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Bearing Health and Safety Analysis to Improve the Reliability and Efficiency of Horizontal Axis Wind Turbine

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The role of renewable energy has grown considerably in various regions of the world, particularly solar and wind energy sources. Both energy sources are capable to meet energy requirements in an efficient and environmentally sustainable manner in solar and wind rich regions of the world. South and north Asian regions are one of them, where solar and wind energy resources are utilized with the help of available energy conversion machines. The wind turbine is one of them and its various types have played a vital role in the utilization of wind energy in the industrial sector for power generation. Horizontal wind axis turbine is one such type and it is capable to achieve better power output plus energy efficiency. It is used therefore in large-scale wind electric power generation. Although, there are certain technical problems related to the performance of wind turbines, for instance bearing failure rate. Due to the failure of bearings and other parts of wind turbines, considerable costs of specialized maintenance have incurred on the purchase of parts, installation, and trained workmanship which contribute towards an increase in downtime of power generation. Bearing faults are extremely complex and sometimes cannot be resolved using reconfigurable control. Therefore, early detection of bearing faults is critical to its performance and lower downtime. This paper investigates the requirements of bearing health and safety assessment. The assessment is based on the principles of estimation of the Remaining Useful Life (RUL) of bearing. A proposed prognosis model of Reliability Health and Safety Analysis (RHSA) is used for the evaluation of the performance of the bearing. The reliability model is used for the assessment of the useful life of the bearing subsystem of the Horizontal axis wind turbine and early detection of RUL leads to improve the performance and to avoid its failures.

Keywords: Horizontal Axis Wind Turbine (HAWT), Reliability Health and Safety Analysis (RHSA), Remaining Useful Life (RUL), Wind Energy.

1. Introduction

Wind turbines are frequently positioned in severe environmental conditions, making their parts' operation and maintenance difficult. The most vulnerable mechanical components in rotating machines are rolling elements like bearings[1]. A bearing failure can result in a complete machine breakdown, causing unintended interruptions in production and financial losses. The Remaining Useful Life (RUL) of wind turbine bearings and gearbox are the major components in their maintenance and operation. It is critical to install an effective bearing Condition Monitoring (CM) and fault diagnosis system. So that incipient bearing faults can be detected and diagnosed for preventing machine damage[2]. Such as early detection of a rolling element bearing defect in a high-speed wind turbine can lead to timely maintenance to avoid potentially disastrous consequences such as fire and human loss caused by unexpected failure. Wind turbine bearing reliability and performance are critical for the long-term smooth operation of wind turbines under hazardous conditions. RUL prediction is one of the most important tool in decision-making, for the prediction of time to failure of machine parts in advance. This makes it convenient for maintenance engineers to carry out qualitative risk analysis and formulate successful maintenance strategies[3].

In the Wind Turbine Generation Systems (WTGs) inspections and maintenance are very important for the improvement of the life span of a gearbox, bearings, blades, and other components of the wind turbine [4,5]. Parts such as the gearbox, generator, main bearing, blades, and tower cause sometimes unexpected downtimes and thus require the most attention of users. The wind turbine main bearing failure may result in the rise in the cost of repair and maintenance [6]. The bearing failure can damage the drive train in the wind turbine generation. As a result, there is an increase in the cost of specialized maintenance, such as the cost incurred on the installation of equipment, rigging plans, and trained workmanship. The bearing failure rate in wind turbines remains very high, up to 76% [7]. Wind farm operation and maintenance practices typically involve a combination of corrective (breakdown or reactive response) and preventive (periodic) maintenance strategies. Preventive maintenance requires regular inspection and small maintenance actions in comparison to breakdown maintenance, which requires huge effort and time. It also facilitates to reduce repair, and other costs incurred on purchase of damaged components. Gear box and bearings are deteriorated with respect to time as per L_{10} criteria due to wear and tear and such problem is serious in the offshore turbines due to decrease in lifespan from 20 years to 10 years[8]. The wind turbine main bearings are subject to a variety of failure modes, such as wear rate of inner and outer race faults, pitting, cracks, brinelling, and damage to the cage. The bearing health is the ratio of current time to failure time which illustrate the state of degradation. The failure modes are dependent on certain factors such as wind air density, ambient temperature, humidity, dust, risky climate conditions, and variation in the wind load due to rain, storm, and poor maintenance.

Typically, the prediction of Remaining Useful Life (RUL) has been accomplished using various models such as Support Vector Regression (SVR) based on the well-known support vector machine (SVM) algorithm, Long Short-Term Memory (LSTM) models based on the architecture of Recurrent Neural Networks (RNNs), as well as Convolutional Neural Network (CNN) and Deep Neural Network (DNN) models. These models have been widely employed in RUL prediction tasks. While considering the various models used for predicting Remaining Useful Life (RUL), it is important to note that each model has its limitations. For instance, the SVR model may encounter difficulties in handling large datasets and capturing non-linear relationships, as it lacks the ability to automatically learn features[9]. On the other hand, LSTM models, which are based on the architecture of Recurrent Neural Networks (RNNs), excel in handling sequential data. However, they may not be as flexible when it comes to non-sequential data [10]. It captures sequential dependencies by maintaining an internal memory state, so the training process is slower and takes more time than the other models. CNN model learns hierarchically from image patches and abstract features in addition to that its architecture consists of multi hidden layers which makes the network complex and more challenging for features analysis[11]. DNN model is computationally expensive and complex because it requires a large amount of labeled training data to achieve good performance[12]. DNN is the best combination of hyperparameters, model hyperparameters must be tuned based on learning rate, batch size, number of layers, and activation function. If the data is small, there is a risk of overfitting during training, and the iterative process is time-consuming. Many authors are working on DNN to improve network performance. However, ANN is interchangeable with DNN, which has demonstrated great success in a variety of applications by overcoming all limitations. ANN model is the reliable solution for the health monitoring of WTGs to enhance the life span of wind turbines up to its estimated life. The reliability and health of bearing as a sub-component be ensured through time management of lubrication which avoids catastrophic bearing failures to avoid fire, premature gear box failure and other components.

2. Condition Monitoring System (CMS)

Condition Monitoring (CM) and RUL showed a significant role to decrease downtime, leading to creating cost-saving opportunities. The condition monitoring of Wind Turbines (WT) based on vibration, noise, and temperature signals has been gaining significant attention in the past few years. The vibration monitoring of wind turbines is on the rise. Vibration monitoring is used to detect bearing and gear faults based on AI and deep learning methodologies are gaining popularity in the age of automation and complex machines.

The RUL of a Wind Turbine component can be estimated by using ANNs. The CM as shown in Fig. 1., is based on multivariate data signals such as vibration and temperature. Data acquisition is the primary part, and data is processed to the ANN model to identify the degradation and finally, RUL is calculated. The process as shown in Fig. 1. is handled in the Condition monitoring server.

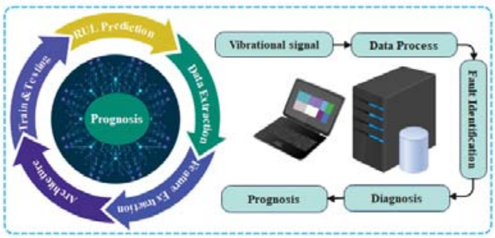

Fig.1. Condition Monitoring Flow Diagram

The data is first extracted as raw signals, and then features are identified and then classification is carried out to obtain the desired outcomes using a deep learning model. All the data is then fed into the ANN model for the prediction of residual useful life.

3. Methodology of Proposed ANN Model

3.1. Remaining useful life prediction methods

Remaining useful Life focuses on condition-based maintenance on time and ensures the safety of the equipment. Physics-based method, data-driven method, and hybrid method are used to calculate the RUL of equipment according to the nature of the complex machine system and the availability of data and expertise within the organizations. Bayesian networks (BN) structure and probabilities for each node are used for fault diagnosis of bearing. Other tools which are also used to generate are the tree structure fishbone diagrams[13], and similar variation sensitivity matrix[14]. The structure of the tree based on data is utilized to optimize the problems [15]. Equipment maintenance databases are used to produce the provisional likelihoods of the network. Data sources for BN include QMS, MES, RMS, CMMS, and CMM which are based on the algorithms, and determine the tree structure. The tree topology initializes and is completed.

The original contribution of this method lies in its amalgamation of machine learning algorithms to develop a prediction procedure for RUL. Comparing the proposed method to existing approaches reveals several differentiating factors. Traditional methods for RUL estimation often rely on simplified models or else on rule-based approaches, which may have limitations in capturing complex degradation patterns and variations. In this identified gap, the proposed ANN model leverages the power of machine learning algorithms to overcome these limitations and provides a more data-driven and accurate RUL prediction framework. The integration of artificial neural networks enables the method to handle non-linear relationships and capture subtle degradation patterns that may not be captured by conventional approaches.

3.2. Artificial neural network models

The ANN articulate a relationship between the inputs, outputs, and their structure constituent is known as a neuron. The fundamental element of ANN is the artificial neuron, and such a relationship is expressed in Eq. (1) works by taking the x_{input} and transforming it into the y_{output} by using:

$$y_{output} = Weight \times x_{input} + Bias \qquad \text{Eq. (1)}$$

Where Weight and Bias are parameters for ANN, and it symbolizes the actual relationship between inputs and outputs. This relationship corresponds to a linear input dataset and a non-linear input dataset as in Eq. (2). A non-linear activation function is also added to this relationship.

$$y_{out} = f(w_i x_i + b_i) \qquad \text{Eq. (2)}$$

The prerequisite features of root mean square error are as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{I=1}^{N}(x_I - \hat{x}_I)^2} \qquad \text{Eq. (3)}$$

The actual linear RUL value is denoted by the x_I and the predicted RUL is denoted by $\hat{x}_I$ and the length is represented with n. The first parameter as shown in Eq. (3), is applied to measure the accuracy and precision of prediction because of the existence of some error with the predicted e value. The mean of the data series is calculated with the help of the feature of Kurtosis, and the relationship is expressed in the following expression.

$$Kurtosis = \frac{\sum_{k=1}^{k}(x(k)-x_m\ )^2}{(k-1)x_{std}^4} \qquad \text{Eq. (4)}$$

Kurtosis as in Eq. (4), x_m mean of data series $x(k)$ it works on the signal's series data such as k = 1, 2..., K, K represent data points. Standard deviation is also calculated as represented in Eq. (5).

$$x_{std} = \sqrt{\frac{\sum_{k=1}^{k}(x(k)-x_m\ )^2}{k-1}} \qquad \text{Eq. (5)}$$

For the probability density function and hazard rate in real-world applications, peripheral noise in the data is reflected in Eq. (6).

$$h(t) = \frac{f(t)}{1-F(t)} \qquad \text{Eq. (6)}$$

The cumulative density function is calculated with the use of the relationship expressed in Eq.(7). Where $f(t)$ is (PDF) and $F(t)$ is the cumulative density function as shown in Eq. (7).

$$F(t) = 1 - exp\left[-\left(\frac{t}{\gamma}\right)^{\eta}\right] \qquad t \geq 0 \qquad \text{Eq. (7)}$$

Weibull hazard rate function is obtained as (γ1 = 0.4077, γ2 = 0.4360) where (η1 = 1.2017, η2 = 1.2970) respectively. The fitted quantities of features are used as the input to represent the bearing's decline. RMS Weibull hazard rate relationship is expressed in Eq. (8) and Eq. (9). relationship for kurtosis Weibull hazard rate is expressed in Eq. (10) and Eq. (11) are given below.

$$Z_i^1 = \frac{f_i^1(t)}{1-F_i^1(t)} \qquad \text{Eq. (8)}$$

$$Z_{i-1}^1 = \frac{f_i^1(t)}{1-F_i^1(t)} \qquad \text{Eq. (9)}$$

kurtosis Weibull hazard rate equation

$$Z_i^2 = \frac{f_i^2(t)}{1-F_i^2(t)} \qquad \text{Eq. (10)}$$

$$Z_{i-1}^2 = \frac{f_i^1(t)}{1-F_i^1(t)} \qquad \text{Eq. (11)}$$

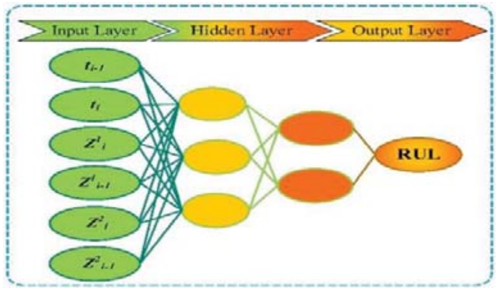

Fig.2. Structure of Proposed ANN Model

ANN Proposed model structure, as shown in Fig. 2. includes six inputs. Input, t_i and $t_{i-1}$are the time values, respectively. Z_i^1 and Z_{i-1}^1 are present and previous state of maintenance Z_i^2 and Z_{i-1}^2 are kurtosis values respectively. Here it is important to mention that the time, RMS, and kurtosis values are used for the calculation of the RUL of a bearing through the ANN Model. It has two hidden activation layers where bias weight propagates with normal weights linearly and nonlinearly and it facilitates to predict RUL.

The process flow diagram shown in Fig. 3. demonstrates the input data parameter of time and vibration signals. Weibull hazard rate function is fitted to each vibrational value. The time and fitted RMS and Kurtosis values are based on present and previous states and it is used to establish a dataset for validation of data up to +5%. In the training process, the same validation data set may also prevent overfitting, so ANN is trained with the Levenberg-Marquardt algorithm which helps an algorithm for training. the proposed network after training. It is used to forecast the RUL of bearings. The minimum error value is fed to the network before new vibrational signals, whose features are based on RMS and Kurtosis, which is fitted with the Weibull hazard rate function to resolve the nonlinearity of wind turbine problems. Bearing RUL is preferred for ANN which is referred T_i as output and for mapping the best health condition over the period

RUL. It is considered a benchmark parameter. It specifies that once the bearing reaches its specified life. it will be fully destroyed. The FEMTO dataset has been extensively utilized to illustrate various methods for condition monitoring and prognostics.

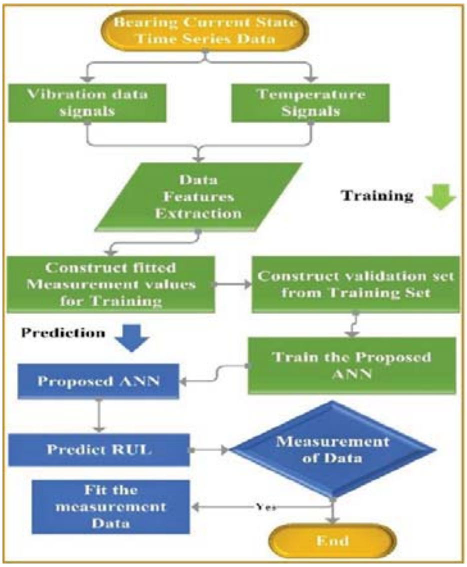

Fig.3. Proposed Reliability ANN Model

Some research is carried out on rolling element-bearing health condition monitoring, signal processing techniques, and high-frequency resolution of the vibration signals [16]. This dataset was also used in some publications to study the method of construction of HI from vibration signals[17]. This dataset is used to develop the RUL model[18]. Data analysis is used to train neural networks. Once an overfit is detected, it is discontinued training. The model performs well during the training process but performs poorly when tested with unknown data. The cross-validation method is used for overcoming this issue. For training and validating the network, two distinct sets of data are used. During an overfit situation, the validation set's mean square error (MSE) first decreases, till it reaches a minimum and then increases.

Training is discontinued as the validation set escalates. The mean square error starts increasing as a result of the regression algorithm which is based on overfitting of data. There is no specific method for the selection of an ANN topology. The evaluation of network topology test and error quest scheme occurs in two stages such as, divided data is first training and it is followed in the second stage by validation for instance training holds the actual data set beginning of input, and validation within +5% feed of data. ANN model is normalized at the output to obtain a similar order of magnitude between zero and one (0-1) to avoid the issues of instability with the modeled result. It is necessary to choose the minimum validation error for the prediction of RUL. The hidden layers are configured with a log-sigmoid transfer function and transfer function (linear) at the layer of output. By applying this combination network, it is possible to easily approximate any of the assigned function, Levenberg Marquardt (trainlm) algorithm provide satisfactory results in the training algorithm. The training algorithm is proposed for curtailing functions which is the square of the sum of the nonlinear function. The second-order convergence approach is performed by not considering the calculation of the Hessian matrix. The performance function is equal to the sum of squares followed by Hessian matrix approximation is performed as defined in Eq. (12).

$$H = g^T J \qquad \text{Eq. (12)}$$

where $g = J^T$ and J represents the Jacobian matrix, which includes network error with respect to biases and weights as the first derivative. ANN Algorithm standard back-propagation method can be used to compute the algorithm more easily than the Hessian matrix. Network error "e" can be calculated by the application of the ANN algorithm. Levenberg-Marquardt ANN logarithm is used for Hessian matrix approximation which is expressed as in Eq. (13).

$$X_{k+1} = X_k[-(J^T J + \mu l)^{-1}]J^T e \qquad \text{Eq. (13)}$$

Hessian matrix is used to initialize scalar value μ= 0 by using approximate same, which is similar to Newton's method. If the value is large, then it is transformed with a small step size by using the gradient descent method. Newton's method is found as quick and accurate with minimum error. The core goal is to switch on as possible as early as Newton's method. On each updated step the performance is lowered and vice versa so the performance function inductee is decreased at separate algorithm iterations. Network MSE [19] is applied to the data as shown in Eq. (14).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \text{ Eq. (14)}$$

Where, e_i, a_i, t_i, N are error, the actual value, desired value, and number of data points respectively. The proposed model approach with FEMTO data is used to verify the performance of ANN network. During this procedure, the training set data is fed into FFNN model. Fig. 3. and Fig. 4. depict the testing process' output performance. This performance demonstrates the use of the ANN model with time and RMS and kurtosis hazard rates as inputs and normalized life percentage of their output. The proposed ANN model is a suitable tool for the prediction of the RUL of Bearing.

3.3. Significance and validation of ANN

In this paper, the proposed ANN model is validated by using the actual and predicted test data of bearing to forecast the RUL. The prognosis of model RHSA assesses the useful life of a bearing, which can enable one to choose an option related to the reduction of downtime through early detection. In wind turbines and complex machine components, the ANN model can minimize downtime and maintenance costs due to early accurate prediction of RUL. it is effective for improving RUL prediction accuracy, particularly in noisy environments, hence it has significant practical application. In the decision making it saves the time, cost of scheduled maintenance and minimizes associated risks, and leads to ensuring the operation of power generation confidently.

4. Results

4.1. Proposed ANN model results

The Proposed model of ANN has generated desired results and it works efficiently under linear and non-linear machine problem situations. In bearing1_1 health vibrational signals are plotted in Fig. 4. The initial signals of the bearing are up to 2000 secs, which predict the health of the bearing, and signals above that level it shows the failure of the bearing. These signals are useful and change the signal intensity up to the peak value. Such sensed signals reflect the impact force or a fault point of the bearing due to wear and tear, which helps to obtain information for the RUL of the bearing.

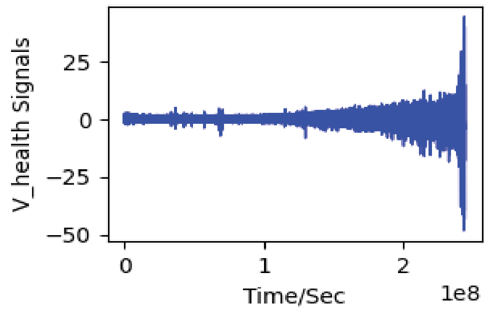

Fig.4. Bearing1_1 vibrational Health signal

The Temperature signals are assigned as input parameters to the ANN model with the vibrational signals for training. The temperature signals are shown in Fig.5. where signals are increasing with respect to time which indicates a direct relationship between vibration and temperature parameters and inverse proportionality between vibration and viscosity. It also reveals that rising temperature may lead to high friction, and consequently, it deteriorates the life of the bearing. Such information is supplied to the Neural Network to calculate the degradation process and prediction of the RUL of bearing.

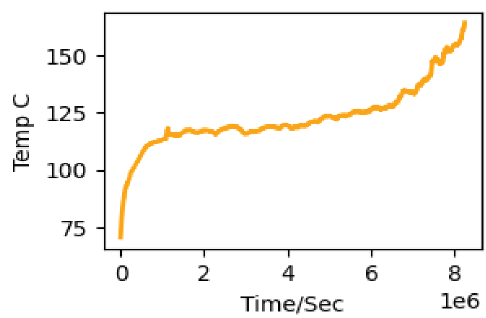

Fig.5. Temperature Signals for Proposed ANN Model

The RMS of the bearing shown in Fig. 6. describes the changing state of vibrational signals. It serves as a significant indicator regarding health conditions and degradation of bearing. The results represent the RMS behavior changes with subsequent changes in weights and bias with respect to time. Hence, the findings suggest that when the time surpasses 2500 seconds, there is a noticeable shift in the pattern and intensity of vibration signals, indicating the onset of bearing degradation and imminent risk of failure.

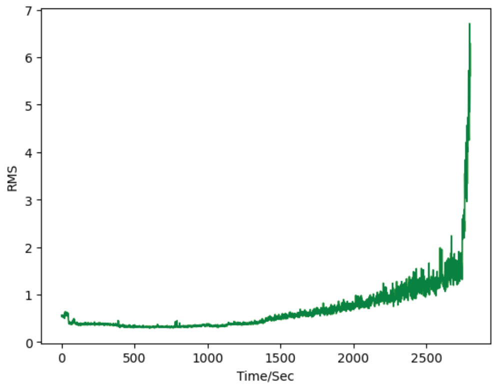

Fig. 6. RMS of Bearing1_1

ANN model can learn to associate certain vibration patterns with different stages of bearing health, enabling it to make predictions about the remaining useful life of the bearing. Therefore, this feature works like an actual scenario to forecast the bearing life and fault identification.

In Fig. 7. Kurtosis values are used to scale the data, based on the previous and present state of condition of the bearing. Since Kurtosis is sensitive to impact signals, it diagnoses the surface damage faults. However, it is fourth-order static, so it is very difficult to distinguish the fault signal from the noise.

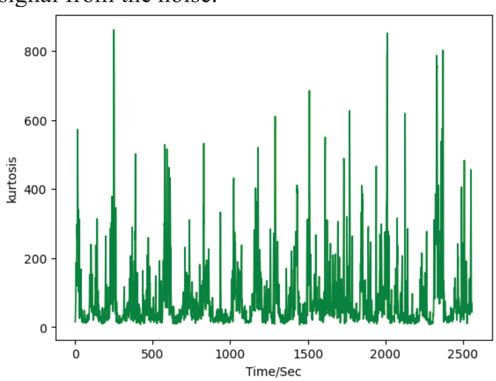

Fig.7. Kurtosis of Bearing1_1

Pulse reflecting surface fault characteristic extracted from pulse modulation signals mixed with noise. kurtosis helps to assess the presence of abnormal or extreme values in the vibration signals alongside other relevant features, and behavior of vibration signals.

ANN can learn the relationship between the statistical properties of the vibration signals and the health state of the bearing leading to improved prognostic capabilities.

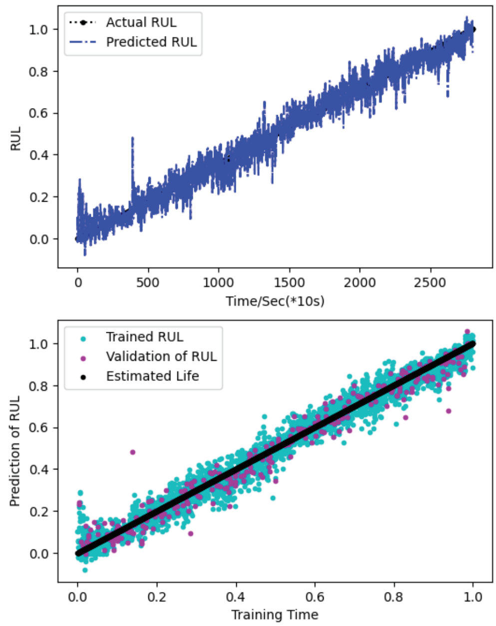

Fig. 8. Result of ANN Model

Fig. 8. shows a linear relationship that exists between predicted RUL and the behavior of vibrational signal, which shows the capability, efficiency, and effectiveness of the proposed ANN model under the specified condition in the prediction of the remaining useful life of the bearing, as indicated with a blue line across the black line. However, it is important to note that a here ANN model is showing the linear relationship between the actual and predicted RUL because of lower RSME and MSE error which reflect the better performance of ANN model results near to actual RUL but this may not always be expected or feasible in all cases. The suitability of a linear trend depends on the specific degradation pattern. Different degradation mechanisms may exhibit different patterns and the proposed model can capture non-linear relationships between predicted and actual RUL. In brief, the presence of a linear relationship between the actual and predicted RUL in Fig. 8.

indicates that the proposed ANN model is performing accurately in estimating the remaining useful life of the bearing, providing valuable insights for maintenance planning and decision-making. The trained (RUL) refers to the predicted remaining lifespan of the bearing based on the training data in the developed model. It represents the estimated time to reflect the operation of the bearing before reaching failure. The Validation RUL of bearing involves assessing the accuracy and reliability of predictions by comparing the predicted RUL values with the actual RUL values as acquired from real-time monitoring. The estimated life indicates the predicted residual life of the bearing at different time points. It is plotted against the corresponding time on the X-axis where estimation is based on the trained model's analysis of the bearing's health condition, depicted through various sensor signals or input features. As a result, the estimated life of the bearing provides insights into the expected longevity that allows one to make decisions regarding proactive maintenance. The ANN Model is further applied to additional training datasets, including bearings 1_2, bearing2_1, bearing2_2, bearing3_1, and bearing 3_2, along with testing bearings, to evaluate their reliability and predict the remaining useful life of bearings. The model demonstrates robust performance in predicting the Remaining Useful Life (RUL) of bearings.

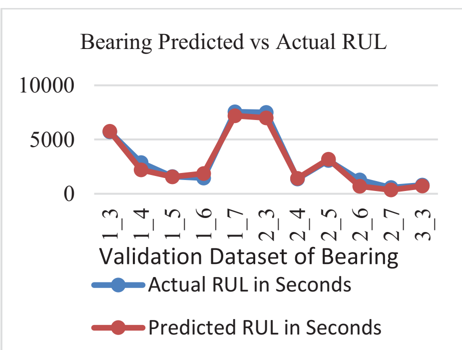

Fig. 9. Trained Predicted and Actual Tested Result

The results obtained from the conducted experimental test data were completely analyzed. These results were compared with the predicted values of the remaining useful life (RUL), as illustrated in Fig. 9. The X-axis represents the samples from the validation dataset of the test bearings, while the Y-axis represents the corresponding predicted and actual RUL values of each tested bearing. Fig. 9. shows the accurate and precise determination of the actual and predicted RUL of the bearings by the ANN model. The validation set of testing data for the test bearings illustrated as shown in Table 4.1., was utilized to derive and predicted RUL values over time. The comparison in Fig. 9. predicted and actual values further confirm the superior performance of the ANN model in accurately predicting the RUL of the bearings.

4.2. Result in Comparison with Other Models

The proposed model was evaluated and compared with some other machine learning models (SVR, LSTM, DNN model) based on key features such as RMSE see Table. 4.1., Score, and RUL. These variables were used to evaluate each model's predictive accuracy, performance, and robustness. Similarly, the estimated score of models such as SVR, LSTM, DNN, and proposed ANN model is 0.306, 0.429, 0.482, and 0.812, respectively. The comparison provides scientific evidence to support the advantages of the proposed ANN model over other machine learning models. The lower the RMSE, the lower the overall prediction error, and high score values represent model accuracy.

Table. 4. 1. RMSE estimation of results comparison with three other machine learning models

Description	SVR	LSTM	DNN	Proposed ANN
Bearing1_3	215.9	131.6	44.5	13.26
Bearing1_4	14.85	15.75	31.2	3.515
Bearing1_5	4.17	3.17	21.5	0.240
Bearing1_6	11.46	9.92	34.2	3.160
Bearing1_7	14.67	17.45	33.5	3.941
Bearing2_3	13.97	15.09	19.6	3.346
Bearing2_4	1.85	1.98	25.2	0.142
Bearing2_5	7.33	7.63	38.5	2.414
Bearing2_6	2.66	3.23	43.2	0.409
Bearing2_7	1.12	0.82	38.7	0.338
Bearing3_3	3.09	3.15	43.5	0.414

Hence, the lower RSME and higher the score confirms the model prediction of RUL is closer to the actual value. The Proposed ANN model demonstrates proficiency in handling intricate data, showcasing its resilience and predictive capabilities, thereby affirming its aptness for the given task more than the other models.

5. Conclusion

The outcomes of the proposed ANN model showcase its better performance in precisely predicting the remaining useful life of the bearing. The proposed model outperforms better than other machine learning methods due to its ability to effectively handle large datasets and complex calculations associated with bearings, considering both linear and non-linear factors. This capability enables the model to provide accurate RUL predictions. The implementation of the proposed model significantly contributes to improving overall bearing efficiency and preventing failures by enabling proactive maintenance in critical areas at offshore horizontal axis wind turbines such as other assembly parts and components. Future research endeavors will focus on further advancing RUL prediction methods by incorporating the real-time provision of maintenance strategies, specifically targeting high-speed rotating bearing failures across diverse operating conditions.

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