Enhancing Remaining Useful Life Prediction of Rolling Element Bearings Using Singular Spectrum Analysis Preprocessing and LSTM Networks

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Publication Date: 2026/03/24

Abstract: Many RUL estimation single models still have problems of low prediction accuracy while dealing with some non-stationary multivariate time series data, such as vibration signal from bearings degradation process. This paper aims to enhancing the prediction accuracy of the bearings remaining useful life from real vibration signals using LSTM model, by inserting SSA as preprocessing technique step in the predictive process of bearing RUL. The results of the study with femto Pronostia bearing dataset show a significant accuracy outperformance, through reduction of root mean square error (RMSE) and mean absolute error (MAE) performance metrics in majority of test data; up to 24.5% reduction with bearing1_3. The most interesting value reached is 74,7 % reduction, case of bearing 2_7. However, the model suffer from generalization over a certain number of data; case of bearing1_5. Thus several ways to leverage the prognosis model must be considered.

Keywords: *SSA, REBs Prognosis, LSTM, RUL Estimation, Time Series, Feature Enhancement.*

How to Cite: Innocent Mpia; Christian Lefi; Rodrick Kanku; Joseph Cimbela (2026) Enhancing Remaining Useful Life Prediction of Rolling Element Bearings Using Singular Spectrum Analysis Preprocessing and LSTM Networks. *International Journal of Innovative Science and Research Technology,*11(3), 1922-1933. https://doi.org/10.38124/ijisrt/26mar1181

I. INTRODUCTION

Bearings have been a focus of research in the machinery prognostics field compared to other components or systems, because it accounts for approximately 45–55 % of operational disruptions in rotating machinery [1-6]. Unplanned breakdowns of production machines often lead to economic losses; therefore, preventing the maintenance needs of machines can lead to financial benefits and reduce the maintenance cost of purely preventive approaches [7]. Thanks to the rapid development of new computer-assisted monitoring technologies, the case of smart sensors; it is possible through the prognostic approach oriented towards relevant data-driven models, to develop new monitoring and maintenance strategies, using data collected from operating systems. An accurate prediction of bearing RUL is often a challenge due to its complex and dynamic nature system. Thus, RUL predictions are involving incertainty ranges [8]. The feature extraction stage is considered the most crucial. Robust preprocessing techniques can enhance the precision of the prognostic approach [9]**.** In this context, the estimation of the remaining service life is a challenge for a predictive maintenance task. To Predict RUL of bearings, advanced likely deep learning techniques and statistical algorithms contribute significantly; such as deep convolutional neural network (DCNN) [2-10], autoencoder (AE) [11], LSTMNN [12-17], etc. Tian Han et al. (2021) proposed an LSTM-Autoencoder model for bearing degradation detection and RUL estimation [18].

Eyyup Akcan and Yilmaz Kaya (2023) used a 1D CNN model on PRONOSTIA data, starting from vibration signals transformed into spectrograms to automatically extract discriminative features from image signals [19]. These methods make it possible to construct health indicators (HI) from vibration signals and predict RUL with good accuracy [20]. Most of the signals due to bearing defects are masked by noise, because of their low energy level; the use of prior signal decomposition method to decompose the vibration signal into a series of sub signal components with a clear physical meaning and then extracting fault feature components from them is particularly important for mechanical fault diagnosis and prognosis [21] ,case of SSA. In addition, enhanced average envelope spectra (AES) are used as network input for its physical robustness in bearing condition assessment and fault detection. The use of the envelope spectrum ensures that it contains only bearing-related information by removing other unwanted frequencies;

hence it improves the RUL prediction [22]. This study aims to:

- Predicting Remaining Useful Life (RUL) from vibration signals,
- Evaluating the performance of the LSTM model on real data, and
- Quantifying SSA's impact as preprocessing techniques on the RUL prediction accuracy.

The rest of the paper is organized as follow, section two exposes the method used, section three presents the results follow by the result discussion, and section four concludes the paper.

II. OVERVIEW OF THE PROPOSED METHOD

Figure.1 gives the overview of the method, starting from FEMTO bearing data choice, signal preprocessing using SSA technique and feature engineering, up to RUL estimation with LSTM model.

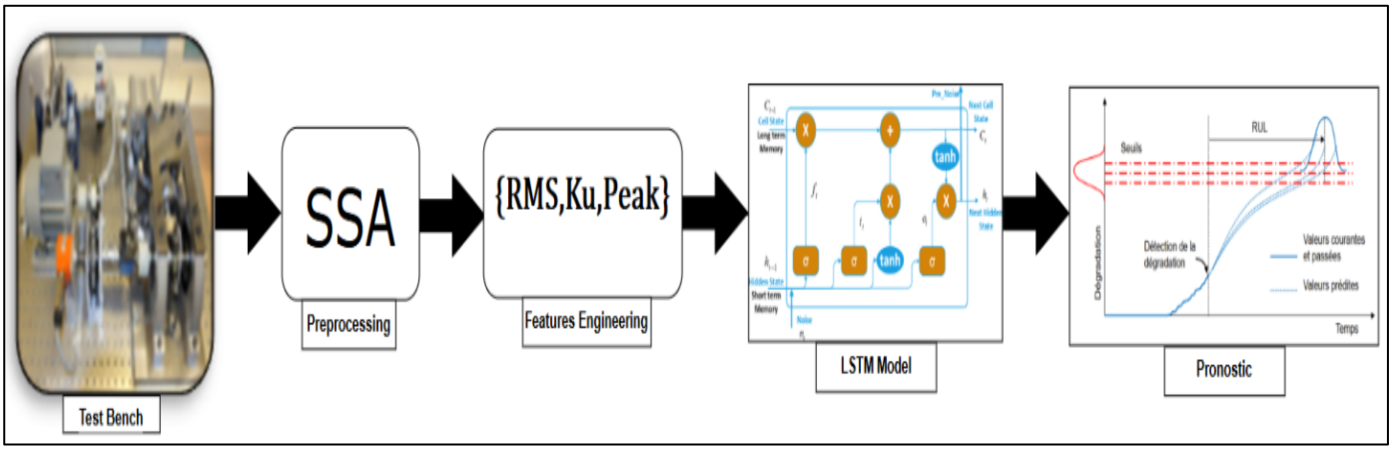

Fig 1 Overview of the Method

- *Dataset Description*

The FEMTO PRONOSTIA Bearing dataset is a widely recognized source of experimental data under variable operating conditions, particularly in the field of bearing prognosis; containing vibration signals recorded on NSK 6804-DD type ball bearings operating until failure as specified in table.1. It allows for the testing, verification, and validation of methods for evaluating, diagnosing, and predicting the health status of bearings. Its principal parts are: ensemble motor- reducer coupling (the rotating part), the degradation generation part incorporated a pressure cylinder, and the measurement acquisition system using accelerometers and a PT100RTD. The measurements were sampled at a frequency of 25.6 kHz. [23]

Table 1 Dataset Specifications and Operating Conditions

Conditions	**Load [N]**	**Speeds**	**Learning sets**	**Test sets**
1	4000	1800	Bearing1_1 Bearing1_2	Bearing1_3; Bearing1_4 Bearing1_5; Bearing1_6; Bearing1_7
2	4200	1650	Bearing2_1 Bearing2_2	Bearing2_3; Bearing2_4 Bearing2_5; Bearing2_6; Bearing2_7
3	5000	1300	Bearing3_1 Bearing3_2	Bearing3_3

Source réf. (23)

- *SSA-Based Preprocessing*

Singular spectral analysis (SSA) decomposes the initial time series signal into independent signals. These components are essentially the trend, oscillatory content, and noise [24, 25]. The main steps of SSA are shown in the schematic diagram of figure2.

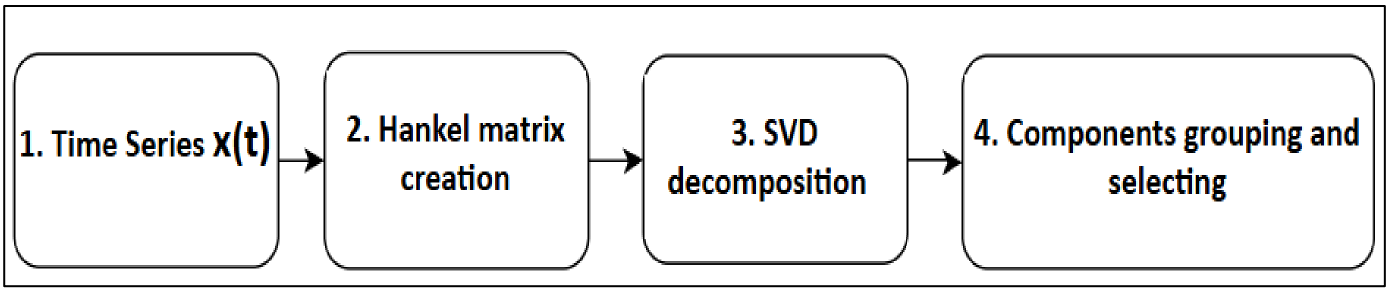

Fig.2 Schematic Diagram of SSA Process

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1181

- Let {x (t) |t = 1...N}} (1) be a Time series;
- Embedding: $X = [x_1, x_2, \dots, x_k]^T$

With

$$X_i = [x_i, x_{i+1}, \dots, x_{i+L-1}]^T \tag{2}$$

For Hankel matrix creation;

- *SVD Decomposition:*

$$X = \sum_{i=1}^{d} \sqrt{\lambda_i U_i V_i^T} \tag{3}$$

Helps to identify dominant components, with the eigenvalue λ_i representing energy content U_i and V_i eigenvectors left and right.

- *Signal Reconstruction:*

$$\tilde{x}_t = \sum_{i \epsilon I} \tilde{x}_t^{(i)} \tag{4}$$

According to components energy, spectral similarity and correlation.

The most important parameter here is the window length L given by

$$L \geq \frac{F_s}{F_{bpfo}} \text{ [26]} \tag{5}$$

F_s and F_{bpfo} representing the sampling frequency and the ball pass frequency outer respectively.

➢ *Features Engineering*

The richness of vibration data makes it possible to extract various time-domain (RMS, kurtosis, skewness), and frequency-domain features to feed the predictive model. The most important features used in this study are:

- The RMS value which is a measure of the overall energy of the signal. It represents the average power of the signal and is sensitive to amplitude variations [4]. For a healthy bearing vibration signal, the RMS value is generally low. In the event of degradation or fault, it increases significantly. The RMS is calculate with the relation given here after

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} x_i^2} \tag{6}$$

- The kurtosis measures the pointedness of a signal distribution comparatively to normal distribution. It is sensible to chocks and impulses, which makes it suitable to sudden defaults detection [3]. It is calculated from relation:

$$K = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^4}{\left[\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2\right]^2} \tag{7}$$

- The crest factor is defined as the ratio between the peak value and the effective value, is a sign of possible degradation if its value exceeds six. It is calculated from relation:

$$FC = \frac{\max(x_i)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}} \tag{8}$$

- Skewness measures the asymmetry of the signal's distribution relative to the mean. A positive skewness indicates a signal with defects generating strong impulses. One calculates Skewness by:

$$SK = \frac{\sum_{i=1}^{N}(x_i - \bar{x})^3}{(N-1)Sdt^3} \tag{9}$$

- Spectral entropy is a measure of the spectral complexity or disorder of a signal. It is derived from Fourier analysis and evaluates how the signal's energy is distributed across different frequencies. It is given by:

$$H = -\sum_{i=1}^{N} p_i \log_2(p_i) \tag{10}$$

With

$$p_i = \frac{P(f_i)}{\sum_{i=1}^{N} P(f_i)} \tag{11}$$

The normalized power spectral density

➢ *LSTM Model Building and Training*

Long Short-Term Memory typical architecture includes layers with a feedback structure using gates to control the memorization process. This eliminates the problems of vanishing and exploding gradients that conventional RNNs face [27 28]. The figure3 below specifies the five inputs used to feed the LSTM model.

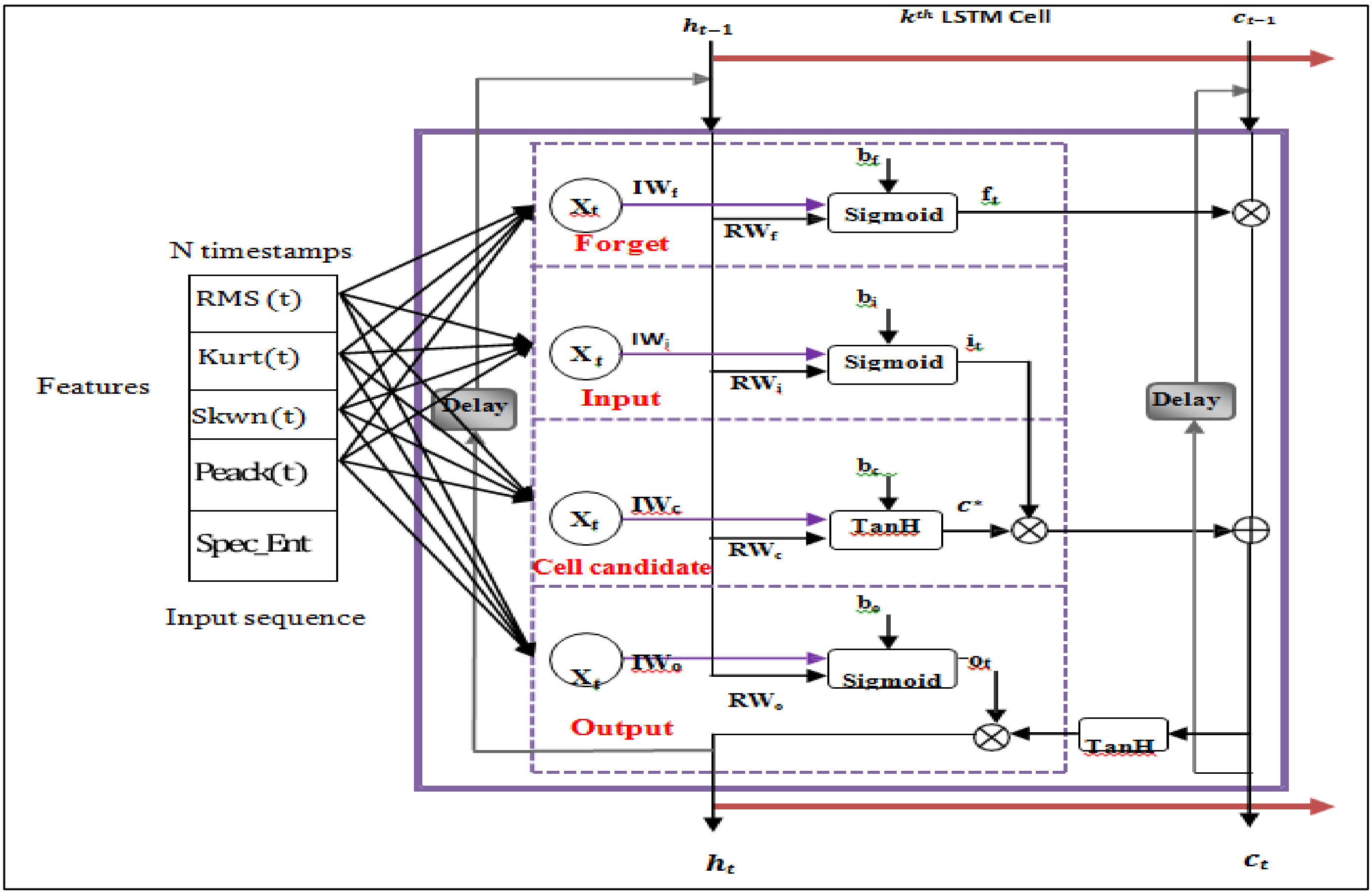

Fig 3 Input Sequence Connexions for Kth LSTM Cell Architecture LSTM

Different functions to forget, to stock, to update or to output are given through following relations [29]

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (12)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (13)$$

$$c_t = \tan(W_c[h_{t-1}, x] + b_c)\ ;\ c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \quad (14)$$

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (15)$$

$$h_t = o_t * \tan(c_t) \quad (16)$$

The sigmoid activation σ (.) required as a crucial tool for mapping variable outputs and inputs of complex and complicated nonlinear functions, brings the output between one and zero [25].

$$\sigma(x) = \frac{1}{1 + e^{-x}} \quad (17)$$

Tanh (.) is an hyperbolic tangent activation function which gives values comprises between -1 and 1 [23]

$$tanh\ (x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \quad (18)$$

x_t represents the input at time t; w_f, w_i and w_o being the weights for each neuron part, while b_f, b_i and b_o their biais respective.

Model hyperparameters definition: Batch size: 700

- Sequence length: numFeatures
- Split: 70% train, 30% test
- Hidden Units number: 200,
- Initial Learn Rate and dropout are respectively 0.01 and 0.5 to prevent instability and overfitting.

Actual RUL is constructed using exponential degradation function:

RUL(t) = d- exp (-a*t+b) (19)

Constantes a and d are calculated from conditions:

RUL (t=0) =1, RUL (t=t_final) =0 (20)

The parameter b representing the convergence rate. One uses b= 0,0001.

III. RESULT PRESENTATION INTERPRETATION AND DISCUSSION

➢ *Health Indicators Trends*

Figure4 below highlights the noise reduction on the bearing1_1 SSA signal (green coloured) compared to bearing1_1 raw signal (blue coloured).

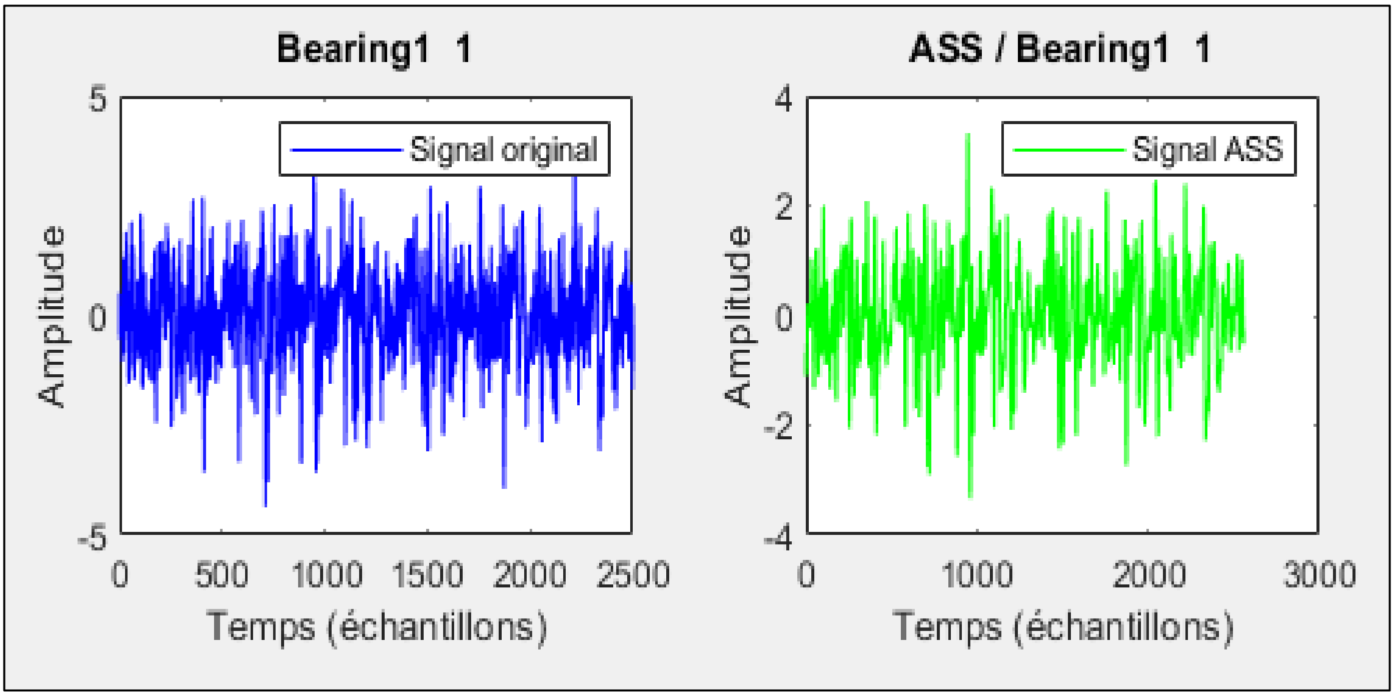

Fig 4 Bearing1_1 Signal Before and After SSA Preprocessing

The following figures show the trends of three indicators.

The onset of degradation using the RMS indicator was detected in sample 2758, corresponding to 84.3% of the cycle as shown in figure.5

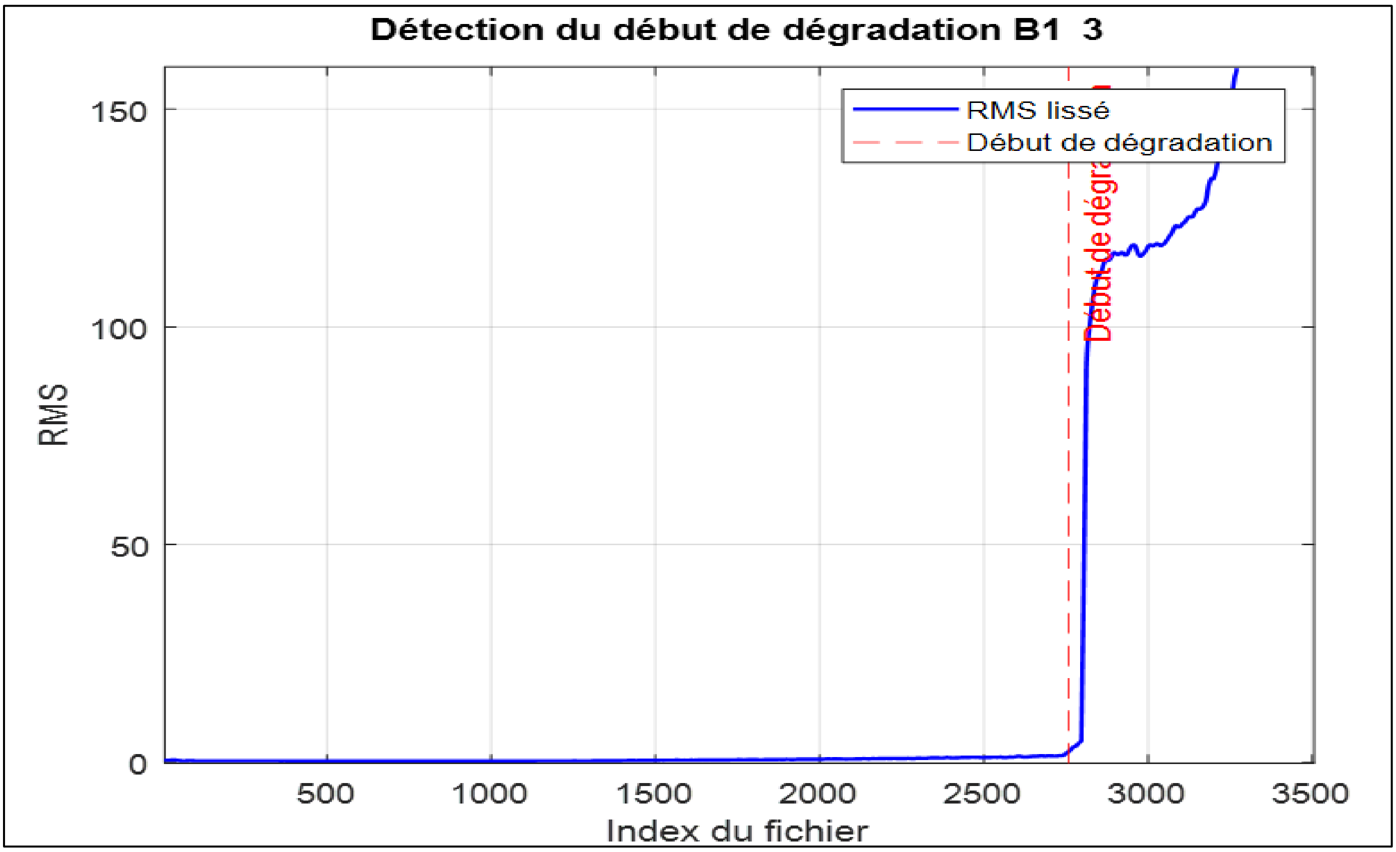

Fig 5 RMS Indicator Trend for Bearing1_3

However for kurtosis indicator the initiation degradation is detected in sample 62, meaning at 1.9 % of the cycle (Fig.6) ; and in sample 2363, or at 72.3 of the cycle with skewness indicator (Fig.7).

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1181

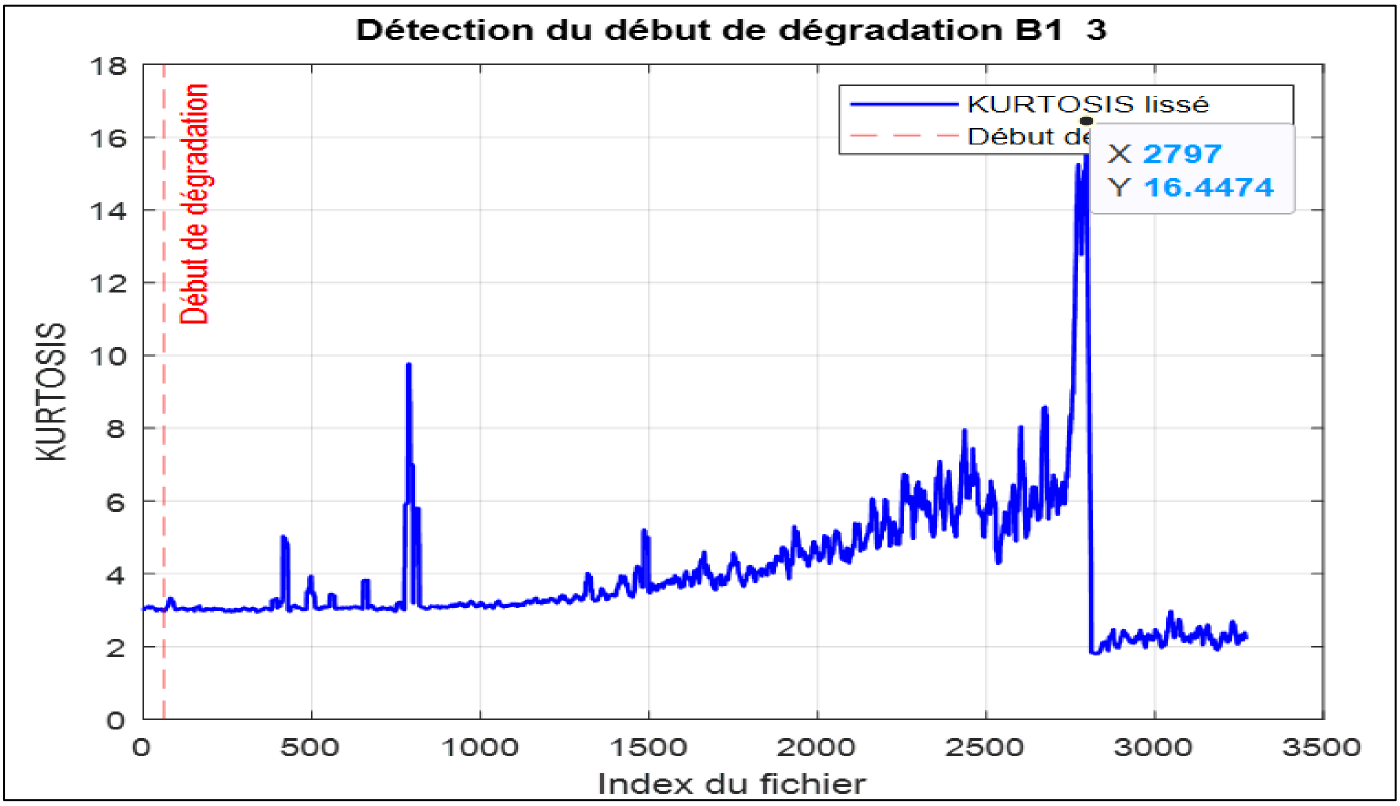

Fig 6 Kurtosis Indicator Trend for Bearing1_3

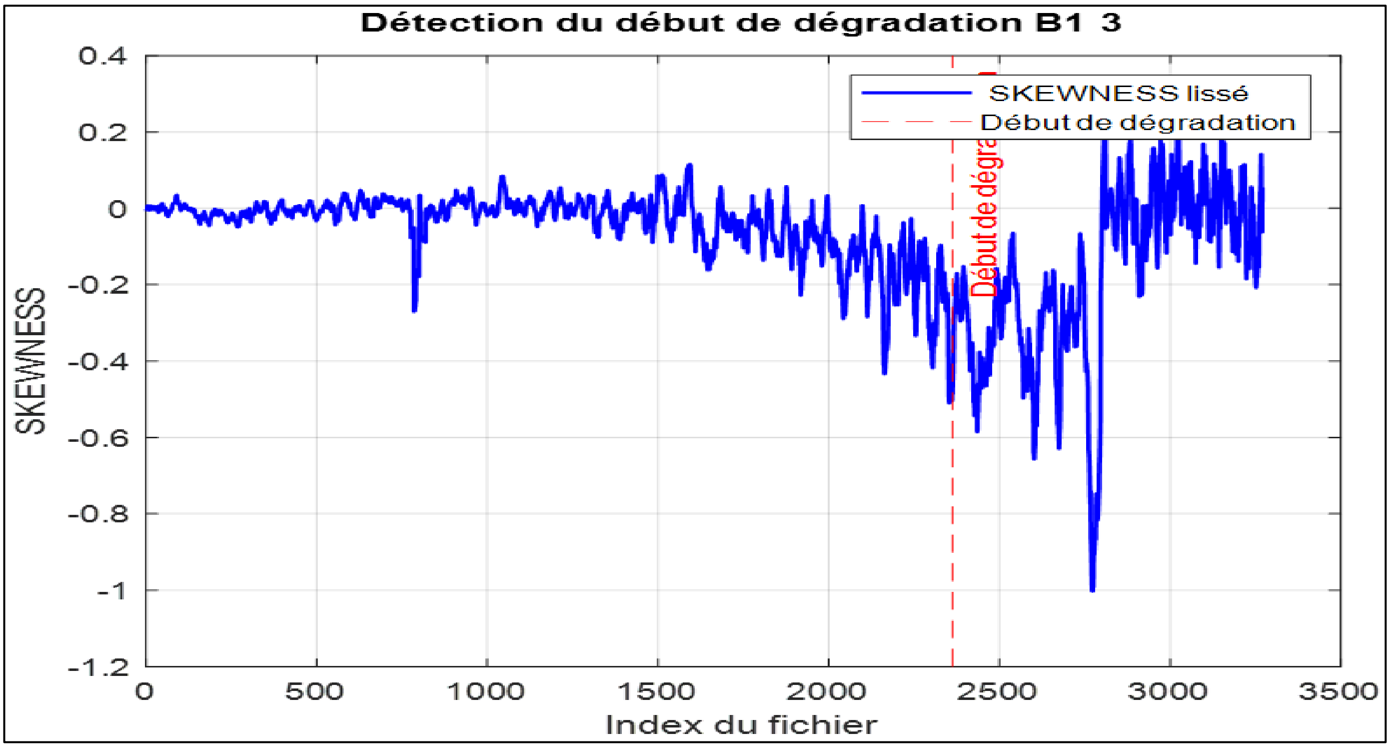

Fig 7 Skewness Indicator Trend for Bearing1_3

➢ *Results Interpretation*

Figure 8 shows that the prediction with the LSTM model is closer to the target before the onset of degradation. Once degradation begins, a progressive gap widens between the prediction curve and the target, resulting in an overestimation of the RUL in the final cycles. In contrast, the RUL predicted by the SSA_LSTM model more closely follows the downward trend of the target at each time step: Figure9 with very little time lag. The shift towards positive values in the error histogram Figure 11 indicates that the LSTM model overestimates the RUL. With the LSTM_SSA model, the error histogram is more centered on the x-axis, as shown in Figure 10.

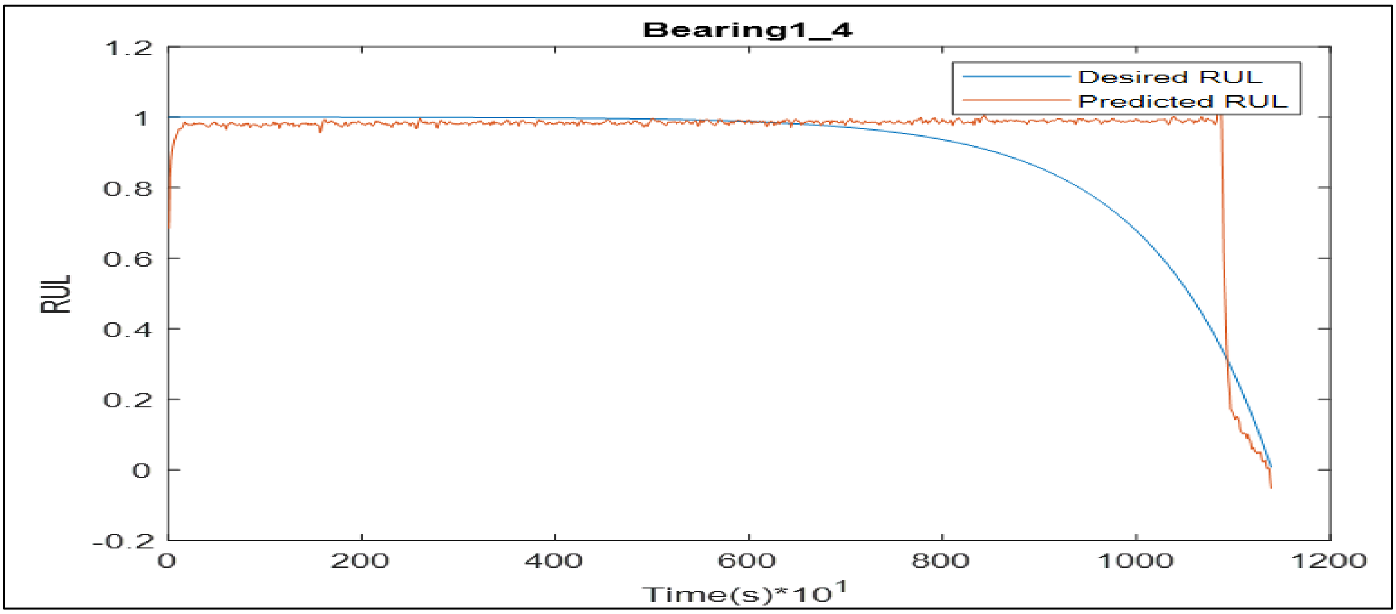

Fig 8 Bear1_3 RUL Plot for LSTM Model

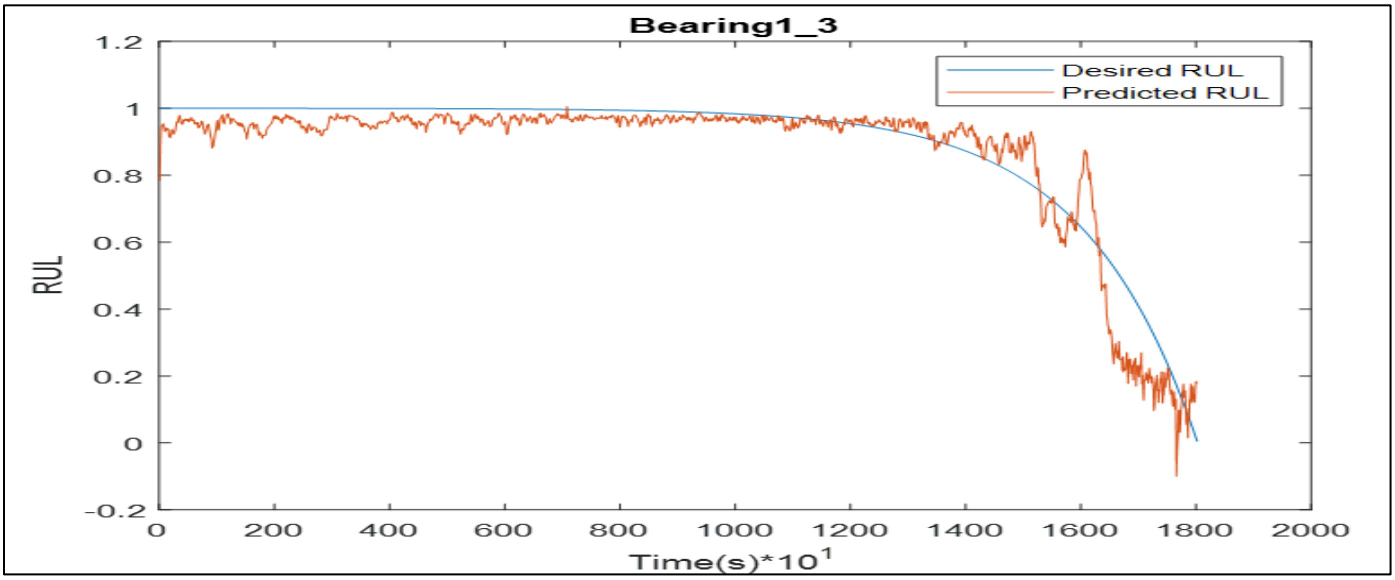

Fig 9 Bear1_3 RUL Plot for SSA_LSTM Model

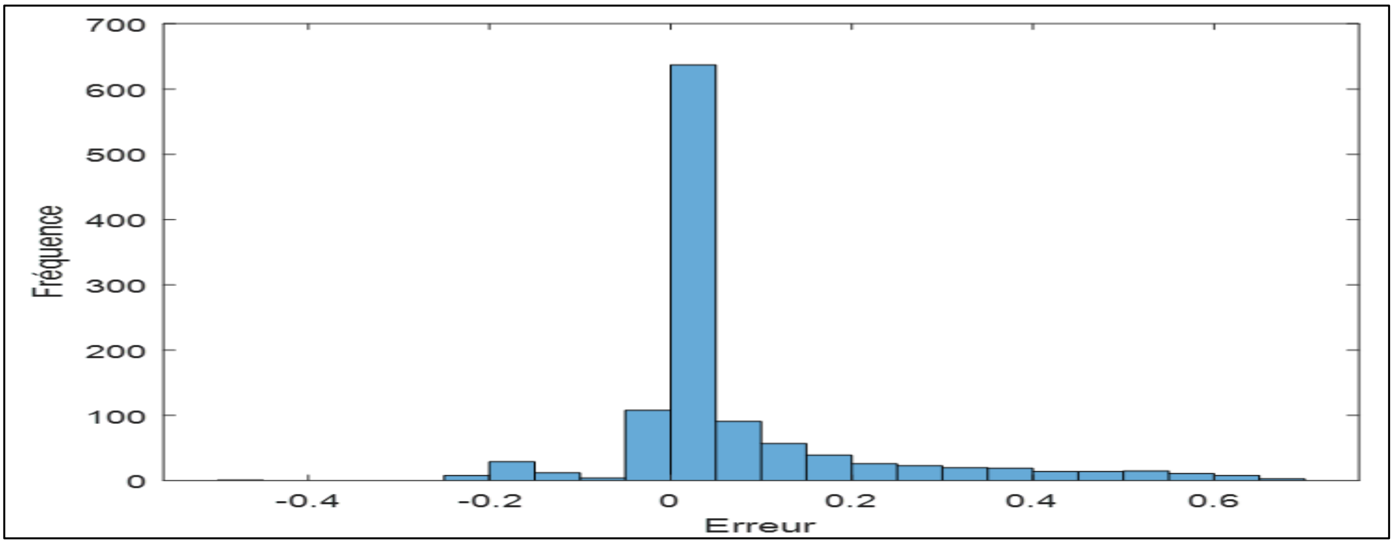

Fig 10 Bear1_3 Histogram for LSTM Model

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1181

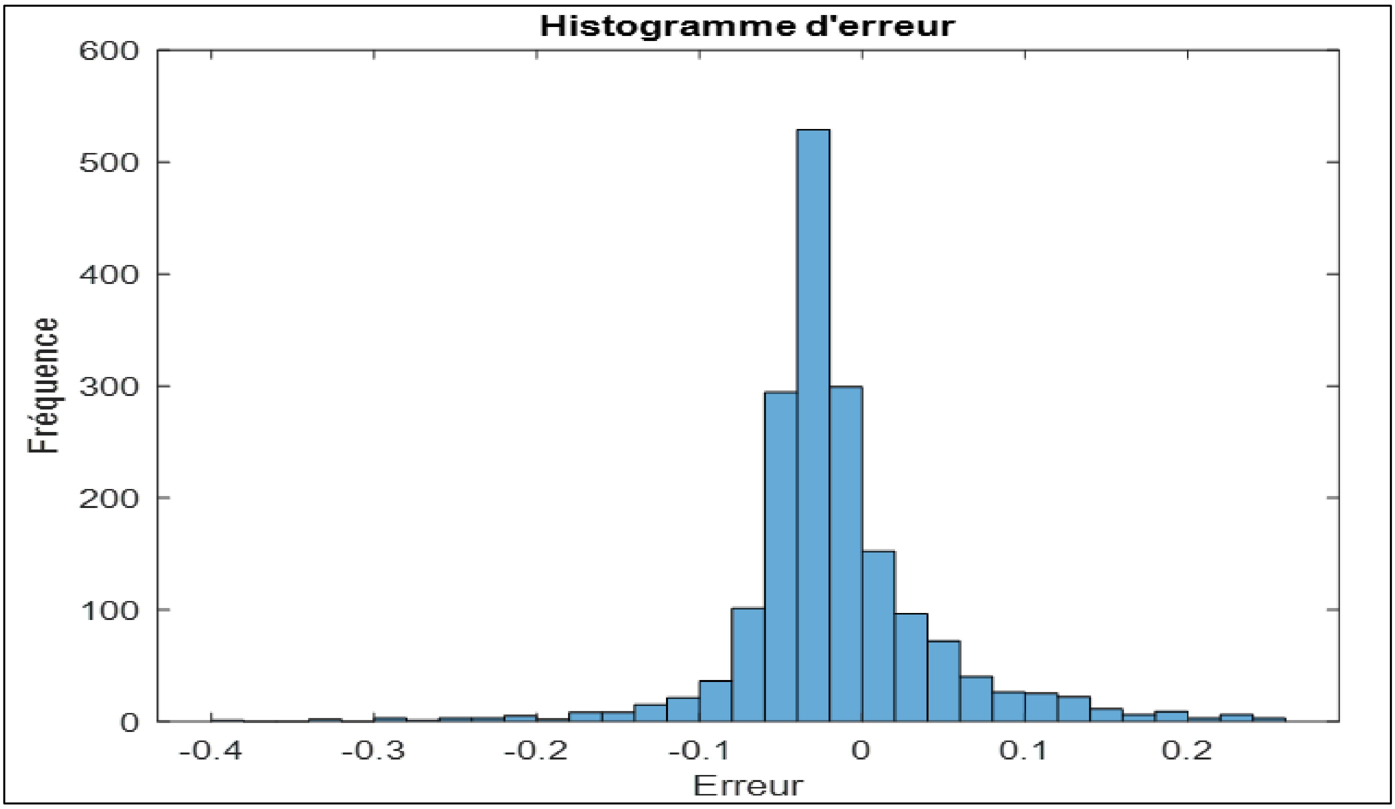

Fig 11 Bear1_3 Histogram for LSTM_SSA Model

With bearing 1_5, the predictions remain below the actual curve for almost the entire life cycle, as shown in Figure 12. At the end of life, the prediction still indicates 20 to 30% of bearing life remaining. The underestimation of the RUL is evident from the leftward shift in the error histogram in Figure 13. The results with bearing 1_7 are similar to those of bearing 1_5, with a prediction improvement in the mid-cycle of bearing life figures 14 and 15.

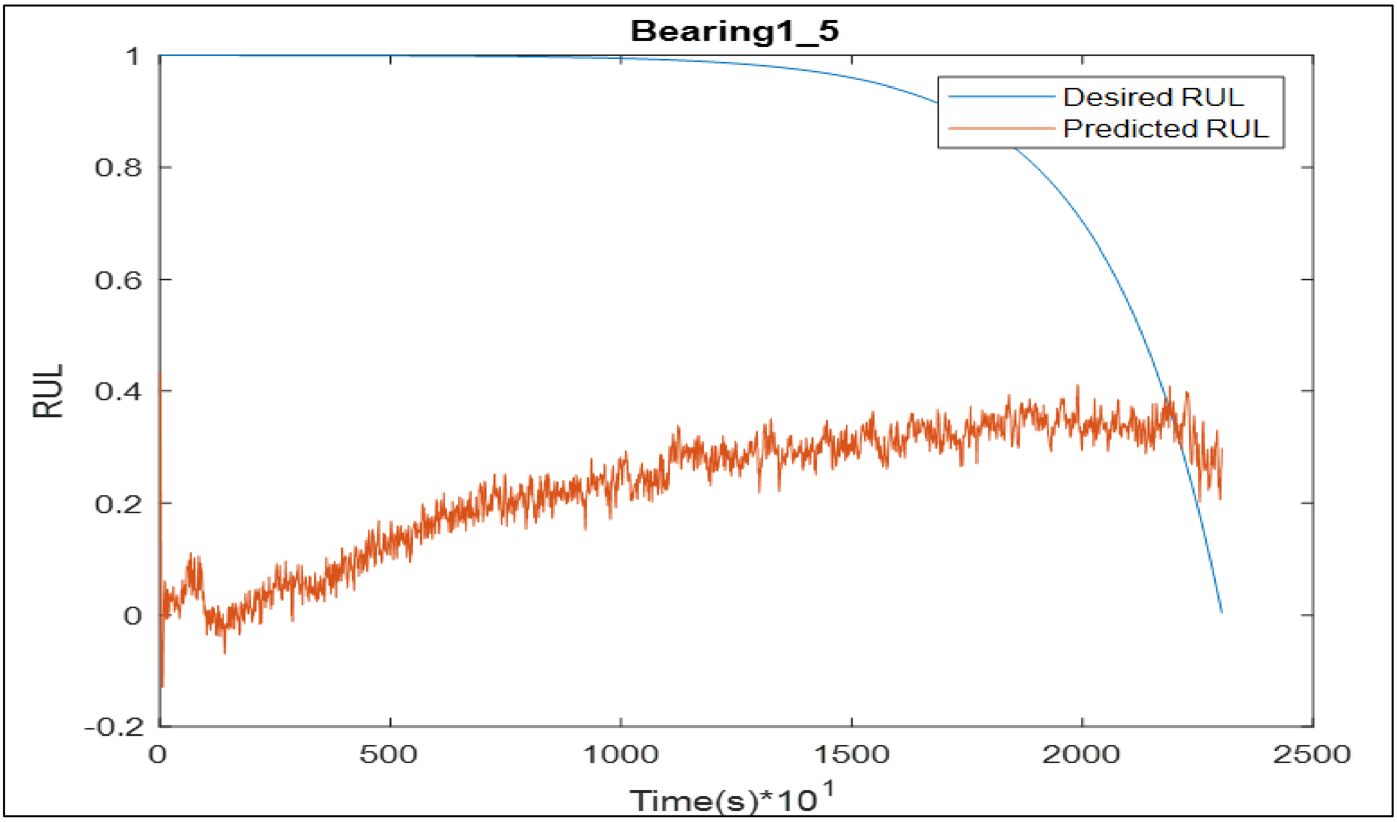

Fig 12 Bear1_5 RUL Plot for SSA_LSTM Model

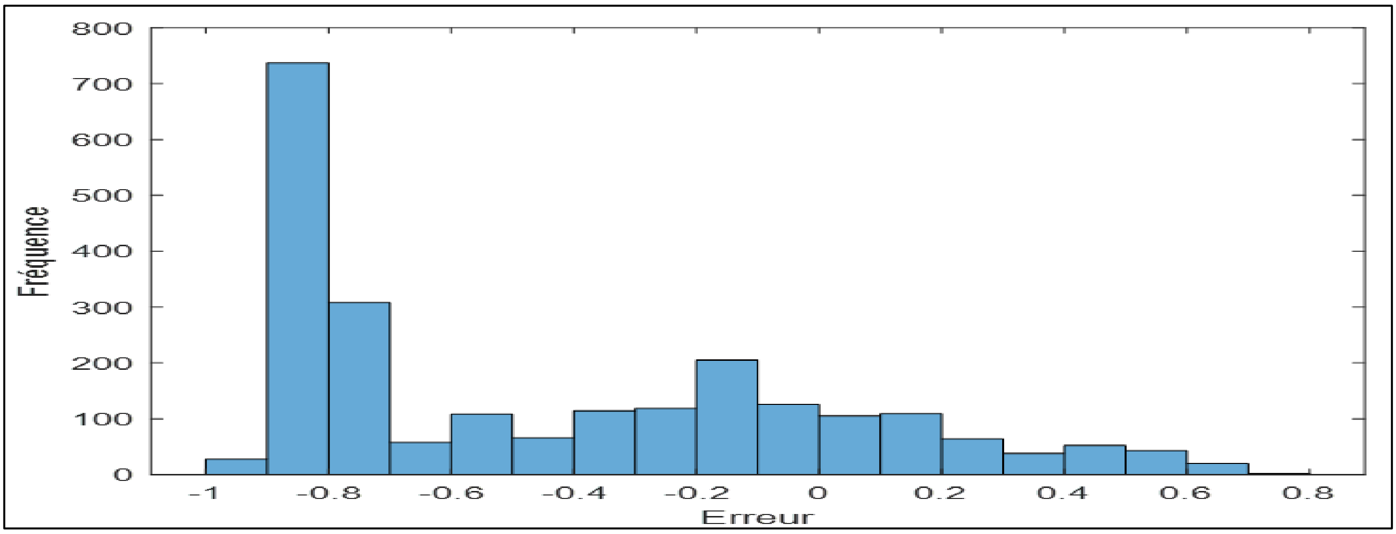

Fig 13 Bear1_5 SSA_LSTM Histogram Model

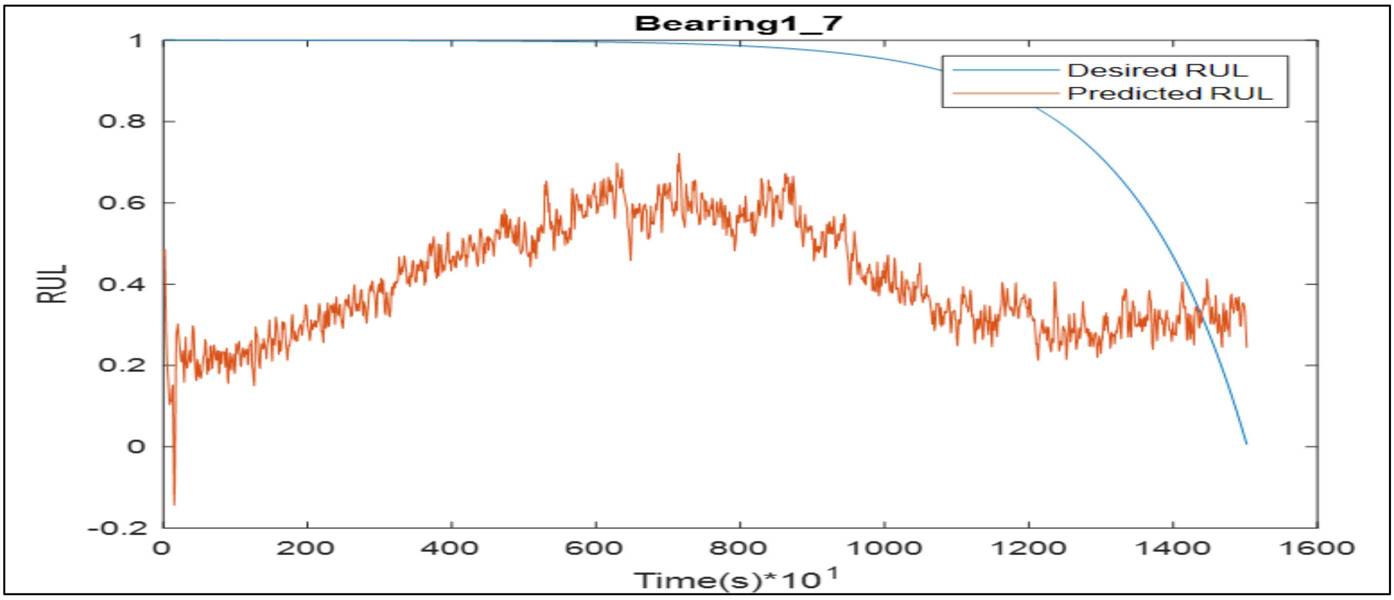

Fig 14 Bear1_7 RUL Plot for SSA_LSTM Model

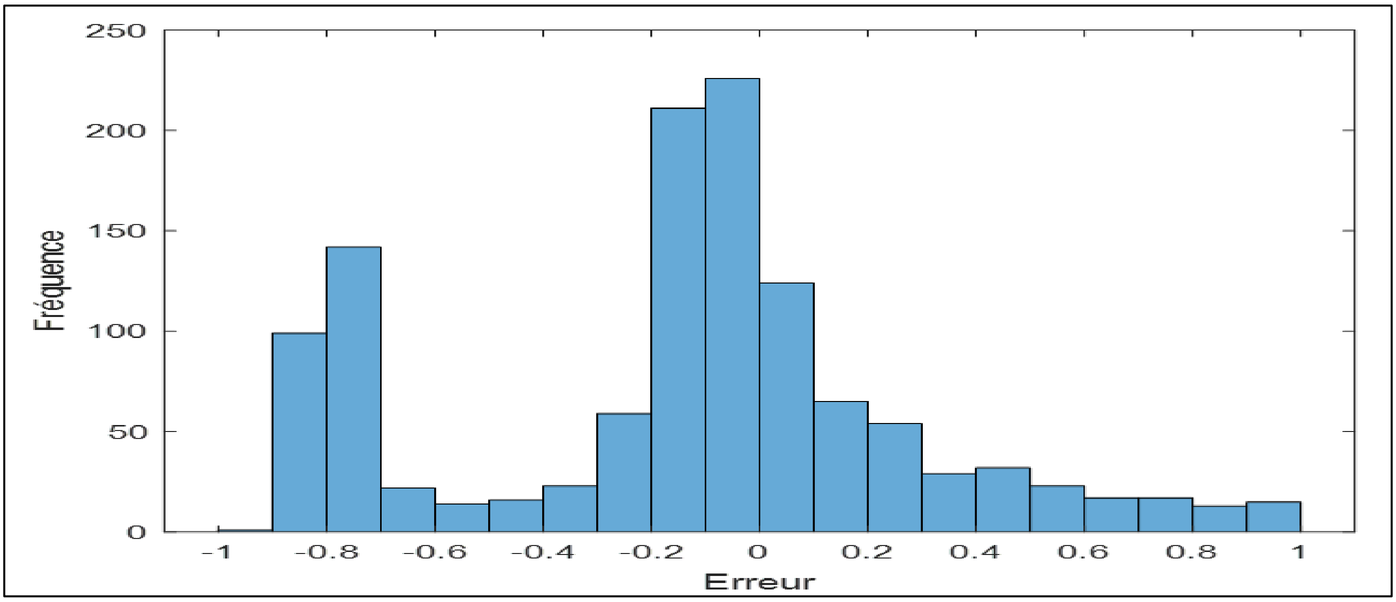

Fig 15 Bear1_7 SSA_LSTM Histogram Model

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1181

This following series of signals yields results close to those of bearing 1_4, with a good RUL estimation as long as the bearing is healthy. The influence of the signal preprocessing step with SSA improves the accuracy of the RUL prediction towards the final degradation phase figure 16. However, the model exhibits a longer remaining lifetime. The bars at higher frequencies are closer to the zero error intervals on the histogram in Figure 17.

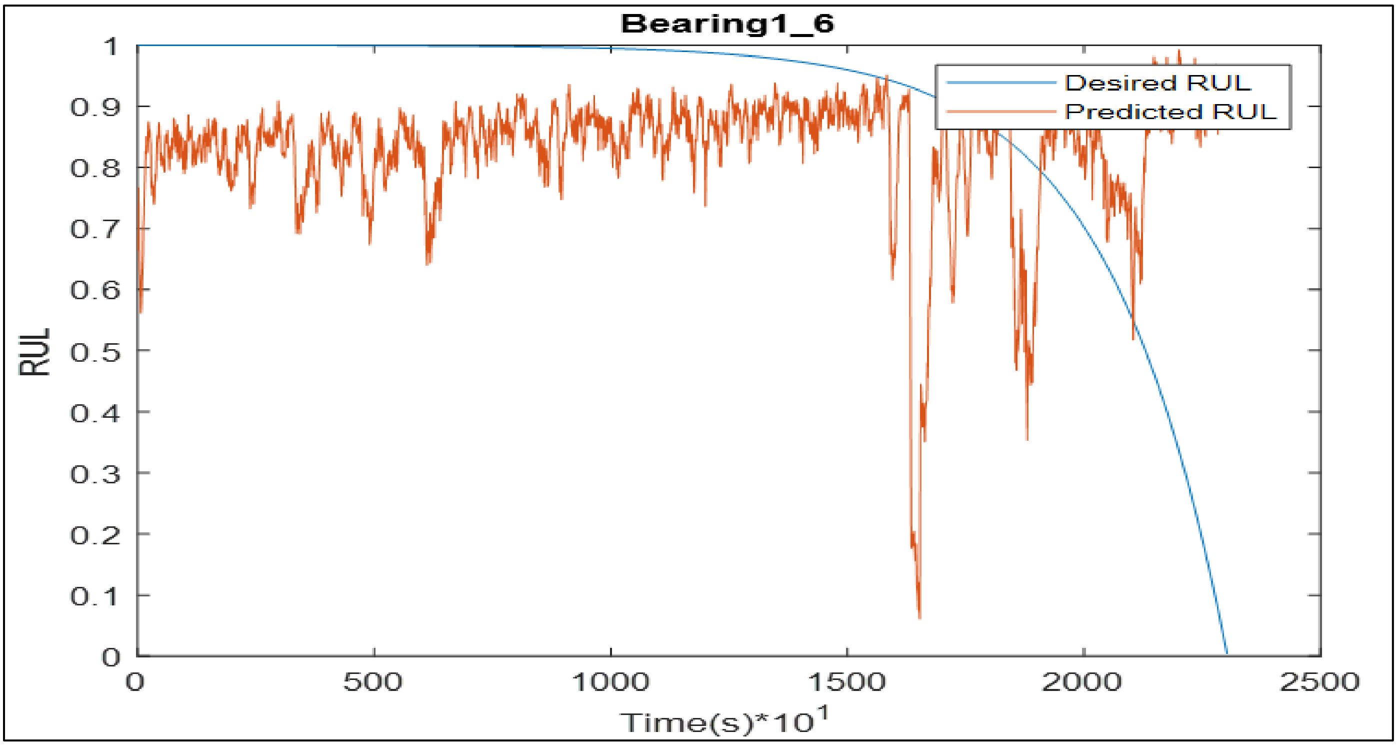

Fig 16 Bear1_6 RUL Plot for SSA_LSTM Model

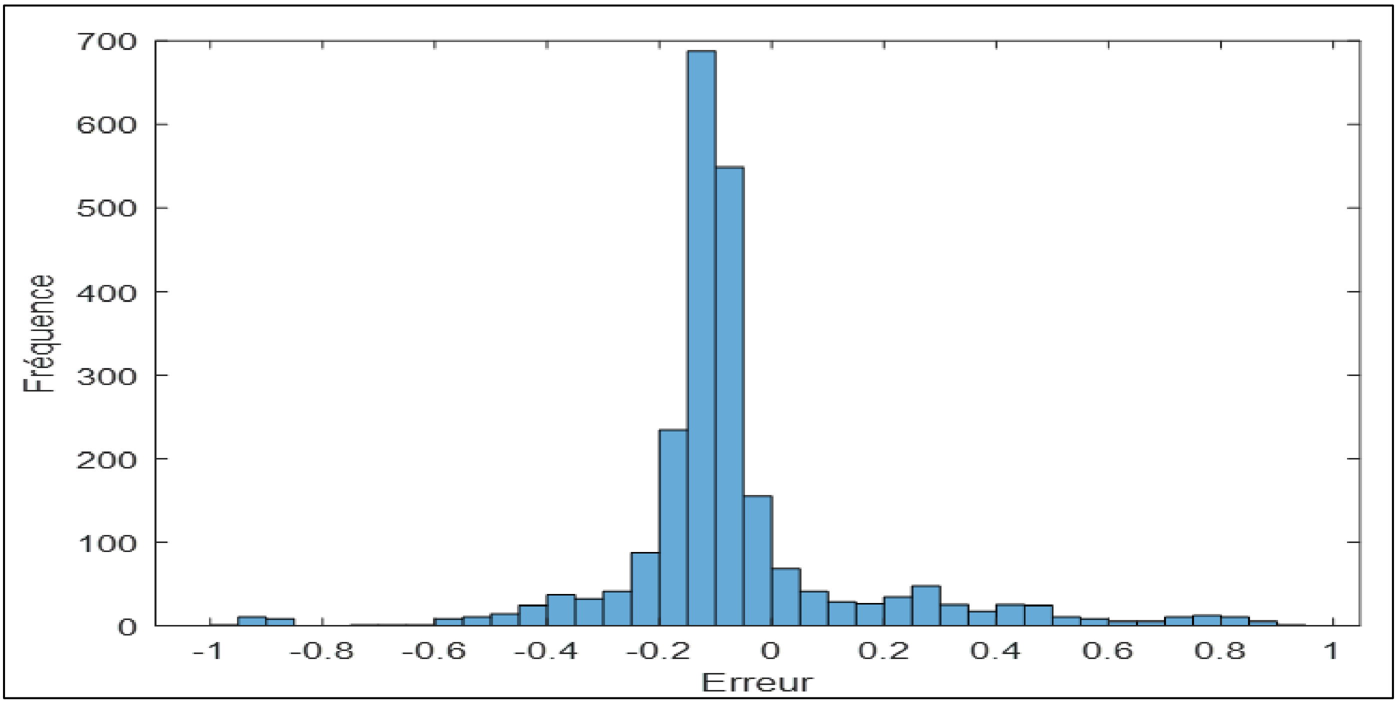

Fig 17 Bear1_6 SSA_LSTM Histogram Model

➢ *Results Discussion*

Table 2 shows the values of the metrics used for the model evaluation, across all datasets.

The lowest errors (error below 30%) are observed with bearing1_3 at about 4% for MAE and 7% for RMSE, followed by bearing1_4 at about 7% for MAE and 15% for RMSE, and finally bearing1_6 at about 18% for MAE and 24% for RMSE.

Table 2 Metrics Values Before and After SSA Preprocessing with Test Bearings

RMSE	MAE_LSTM	MAE_LSTM_SSA	RMSE_LSTM	RMSE_LSTM_SSA
Bear1_3	0.0489	0.0412	0.098	0.074
Bear1_4	0.079	0.078	0.156	0.1527
Bear1_5	0.610	0.673	0.6588	0.7168
Bear1_6	0.19659	0.1855	0.2524	0.2472
Bear1_7	0.6857	0.49607	0.7065	0.5247

From values presented In table 2 one can calculate the errors variations while moving from LSTM model to SSA_LSTM with formula below, and group them in table 3

$$\boldsymbol{\varepsilon}\% = \frac{Err_{lstm} - Err_{lstm\_ssa}}{Err_{lstm}}$$

With: Err_{lstm} : the error calculated with the code not integrating the SSA step before prediction,

Err_{lstm_ssa} : the error calculated with the code integrating the SSA step before prediction

Table 3 Percentage Error Reduction

ε%	$Bear_{1\_3}$	$Bear_{1\_4}$	$Bear_{1\_5}$	$Bear_{1\_6}$	$Bear_{1\_7}$
MAE	0	0	0	0	0
MAE_{SSA}	15.74	0.83	-10.35	5.6	27.65
RMSE	0	0	0	0	0
$RMSE_{SSA}$	24.48	2.11	-8.8	2.05	25.73

- *Influence of SSA Pretreatment*

Table 3 here high show that by switching from the LSTM model to the LSTM_SSA model one gets the expected result with bearings 1_3, 1_4, 1_6, and 1_7. The highest reduction is obtained with bearing 1_7 nearly 28%. Thus, inserting SSA step before RUL estimation makes the LSTM prediction more precise. The best model accuracy is achieved when working with bearing1_3 data, since the metrics MAE and RMSE never exceed 10% (table.2).

- *Gaps Justification*

Other disparities observed in the results are logic, since similar bearings submitted on the same working conditions often show different results (bearing1_4, 1_6 and 1_7). Because degradation can be developed differently (on the outer; inner; ball, etc.) due to tolerance differences; thus leading to different vibratory signature and LSTM model prediction quality.

- *Failure of the SSA Pretreatment Influence*

Some data such as bearing1_5 did not give the expected results, for which the prediction error increased with the LSTM_SSA model up to -10.35 (tab.3). This seems to be due to the difficulty of optimally choosing the best size of the SSA window "M"; despite the disparities in vibration signatures offered by different datasets, insufficient or excessive denoising can alter the useful information, and then reduce the LSTM capacity.

- *An Overall Underestimated Model*

Considering all histograms, the majority of predictions are close to the truth, as its peaks are located around ±0.1; ±0.2 and ±0.5 errors. This shows that the model is globally accurate.

- *Comparison of Results with Other Models*

Tab.4 compares the MAE values of the different approaches (Wei Hao et al, 2023) [30] with that proposed by our study (last column).

Table 4 MAE Comparison of Several Prognostic Approaches with LSTM_SSA Model

R_test	CNN	Bi_LSTM	GRU	Bi_GRU	SRD-LSTM	BCVHIT	LSTM_SSA
Bear1_3	0.1425	0.1637	0.121	0.1281	0.1633	0.1044	0.0412
Bear1_4	0.2977	0.1314	0.0637	0.1389	0.4106	0.0941	0.0783
Bear1_5	0.1830	0.1976	0.1718	0.1731	0.1855	0.0917	0.6732
Bear1_6	0.2337	0.2078	0.2307	0.2193	0.2243	0.2453	0.18554
Bear1_7	0.1747	0.2093	0.1798	0.1798	0.1929	0.1069	0.49607

Our LSTM_SSA model and the BCVHIT model give the best results followed by the GRU model on all datasets.

IV. CONCLUSION

The results obtained show that the LSTM networks preceded by SSA as preprocessing step are particularly suited to outperform the prediction accuracy in bearing RUL estimation, since the metrics errors can be reduced up to 20% for several dataset (bearing1_3). And therefore these results confirm the interest in using machine learning and in particular, deep learning in the field of industrial prognosis. However, these results were not generalizable across the entire dataset (bearing1_5). From this, several research perspectives as to be considered, such as the use of Stacked LSTM, or the integration of hybrid architectures combining LSTM_SSA with convolutional networks (SSA-CNN-LSTM) to capture more complex dependencies.

ISSN No: -2456-2165 https://doi.org/10.38124/ijisrt/26mar1181

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