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Prognosis of Bearing Acoustic Emission Signals Using Supervised Machine Learning

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Abstract— Acoustic Emission (AE) technique can be successfully utilized for condition monitoring of various machining and industrial processes. To keep machines function at optimal levels, fault prognosis model to predict the Remaining Useful Life (RUL) of machine components is required. This model is used to analyze the output signals of a machine whilst in operation and accordingly helps to set an early alarm tool that reduces the untimely replacement of components and the wasteful machine downtime. Recent improvements indicate the drive on the way towards incorporation of prognosis and diagnosis machine learning systems in future machine health management systems. With this in mind, this work employs three supervised machine learning techniques; Support Vector Machine Regression (SVMR), Multilayer Artificial Neural Network (ANN) model and Gaussian Process Regression (GPR), to correlate AE features with corresponding natural wear of slow speed bearings throughout series of laboratory experiments. Analysis of signal parameters such as Signal Intensity Estimator (SIE) and Root Mean Square (RMS) was undertaken to discriminate individual types of early damage. It was concluded that neural networks model with back propagation learning algorithm has an advantage over the other models in estimating the RUL for slow speed bearings if the proper network structure is chosen and sufficient data is provided.

Index Terms— Acoustic Emission, Condition Monitoring, Remaining Useful Life, Slow Speed Bearings, Artificial Neural Network, Support Vector Machine Regression, Gaussian Process Regression.

Abbreviations and Acronyms

RUL	Remaining Useful Life
SVMR	Support Vector Machine Regression
ANN	Artificial Neural Network
GPR	Gaussian Process Regression
SIE	Signal Intensity Estimator
RMS	Root Mean Square
AE	Acoustic Emission
SCSsegment	Sum of Cumulative Sum of a Segment
SCSoverall	Sum of Cumulative Sum of a Signal
MAGF	Magnification Factor
k	Proportionality Constant
W	Window Ratio
N	Size of a Signal
n	Size of a Segment
x	Individual Events in a segment
σ	Standard Deviation of a Sample
SE_{μ}	Standard Error of the Mean

I. Introduction

VIBRATION is a widely measured parameter in many industrial applications. Analysis of displacement, velocity, and acceleration for identifying and predicting machine fault has remained a subject of intense research since several decades. Although intensive work was undertaken in the diagnosis and prognosis of bearing fault, there is still need for prognostic tools for bearing fault. Prognostic action deals with the estimation of the RUL of physical systems to monitor their current health state and predict their future operating conditions. RUL is defined as the remaining useful time for a certain part or component to perform its functions before final failure [1]. In general, three aproaches are commonly used for the estimation of RUL, see Fig. 1. To train the prediction tools in the data-driven approach, the acquired signals are further analyzed using parametric and/or non-parametric models [2, 3 and 4] whilst the model based technique uses a crack growth modelling method to estimate the RUL [4]. In the hybrid approach both reliability and prognostic techniques are integrated to increase the accuracy of the estimation of RUL. This leads to more complexity as events and condition data must be provided for modelling process [5].

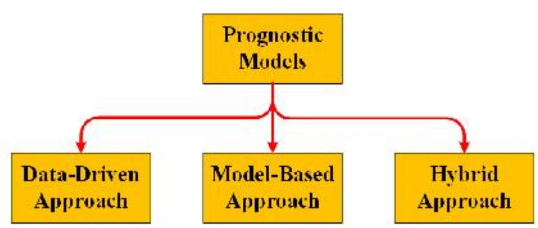

Fig. 1. Main Prognostics Approaches

Over a number of recent decades, tremendous work was undertaken to develop RUL prediction models for bearing vibration signals, using these approaches. For instance, Shao et al. [6] proposed Progression Prediction of Remaining Life (PPRL). In this model, different prediction methods were applied to different operation stages. Nathan et al. [7] undertook an experimental work to predict the RUL for an aircraft engine bearing. This model was based on the developing of the spall propagation throughout experimental bearing tests. Nathan et al. reported that the proposed model could accurately predict the spall propagation and the corresponding RUL. Throughout a research study, Moving Average Spectral Kurtosis and Bayesian Monte Carlo, Support Vector Regression and Anomaly Detection were employed by Sutrisno et al. [8] to estimate the bearing RUL. Sutrisno et al. analyzed a data set from seventeen ball bearings provided by the FEMTO-ST Institute. This study showed that Anomaly Detection method was most accurate overall. Support Vector

Machine (SVM) was employed by Kim et al. [9] to evaluate the bearing health state. Signal processing techniques such as time domain, frequency domain, and time scale domain through a wavelet transform features were used by Loutas et al. [10] to extract statistical vibration features. For condition assessment and life prediction of bearings, nonlinear Support Vector Regression (SVR) model was trained using these features. Vibration signals features were also extracted by Ghafari [11] to feed an Adaptive Neuro Fuzzy Inference System (ANFIS). Ghafari reported that the trained ANFIS could successfully identify the damage propagation on bearings and predict the future status at different operating conditions. The data driven approach was employed by Ben Ali et al. [12] to develop a prediction ANN model. In this work, a modified Weibull Distribution function was selected to fit the RMS, kurtosis and Root Mean Square Entropy Estimator (RMSEE). Ben Ali et al. postulated that the proposed technique successfully predicted the RUL using both fitted and unfitted data.

RUL for faulty bearing in the gearbox was estimated by Teng et al. [13] using an artificial neural network (NN). Data from faulty wind turbine bearing was used to validate the performance of the proposed model. In another work, Boskoski et al. [14] employed Gaussian process models and Renyi entropy based features to predict the RUL of bearings. Benkedjouh et al. [15] proposed a prediction model to estimate the residual useful life of bearings. In this model, classical support vector machine was integrated with isometric feature mapping reduction technique (ISOMAP). The authors reported that the model could efficiently predict the bearing RUL using the acquired experimental data. To overcome the issues of the selection of the first predicting time (FPT) and random errors of the stochastic process that lead to poor prediction accuracy, an improved exponential model was employed by Li et al. [16]. The FPT is selected based 3σ interval and random errors of the stochastic process is reduced using particle filtration. The proposed model was applied to both simulated data and a dataset collected from four degrading bearing tests. Authors postulated that the approach could successfully select an appropriate FPT and reduce random errors of the stochastic process. An investigation undertaken by Malhi et al. [17], statistical parameters were extracted from vibration signals of a defect-seeded rolling-element bearing to feed Recurrent Neural Networks (RNN) model. The study reached a conclusion that the developed model has shown a good accuracy in predicting the bearing RUL.

Nevertheless, the vibration analysis for diagnosing and prognosing bearing faults can be found in many kinds of industrial processes, Jamaludin et al. [18] reported the limitations of the application of vibration for slow speed rotating machines. Unlike the vibration, most recent work ascertained the feasibility of Acoustic Emission (AE) to detect very small energy release rates. Different techniques such as Empirical Mode Decomposition (EMD) were employed to extract AE features [19]. However, most of the published diagnostic and prognostic work on the use of AE was undertaken using artificially ('seeded') damage or ground metal debris that was introduced to machine components prior to the real tests [20]. Off the shelf, the first known investigation to address the identification and location of incipient natural cracks and propagation to spalls on slow speed conventional bearings using AE was undertaken by Elforjani et al. [21 and 22]. The second phase of this work involved two prognostic attempts by Elforjani [23 and 24] to estimate the RUL for naturally degrading slow speed bearings using AE signals at different operating conditions. The work presented in [23] is the first known attempt at estimating RUL for naturally degrading bearings using AE under normal operating conditions whilst the work in [24] represents the only research work on predicting the same type of bearings but under the grease starvation conditions. It is also worth to note that these two attempts are not only the published work in the literature that discussed the estimation of the RUL for slow speed naturally degrading bearings but also they are the only work that correlated the SIE as a new fault indicator with corresponding bearing natural wear throughout experimental AE tests. In the condition monitoring applications, adoption of proposed models and/or tools cannot be decided based on undertaking two attempts only. Reasons behind this may include for instance, different observed trends from one bearing case to another, advantages and feasibility of the proposed model and/or need to be further examined, better data fitting functions can be obtained, test the proposed model to a limited number of bearing cases, different operating conditions applied to test bearings etc. As a result of this, there is still an on-going need for further investigation of the proposed models by Elforjani and proposing more prognostic tools for measuring deviations from the normal conditions using AE measurements. This can be implemented if different bearing cases, new prediction models, and more appropriate regression functions are analyzed and discussed. With this in mind, the advantages of this work over the work by Elforjani [23 and 24] can be summarized as following:

- Reproof of the feasibility of SIE as an alternative fault indicator in the condition monitoring area using new slow speed naturally degrading bearing cases.
- Using new and more appropriate regression functions to improve the fitting of the extracted features from the AE signals.
- Ascertain the feasibility of ANN model to estimate the RUL for slow speed naturally degrading bearings using new bearing cases.
- This work is first known attempt to undertake a comparative results study between the well-established ANN, GPR and SVMR that are used to estimate the RUL for slow speed naturally degrading bearings using AE signals.

II. Acoustic Emission Measurements

Especially designed test rig was employed to undertake natural run to failure bearing tests; schematic is presented in Fig. 2. The tests were run under operating conditions of 72 rpm rotational speed and axial load of 50 kN was applied to the test bearing. The geometry of the test bearing consisted of a bearing cage, one grooved race of ball bearing (SKF 51210) and one flat race of roller bearing (SKF 81210 TN). This combination caused very high contact pressure on the flat race in the excess of (6 x 10^3 MPa) and eventually led to accelerate the initiation of natural crack. AE parameters were continuously recorded at a sampling rate of 100 Hz by a data acquisition system connected to AE sensors through preamplifiers, set at 40 dB gain. The type of AE sensors was commercially piezoelectric sensors (Physical Acoustic Corporation type "PICO" with operating frequency range 200-750 kHz and allowable temperature range of -65 to 177 ^{o}C). The tests were terminated once a significant rise in AE levels (16 hrs. into testing) was noted. This approach was adopted based on the several tests undertaken prior to the reported cases. Results from these pre-tests along with the visual inspection showed that significant rise in AE is a clear indication of fully developed damage on the flat bearing races. More sufficient details about the test rig layout, instrumentations, diagnosis results and analysis can be found in [21 and 22].

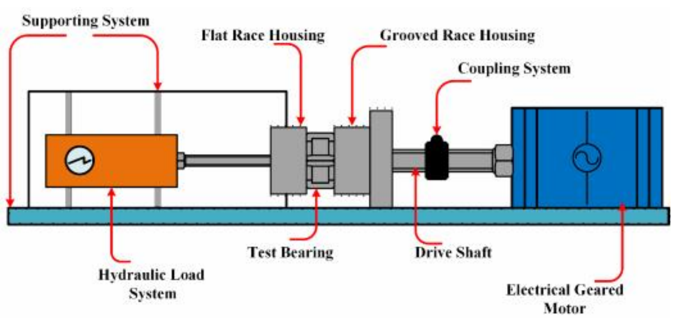

Fig. 1. Schematic of Test-Rig Layout

III. Extraction And Fitting Of AE Features

There are standard statistical features that can characterize the trend of the data. These features include mean, standard deviation, kurtosis, crest factor and RMS. For continuous monitoring of bearings using AE, Elforjani et al. [22 and 23] showed that techniques such as kurtosis and crest factor cannot be employed for observing high transient events. Further, in the condition monitoring applications, the commonly used RMS concerns only a period of time and therefore some transient short events may be lost. In other words, RMS typically concerns with a predefined time constant and therefore its values are not necessarily sensitive to high transient deviations that may typically occur over a few micro of seconds. Hence, Elforjani [23 and 24] developed the SIE as more sensitive fault indicator to overcome this inadequacy.

The SIE is extensively based on the cumulative sums of the events and it is calculated by dividing the sum of cumulative sum of a predefined segment ($SCS_{segment}$) in a given signal by the overall sum of cumulative sum ($SCS_{overall}$) of the same signal. The resulting SIE values are then enhanced by a magnification factor (MAGF). This dimensionless SIE has an advantages over the well-established fault indicators such as RMS and classical envelope in the essence that is the operator can undertake any analysis regardless the complexity of physical dimensions. The SIE also envelops the data without losing the information carried by the signal. The advantage of this over the classical envelope and the other parameters is that the SIE is a normalized piecewise segment technique whilst the envelope is based on the entire signal. This would offer the ability to detect micro-changes, track how the sample values deviate from a target, display the ratio of the total at any given time and chart statistics for both the current and previous data values from the process. It is worth mentioning that for the mathematical manipulation, optimal selection of the size of the segment was achieved by an iterative process; more details are provided in [23 and 24]. For this particular investigation, the following equations are used to extract the SIE and RMS from AE signals.

$$SIE = MAGF \ \frac{SCS_{segment}}{SCS_{overall}} \tag{1}$$

The MAGF can be calculated, if the size of a given signal (N), the size of each segment (n) and the proportionality constant (k) are provided. To calculate the SIE, the acquired AE signals were divided into several segments. Each segment contains 100 elements and the optimal value of k equals to 4 was selected.

$$W = \frac{N_{overall}}{n_{segment}} \tag{2}$$

$$k = \sum 2,3,4,5,6,\ldots\ldots * \tag{3}$$

$$MAGF = kW \tag{4}$$

With the knowledge of individual events (x) in each segment, RMS for the same number of segments can be calculated as:

$$RMS = \sqrt{\frac{x_1^2 + x_2^2 + \ldots\ldots + x_N^2}{n_{segment}}} \tag{5}$$

To ensure a strong monotonic relationship between the AE features (SIE and RMS) and the test period, the next phase of this investigation involved the calculation of what-so-called a correlation coefficient. Correlation is a statistical analysis that is widely used to assess how variables are related to each other. Results obtained from what-so-called Pearson's Product-Moment Correlation showed that there is a strong correlation between AE features and test time (Strong Monotonic Relationship), presented in table 1. Although a relatively monotonic process was observed in the trend of bearing failure, throughout the testing period, the measured features need to be preprocessed to avoid any random prediction that may occur due to the significant noise in the acquired data. As AE parameters were continuously acquired at very low sampling rate of 100 Hz, the data was first cleaned by omitting any NA and missing values and then averaged to reduce the high dimensionality for faster processing without the loss of carrying information. For the prediction of RUL, the degradation signals, originating from bearings, are commonly fitted using appropriate mathematical linear or exponential functions.

TABLE 1
CORRELATION ANALYSIS

Pearson's Product-Moment Correlation				
Feature	t-test	p-value	95% Confidence Interval	Correlation Coefficient
SIE	83.126	2.2×10^{-16}	0.74 : 0.77	0.761
RMS	86.276	2.2×10^{-16}	0.76 : 0.78	0.773

For this investigation, the following exponential function was found to be the most appropriate model to fit the SIE and RMS values.

$$f = y_o + \frac{a\left(e^{bt} - 1\right)}{b} \tag{6}$$

In equation 6 (***t***) is the test period and (***f***) represents the extracted feature of the acquired signal; (***f***) can be the value of SIE and/or RMS. The (***a***, ***b*** and ***y***) are the function constants. When the degradation time is equal to zero, the constant (y_o) is used to identify the feature value. The well-known least-square method was employed to find the best values for the model constants (a, b and y_o). The reported bearing cases in this investigation could appropriately be fitted using the selected exponential function, see Fig. 3 to 6. Four bearing cases were fitted to construct, train and test the performance of the prediction models. For training prediction models, fitted data from case 1 was used to feed the models whereas the bearing RUL was estimated for case 2, case 3 and case 4. The Global Goodness of Fit for the exponential model and general optimal estimated constants are presented in table 2 and table 3 respectively.

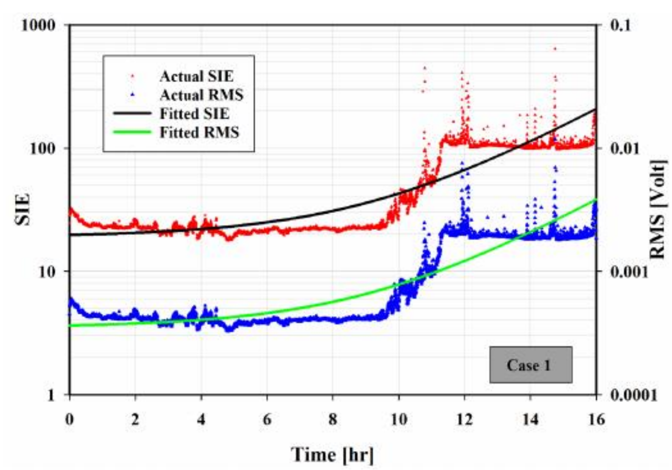

Fig. 3. Actual and Fitted SIE and RMS, Case 1

TABLE 2
GLOBAL GOODNESS OF FIT

Case	SIE		RMS	
	R^2	adj R^2	R^2	adj R^2
1	0.7555	0.7554	0.8838	0.8837
2	0.8671	0.8669	0.8156	0.8155
3	0.9428	0.9427	0.8777	0.8777
4	0.8589	0.8589	0.8718	0.8717

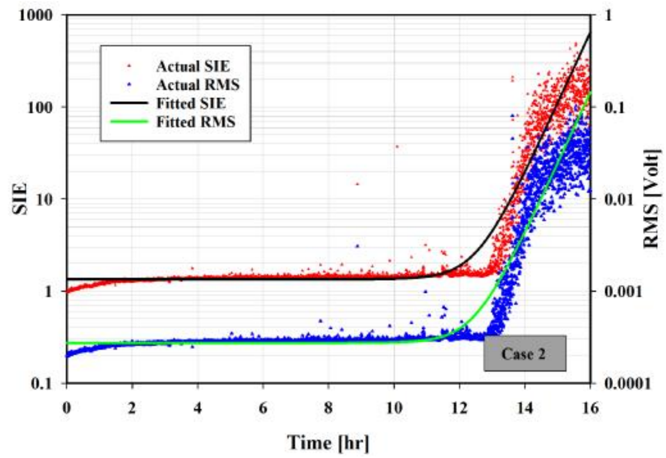

Fig. 4. Actual and Fitted SIE and RMS, Case 2

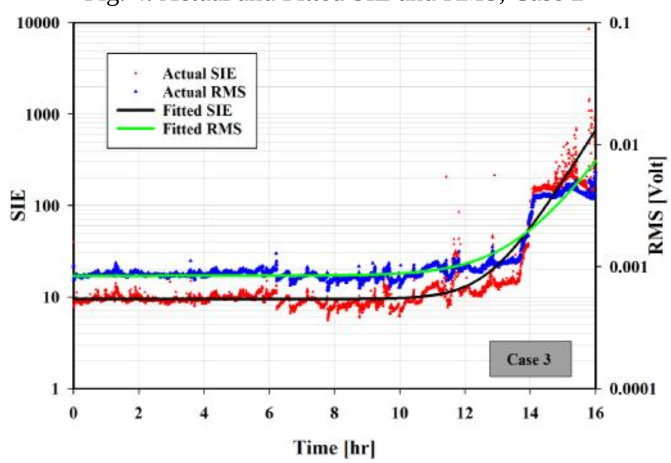

Fig. 5. Actual and Fitted SIE and RMS, Case 3

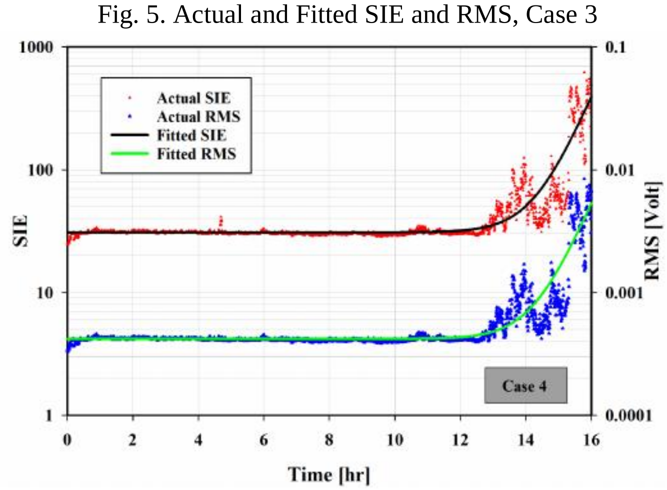

Fig. 6. Actual and Fitted SIE and RMS, Case 4

IV. Machine Learning Techniques And RUL Estimation

Mathematical expressions and detailed of different types of machine learning techniques are well documented. In general, algorithms of machine learning are mainly divided into what-so-called supervised and unsupervised machine learning. The supervised algorithms are created to be guided by labels to train the machine learning model e.g. Regression, Naive Bayes, Neural Nets.

TABLE 3
ESTIMATED CONSTANTS FOR THE EXPONENTIAL MODEL

Case	SIE			RMS		
	y_o	a	b	y_o	a	b
1	19.74	0.26	0.34	0.0004	4.6×10^{-6}	0.34
2	1.347	5.15×10^{-10}	1.77	0.0003	1.1×10^{-13}	1.77
3	9.463	6.86×10^{-7}	1.30	0.0008	6.3×10^{-9}	0.85
4	30.81	3.98×10^{-8}	1.45	0.0004	5.5×10^{-13}	1.45

On the other hand, the unsupervised algorithms are developed based on similarity where they can differentiate basic properties of a certain data such as number of occurrences or class of occurrence e.g. Decision Trees, Clustering. In this research work, ANN model with back propagation learning algorithm, SVMR and Gaussian GPR are employed to estimate the RUL for slow speed bearings. The ANN technique is relatively close to SVM in terms of theoretical structure and weights for multiple dimensions of vectors to achieve classification. Models of neural networks can do both supervised and unsupervised learning such as mapping from numeric to numeric column, pattern matching, clustering and regression [25].

SVM is another great method to maximize the separation boundary of the classifier. This technique relies on the calculation of the components of a vector perpendicular to the classification. Although it is extensively used for 2D class problems, SVM can also be extended to be used for multi-class boundaries of linear or non-linear kind. One of the advantages of SVM over the other techniques is that it does not over fit the data. The SVMR is a one form of Bayesian that has generalized linear functional form similar to the support vector machine [26].

The third technique is the Gaussian Process (GP), which represents a collection of random variables. Any finite number of these variables has a joint Gaussian distribution. Mean and covariance functions are used to describe a real GP. With known of GP functions and a set of training data, a posterior distribution over functions can be derived. This posterior distribution is then employed by GPR for predicting the values of test data [27]. Prior to the estimation of the RUL, the three regression models were fed with the data from case 1, presented in figure 3, for training. Data from cases 2, case 3, and case 4 were employed to test the proposed models, see Fig. 7. To achieve the best performance of the prediction models, all parameters of these models such as algorithm type, learning rate, hidden layers, etc. were kept changing throughout the training process. This was accomplished by making several runs along with cross validation, adjusting and tuning the training models. ANN model showed good performance with a structure that has three hidden layers with (7-3-7) neurons, one output layer represents the estimated RUL and an input layer consisting two inputs parameters (SIE & RMS), shown in Fig. 8. It is worth mentioning that an activation sigmoid function (logistic) and a Resilient Back-Propagation algorithm were employed to improve the results.

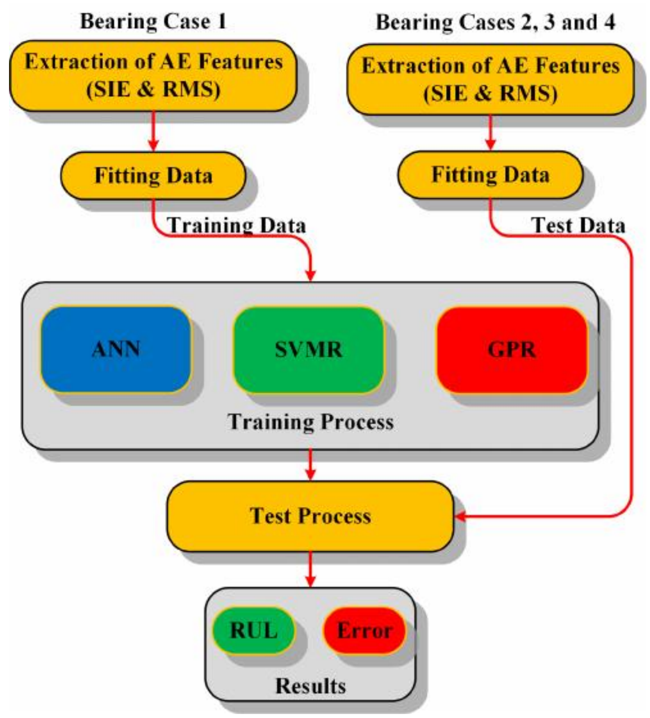

Fig. 7. Schematic of Training and Test Processes

The optimal training results for SVMR were obtained with a cost value of 1000 and epsilon value equals to 0.001. The gamma value, SVM-Type and SVM-Kernel were selected to be 20, regression type and radial function respectively. Further, the C value of 5 and sigma value of 0.88 were also used. In the case of GPR model, the value of hyper-parameter (sigma) of 90 with the use of Gaussian Radial Basis kernel function could reduce the cross validation error to 0.00405.

The next phase of the analysis involved the estimation of RUL for the fitted data from the cases (2, 3, and 4). To compare the estimated RUL by the prediction models with the actual values, equations 7 and 8 were used to calculate the actual RUL and the Error respectively.

$$RUL = t_f - t_i \quad (7)$$

$$Error = \frac{Actual(RUL) - Estimated(RUL)}{Actual(RUL)} \, x\ 100 \quad (8)$$

The (t_f) is the time when the fully mature failure on the bearing race was formed; in this particular investigation this time was selected as the termination of the test period (16 hours). The (t_i) is the instant time at which the remaining useful life was calculated. By visually inspecting the resulting plots of the train case 1, it can evidently be seen that the three models were well trained. Observations from the resulting plots of the test cases show that the RUL values estimated by the ANN model for the case 2, case 3 and case 4 are almost closer to the actual RUL line (a perfect concentration of estimated RUL values around the actual line is a clear evidence of low Error and thus an ideal model performance). Also was noted that both SVMR and GPR failed to predict RUL for the case 2 and case 3 throughout the testing period between 4 hours to 16 hours.

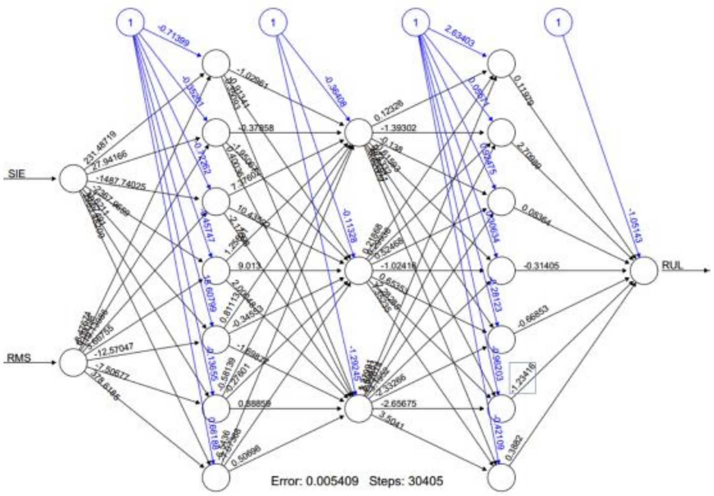

Fig. 8. ANN Structure (Two Inputs RMS & SIE)

In this particular time, for instance, RUL values for case 2, estimated by GPR and SVMR, registered the highest error value of 71% whereas a relatively lower error values of 53% and 58% for case 3 during the same interval of testing time were recorded by GPR and SVMR model respectively. Further, at the onset of testing in case 3, evidence of errors and poor performance by GPR and SVMR was also noted, see Figs. 10 and 11, though relative better performance was made by SVMR model during the run-in stage. However, this is not the case for ANN model where the maximum error in both bearing cases (2 and 3) did not exceed 25%. Interestingly, the error results also show some negative error values calculated by the prediction models for case 4, presented in Figs. 9 to 11. This is due to the overestimation of the RUL. Further, for the same case, ANN, SVMR and GPR show almost significant consistency with the corresponding actual bearing degradation level. Assessment of the performance of the proposed models also involved the analysis of the Standard Error of the Mean. With the known of the sample Standard Deviation (σ) and the sample size (N), the Standard Error of the Mean (SE_{μ}) was calculated using the following equation:

$$SE_{«}\ X \frac{\pm}{\sqrt{N}} \qquad (9)$$

Observations from the error plot, shown in Fig. 12, reinforce the view that the ANN was more sensitive than the SVMR and the GPR in the prognosing of high transient AE events that are typical for natural bearing degradation. Evidence for this was the absence of any overlapping between the data that represents (SVMR and GPR) and the data within the range of the error bar of ANN. Further, the results showed that ANN model has the lowest error average.

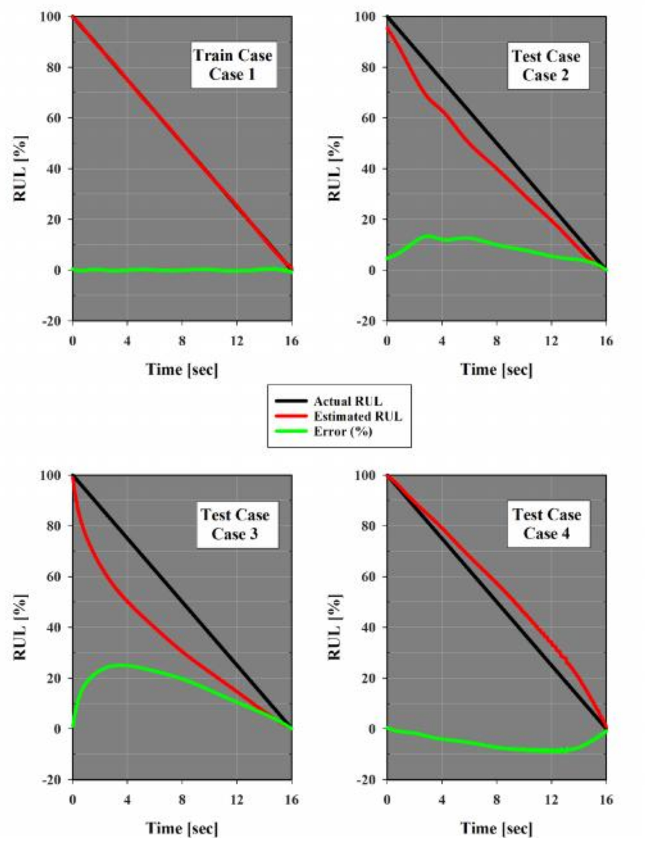

Fig. 9. Results by ANN Model

This means that the obtained results using the ANN model are conclusive and significantly different from the data of the other models. Hence, the ANN model can be considered as the lowest error model. It is also worth to note that identifying of the highest error model could not be ascertained though the SVMR has the highest average of standard error. This is because of the inclusive results due to the presence of high data overlapping between SVMR and GPR; large portion of data from SVMR falls in the range error bar of GPR and therefore they are not significantly different.

V. Conclusion

This research work is the third known attempt, novel in itself, at estimating the RUL for slow speed naturally degrading bearings using AE technology. It can be concluded that the obtained results from the presented bearing cases clearly show that the feasibility of the proposed ANN model, fault indicator SIE and the improved regression function could successfully be verified in predicting the RUL for slow speed bearings; reinforcing the acknowledged view by Elforjani [23 and 24]. In contrary, comparative results study revealed that

SVMR and GPR models would not offer the operator sensitive tools for estimating the bearing RUL.

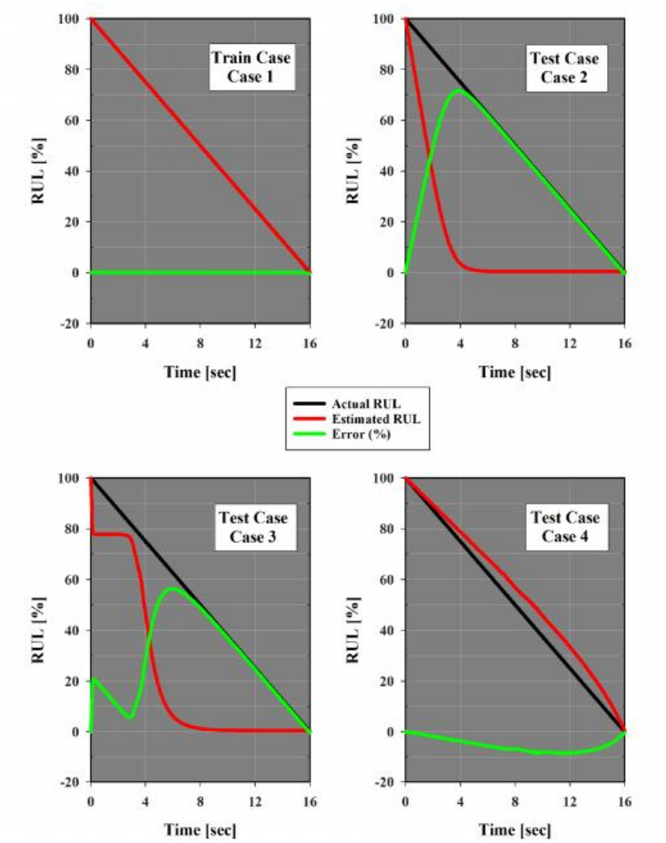

Fig. 10. Results by SVMR Model

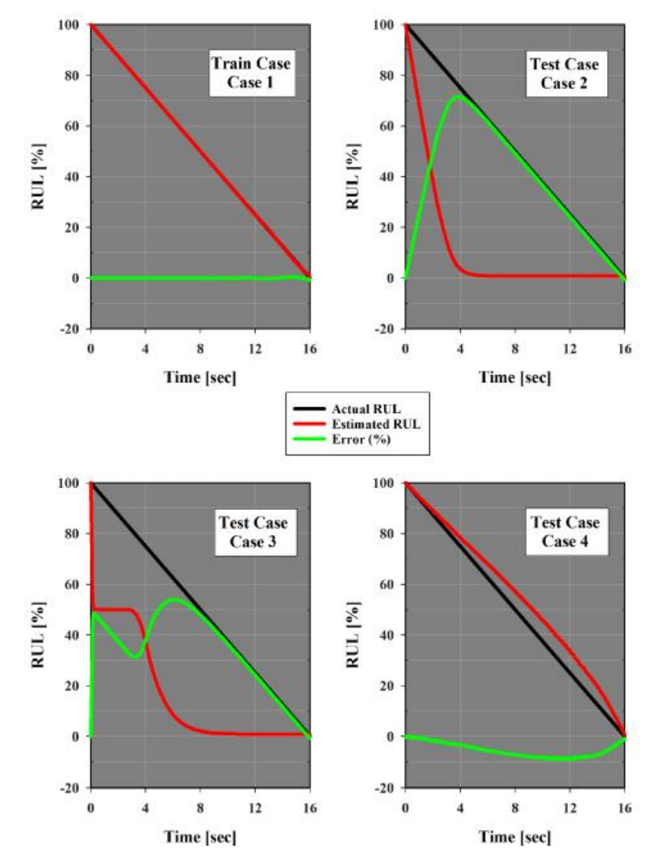

Fig. 11. Results by GPR Model

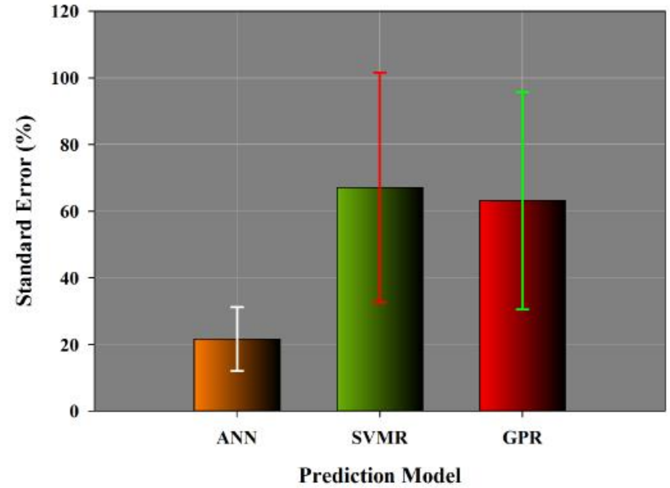

Fig. 12. Results of Standard Error with Mean

Finally, though these prognostic models have successfully been applied to specifically test rig design, instrumentations and particular AE tests, it is a fundamental principle to undertake further investigations and analysis to assess the feasibility of these models in real world applications where other factors such as structural noise and other operating conditions are present.

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