-11253
	(2,0,0)	0.2487	-8699.57
IMF5	(0,0,0)	0.3147	-194.4
	(1,0,0)	0.3706	-5052.21
IMF6	(0,0,0)	0.3767	-631.25
	(1,0,0)	0.3706	-6033.87
IMF7	(0,2,0)	0.4358	-15537
Residue	(0,2,0)	8e-10	-16829

Table 2. Accuracies and AIC of some tested models for the torsional mode.

The accuracy of the estimated results of the chosen ARIMA model applied for each IMF for both torsional and flexural mode is highlighted also in Table 1 and 2.

For the torsional mode, if the original data is not decomposed and we apply ARIMA models, the suitable model turns out to be ARIMA (4, 1, 2) with AIC= 545.62 and RMS= 3.17. For our data, the RMSE value using EMD-ARIMA is equal to 1.26, which is 60% lower than the RMSE given by applying ARIMA directly.

Same as the flexural mode, if we apply ARIMA directly without decomposing the data, the suitable ARIMA model is ARIMA (4, 2, 2) with AIC=-2255.66 and RMS= 1.21. For our data, the RMSE value using EMD-ARIMA is equal to 0.514, which is 57.5% lower than the RMSE given by applying ARIMA directly. This result shows that EMD-ARIMA is better than ARIMA which is not surprising since it decreases the forecast difficulty by treating each IMF at once.

Producing estimates of confidence interval is also an important aspect. We also evaluated the performance of the different ARIMA models in producing forecast intervals. Table 3 and 4 shows the confidence intervals at 95% of some of the tested ARIMA models comparing to the actual values. From table 3, we can note that the suitable ARIMA model for the torsional mode comes generally with the tighter confidence interval. However, from Table 4, we can note that the suitable ARIMA model for the flexural mode comes generally with the larger confidence interval.

	ARIMA (p, d, q)	Confidence interval	
		Lower	Upper
IMF1	(5,0,1)	-0.04154	0.11242
	(5,0,4)	-0.04677	0.107095
	(5,0,3)	-0.04007	0.114003
IMF2	(4,0,1)	-0.17893	0.068152
	(4,0,4)	-0.16497	0.08301
	(5,0,2)	-0.16589	0.08245
IMF3	(1,0,0)	-0.10084	0.06239
	(2,0,0)	-0.09453	0.05671
	(1,0,1)	-0.10925	0.05398
IMF4	(1,0,0)	-0.08257	-0.00178
	(3,0,0)	-0.03191	0.0452
	(2,0,0)	-0.0419	0.0389
IMF5	(0,0,0)	0.00066	0.10155
	(1,0,0)	0.15285	0.25356
IMF6	(0,0,0)	0.04237	0.16025
	(1,0,0)	0.01697	0.13482
IMF7	(0,2,0)	-0.38933	-0.3034
Residue	(0,2,0)	-0.29946	-0.2391

Table 3. Confidence intervals for the torsional mode.

	ARIMA (p, d, q)	Confidence interval	
		Lower	Upper
IMF1	(3, 1, 5)	0.00066	0.06237
	(2, 1, 4)	-0.0033	0.0583
IMF2	(5, 0, 3)	-0.0559	0.02183
	(4, 0, 4)	-0.0551	0.02261
	(3, 0, 2)	-0.0551	0.02263
IMF3	(4, 0, 3)	-0.0125	0.02645
	(2, 0, 3)	-0.0132	0.02684
	(5, 0, 3)	-0.0126	0.02641
IMF4	(1, 0, 0)	-0.0366	0.0217
	(1, 0, 1)	-0.0366	0.0217
IMF5	(0, 0, 0)	-0.012	0.0682
IMF6	(0, 0, 0)	-0.0374	0.0215
	(0, 0, 1)	-0.0382	0.0203
	(0, 0, 2)	-0.0374	0.0215
IMF7	(0, 0, 0)	-0.121	-0.0648
	(0, 0, 1)	-0.3	-0.244
IMF8	(0, 2, 0)	-0.0801	-0.06
	(0, 2, 1)	-0.0784	-0.0586
	(1, 2, 3)	0.033	0.051
Residue	(0, 2, 0)	-0.0102	-0.008
	(0, 2, 1)	-0.0097	-0.00753
	(0, 2, 2)	-0.0102	-0.00803

Table 4. Confidence Intervals for the flexural mode.

As mentioned in section 3.2, the last step is to fix a threshold of the degradation indicator and see when it is reached. In our case, the threshold is fixed to the highest value reached by the original data, which is 1.1387e-13 for the torsional mode, and 3.037e-14 for the flexural mode. According to the forecasted results using the chosen model, these values are reached at day 157 for the torsional mode and the day 147 for the flexural mode, from the start of the test. Based on the original data, the actual value should be 141 days for both modes. We note that there is a 16- and 6-days gap consecutively for the torsional and flexural mode. In Figure 6 and 7, the original curve is represented in black, the curve in light blue represents the forecasted data with the chosen model. The dark blue and the green curve are simultaneously the prediction of one of the tested models and the prediction using directly ARIMA on the original data.

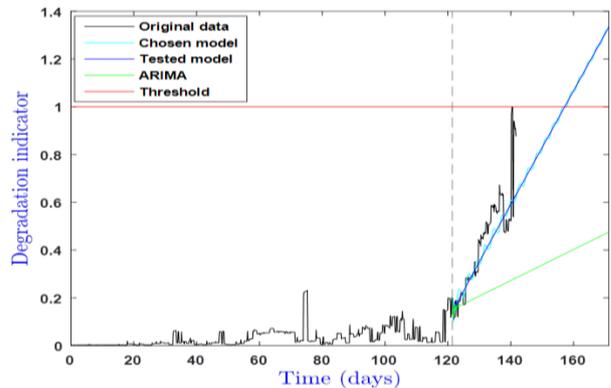


Figure 6. Examples of forecasted data for torsional mode. Normalized by the maxima of the original data.

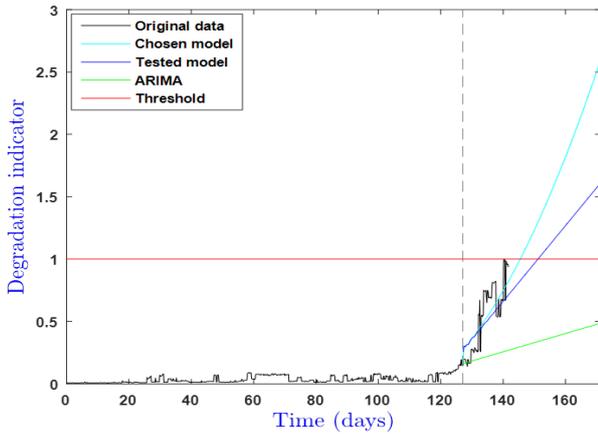


Figure 7. Examples of forecasted data for flexural mode. Normalized by the maxima of the original data.

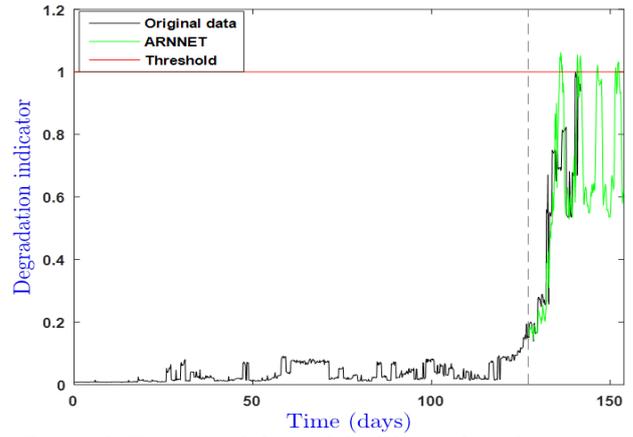


Figure 8. Forecasted data of the Flexural mode using ARNNET.

For the same threshold, we adopt the ARNNET to predict the RUL. According to the forecasted results, this value is reached at day 137 for the Flexural mode which is 4 days before the actual value. However, the forecasted values of the Torsional data didn't reach the threshold.

The RMSE of the forecasted data is 0.11 and 0.148 consecutively for Torsional and Flexural mode.

In Figure 8 and 9, the original curve is represented in black and the curve in green represents the forecasted data using ARNNET method.

The tables 5 and 6 summarize the values of the residual life as well as the RUL found in this research for both torsional and flexural mode. We can conclude that EMD-ARIMA provides better results than ARIMA for both modes.

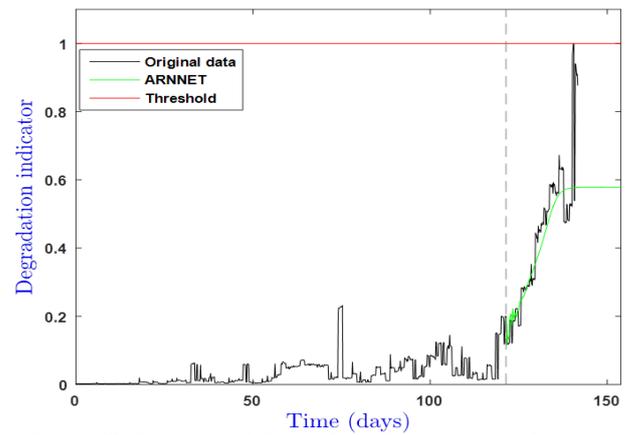


Figure 9. Forecasted data of the Torsional mode using ARNNET.

Flexural mode	Actual Value	Chosen EMD-ARIMA	Tested EMD-ARIMA	ARIMA (4,2,2)	NNETAR
RMSE		0.126	0.16	0.317	0.11
RUL	141	147	152	ϕ	ϕ

Table 5. Residual life and RMSE for the torsional mode.

Torsional mode	Actual value	Chosen EMD-ARIMA	Tested EMD-ARIMA	ARIMA (4,1,2)	NNETAR
RMSE		0.514	0.73	1.21	0.148
RUL	141	157	157	ϕ	137

Table 6. Residual life and RMSE for the flexural mode.

CONCLUSION

Accurate residual useful life forecasting can have a great impact on risk management and predictive maintenance. The purpose of this work is to adopt and compare two methods of time series prediction. The EMD-ARIMA and the ARNNET model were used to predict the residual useful life of tubular products and test its accuracy. The data provided in this study are the evolution of the degradation indicator of a torsional and flexural mode over time. How to effectively model these series and how to improve the quality of forecasts are the outstanding questions.

As one of the most popular forecasting methods, ARIMA turns out to be less effective than the hybrid method EMD-ARIMA. EMD-ARIMA decomposes the time series into IMFs and treats each IMF independently in order to reduce the forecasting complexity.

The hybrid method forecast is able to follow the pattern of the real data better than the ARIMA model but with a certain gap. It shows that the hybrid methodology could significantly increase the forecast accuracy.

The ARNNET is computationally more intensive than the EMD-ARIMA as it has to estimate the weight and bias corresponding to each node, to come up with better results only for the Flexural mode. However, the ARNNET did fit a good model to the torsional data.

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