# A Fault Diagnosis Technique for Wind Turbine Gearbox: An Approach using Optimized BLSTM Neural Network with Undercomplete Autoencoder

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*Received: 21 December 2022 | Revised: 3 January 2023 and 7 January 2023 | Accepted: 9 January 2023*

## ABSTRACT

**The gearbox is one of the critical components of a wind turbine. Proactive maintenance of wind turbine gearboxes is crucial to decrease maintenance and operational costs and the long downtime of the complete system. As the gearbox is a significant part of the wind turbine, a fault in the gearbox leads to the breakdown of the wind turbine system. Hence, it is important to study and analyze the faults in wind turbine gearbox systems. In this article, a neural network-based model, a Bidirectional Long Short-Term Memory (BLSTM) fused with an autoencoder is intended to categorize the condition of the gearbox into good or bad (broken tooth) condition. Feature learning and reduction are achieved extensively through the autoencoder. This improves the performance of the BLSTM model regarding time complexity and classification accuracy. This model has been applied with time series vibration data of the gearbox in a wind turbine system. The suggested model's performance is analyzed using an openly available wind turbine gearbox vibration dataset. The result showed that BLSTM accuracy with an under-complete autoencoder is highly robust and appropriate for the health monitoring of wind turbine gearbox systems using time series data. Also, in order to illustrate the advantage of the projected model for fault analysis and diagnosis in wind turbine gearbox, the throughput or time complexity of training and testing of the split dataset is compared with the conventional BLSTM model.**

***Keywords-autoencoder; bidirectional long short-term memory; fault detection; vibration data; wind turbine gearbox***

## I. INTRODUCTION

Wind energy is very popular, since it is form of clean energy. For the effective production of wind energy, the wind turbines must be maintained with less downtime. Gearbox failure directly impacts the reliability of the gearbox in the wind turbine. The operation and the cost towards the maintenance of wind turbines installed at remote locations is around 15–35% of the installation cost. Around 80% of this is spent on unplanned maintenance issues resulting from defects in the wind turbine's various components [1]. Wind turbine fault analysis and diagnosis are usually performed manually from individuals with a high level of technical expertise. This method is inefficient and incapable of meeting the needs of wind farm operations and maintenance. It also leads to production loss due to the prolonged unavailability of the energy production system and requires a large number of fault diagnosis analysts. The increase in demand for wind energy needs reliable wind farms. To reach the demands, the design of low-cost advanced proactive intelligent fault detection systems is crucial for better performance. The gearbox is one of the most vital and frequently worn parts of the mechanical rotatory system of a wind turbine. Wind turbine gearbox failure diagnosis is critical in mechanical rotating systems, and unpredicted breakdown of this component results in prolonged system downtime. Wind turbine energy production unit maintenance and operating may determine whether the system is cost-efficient or not. Therefore, an intelligent and proactive fault detection system, which reduces the downtime of the wind turbine energy production system, is essential, since it reduces the number of skilled professionals required for maintenance. An expert system enables timely intervention and early warnings and hence reduces production loss due to prolonged unavailability. As a result, a smart system for condition monitoring of wind turbines improves the reliability by reducing downtime significantly. In the current work, the proposed hybrid Bidirectional Long Short-Term Memory (BLSTM) model with an autoencoder achieves an accuracy of 98.68% in wind turbine gearbox healthiness classification and improves the performance by 71.73% in testing and 65.61% in training when compared with the original BLSTM model. In the next section, various efforts to diagnose and analyze wind turbine gearboxes are discussed.

## II. RELATED WORK

A few efforts have been made to use traditional machine learning algorithms to classify the healthiness of the gearbox. The time-domain sequence Approximate Entropy (ApEn) adaptive strategy, a Wavelet Packet Transform (WPT) filter, and a Cross-validated Particle Swarm Optimized (CPSO) kernel extreme learning machine were used to develop gearbox fault analysis models in [1]. The Discrete Wavelet Transformation (DWT) was used to compute wavelet coefficients for vibration signals obtained from wind turbines. Wavelet coefficients are applied to Phase Space Reconstruction (PSR) and singular value decomposition to extract fault attributes in [2]. The Supervisory Control and Data Acquisition (SCADA) process delivers the most frequently used input data for wind turbine anomaly detection [4]. By reducing the feature dimension of the time-series data, Dynamic Principal Component Analysis (DPCA) was used to identify faults in the gearbox of wind turbines in [5]. To extract gearbox vibration features from oscillated vibration signals of gearbox fault diagnosis, a method combining the Empirical Mode Decomposition (EMD) and Time Synchronous Averaging (TSA) was used in [6]. To detect anomalies in the wind turbine gearbox, Twin Support Vector Machine (TWSVM) and an adaptive threshold were used in [7]. To extract features from three-axial vibration data for fault diagnosis of a wind turbine gearbox, a Deep Enhanced Fusion Network (DEFN) was used in [8]. The deep joint variational autoencoder method was used in conjunction with wind farm supervisory control and data acquisition to diagnose faults in the wind turbine gearbox in [9]. By decomposing vibration signals with a wavelet packet, a fast deep graph convolutional network model was used to analyze the wind turbine gearbox in [10]. The fused vibration signals were classified with a multiclass SVM model in [11]. Electrical signals from generator terminals were used to find faults in the gearbox of the wind turbine in [12]. Using fault features of convolution channels and frequency bands of wavelet coefficients, the residual network can be used to identify a fault in the gearbox of a wind turbine [13]. The methods of convolutional neural networks and isolation forests were applied to classify the health of the gearbox of a wind turbine in [14]. The neighborhood component analysis technique for best feature collection was used to evaluate the healthiness of wind turbine gearboxes in [15]. The remaining useful life of a wind turbine gearbox and its failure can be predicted using machine learning methods such as artificial neural networks, SVM, and logistic regression [16]. CNN is used for feature extraction and representation, and LSTM is used to learn the latent time series relationship between features in various periods of time [17]. An optimized LSTM neural network with cosine loss was used to analyze wind turbine gearbox faults in [17]. The Cos-LSTM networks were analyzed using the wavelet energy entropy and energy sequence features of the vibration signals in [18]. The traditional LSTM model was improved using multiple swarm intelligence models for classifying failures in the wind turbine gearbox using vibration signal data acquired from the faulty gearbox in [19]. The Simulated Annealing (SA) algorithm was used to optimize the vibration of the powertrain system in [21]. To analyze the functional schemes of the selected gears, the method for trying to generate a mechanism of kinematics equations for signal dependency graphs was used in [22]. Industrial bearing, fault detection, and isolation using time frequency domain has been applied and compared with the theoretical results in [23]. The following are the main contributions of the current article:

- Design of a gearbox diagnostic model using an undercomplete autoencoder and the BLSTM deep learning model.
- Analysis of vibration data collected through sensors.
- Comparison of the proposed model's training and testing times to those of the conventional BLSTM model.

## III. PROPOSED MODEL

The projected model was created on undercomplete autoencoder along with a BLSTM-based hybrid model to diagnose and classify wind turbine gearbox health conditions. The undercomplete autoencoder and BLSTM architectures are described below.

### *A. Undercomplete Autoencoder*

Autoencoders are unsupervised learning methods used for representation learning. The neural network architecture denotes autoencoders to impose a bottleneck in the neural network, resulting in a compressed feature representation of the original input. Autoencoders contain four layers, namely input layer, hidden layer, bottleneck layer, and output layer. The objective of autoencoders is to minimize the number of nodes located in the hidden layer in order to reduce the information flow through the neural network. An autoencoder model discovers the most important characteristics of the input data. The compressed and essential features are extracted at the bottleneck layer in order to recreate the original data with minimal loss. The number of neurons in the hidden layer is lesser than the number of neurons in the input layer. The bottleneck layer contains fewer nodes than the hidden layer. The reduced features are extracted from the bottleneck layer.

### *B. Bidirectional LSTM*

The bidirectional LSTM recurrent neural network is made up of LSTM cells, which are memory blocks with a hidden unit. Such states have the responsibility to transfer immediately preceding time step data in the network from the input state to the next cell. These cells are made up of input, forget, and output gates. The forget gate forgets irrelevant information, the input gate updates new information, and the output gate passes the updated information to the next cell.

### *C. Design*

Figure 1 depicts the construction of an autoencoder with a BLSTM-based model. To design the proposed model for time series gearbox vibration data analysis, input samples of 3600 (1600×2) with a sample size of 500 time steps were fed to the undercomplete autoencoder. The output of the encoder tapped at the bottleneck has reduced features and contains 350 time steps in each sample. The compressed data are loaded into the BLSTM model, which is trained for 500 epochs. To achieve better results, the model employs the rmsprop optimizer and the sigmoid perceptron at the output layer. The metrics are recorded and discussed below.

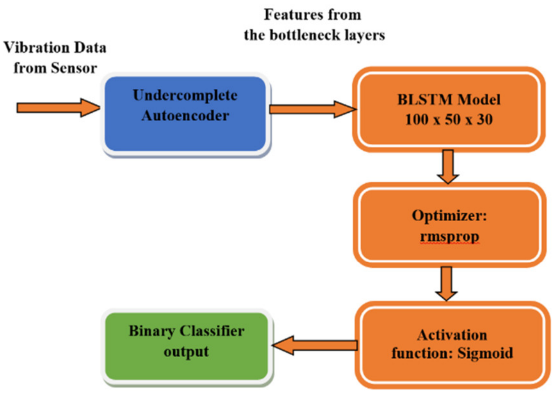


Fig. 1. Proposed autoencoder and BLSTM-based model.

## IV. EXPERIMENTATION AND RESULTS

The developed autoencoder and BLSTM-based model were tested on experimental data collected in a publicly available wind turbine gearbox vibration dataset [20]. Spectra Quest's Gearbox Fault Diagnostics Simulator was used to generate vibration data for two conditions of the gearbox, one for good health and the other for a broken tooth, and both were subjected to bearing capacity ranging from 0% to 90%. Four sensor nodes were positioned in 4 different locations on the body of the gearbox. The dataset contains 10 samples with different loads of wind turbine gearbox vibration data in good and bad conditions. The dataset was created with a 30Hz frequency for a total of 6.9s. Each sample was collected at a rate of 12,800 time steps/s. A total of 69s (6.9×10) for data generation for a broken tooth or bad condition and data generation for a healthy condition was considered. Table I shows the raw recorded data.

TABLE I. WIND TURBINE GEARBOX VIBRATION DATASET

| Wind turbine gearbox condition | Number of samples | Time steps per second | Time steps per sample |
|---|---|---|---|
| Good | 10 | 12800 | 88320 |
| Bad (broken tooth) | 10 | | |

Each sample is made up of 88320 time steps. Because the time series sequence is too long, the data have been divided into subsamples of 500 time steps. As a result, 176 samples from each sample of length 88320 time steps were derived by considering 500 time steps for each individual sample. As a result, we acquired 1760 (176×10) good-condition gearbox samples and 1760 (176×10) bad-condition gearbox samples. The derived dataset contains 3520 samples, as shown in Table II. The purpose of choosing 500 as the subsample's time step is to facilitate experiments, however the size of the sample set can vary. We chose 3200 sample data at random from a total of 3520 for experiments.

TABLE II. GENERATED WIND TURBINE GEARBOX VIBRATION DATASET

| Wind turbine gearbox condition | Number of samples | Total number of samples |
|---|---|---|
| Good | 1760 | 3520 |
| Bad | 1760 | |

To collect vibration data, 4 sensors were placed on the body of the gearbox in 4 different directions. Table III displays the Accuracy, Precision, Recall, F1-score, Training Time (time taken to train a total 80% of the 3200 (i.e. 2560) training samples, and Testing or Execution Time (time taken to test a total of 640 testing samples (20% of 3200)). It is tested with data frequency (dataset sample size in time steps) equal to 500 time steps and a trained dataset with 500 epochs. The results were captured on a machine with the following architecture: GPU: NVIDIA-SMI 460.32.03, CUDA Version:11.2, Tensor Core GPU: A100-SXM4-40GB with a runtime memory of 89.6GB.

TABLE III. PERFORMANCE OF THE BLSTM MODEL

| Sensor | Precision | Recall | F1-Score | Training Time (s) | Testing Time (s) | Classification Accuracy |
|---|---|---|---|---|---|---|
| S-1 | 0.9875 | 0.9783 | 0.9828 | 8697.74 | 9.76 | 98.28% |
| S-2 | 0.9838 | 0.8892 | 0.9341 | 8121.10 | 8.17 | 93.28% |
| S-3 | 0.6451 | 0.8695 | 0.8480 | 8722.22 | 13.30 | 78.12% |
| S-4 | 0.9062 | 0.6904 | 0.7837 | 8200.48 | 19.03 | 75.00% |

TABLE IV. PERFORMANCE OF THE UNDERCOMPLETE AUTOENCODER WITH THE BLSTM MODEL TESTED WITH VIBRATION DATA FROM SENSOR-1

| No. of time steps tapped at the bottleneck | Precision | Recall | F1-Score | Training Time (s) | Testing Time (s) | Classification Accuracy |
|---|---|---|---|---|---|---|
| 50 | 0.9617 | 0.9123 | 0.9364 | 1175.35 | 2.16 | 93.59% |
| 100 | 0.9593 | 0.8924 | 0.9246 | 1334.07 | 2.68 | 92.19% |
| 150 | 0.9693 | 0.9080 | 0.9376 | 1776.15 | 2.70 | 93.44% |
| 200 | 0.9660 | 0.9260 | 0.9456 | 1997.61 | 2.61 | 94.38% |
| 250 | 0.9670 | 0.9376 | 0.9571 | 2188.04 | 2.31 | 95.12% |
| 300 | 0.9793 | 0.9776 | 0.9421 | 2792.95 | 2.46 | 96.53% |
| 350 | 0.9895 | 0.9783 | 0.9857 | 2991.74 | 2.76 | 98.68% |

Since the Classification Accuracy using Sensor-1 and Sensor-2 vibration data is optimum, the significance of Sensor-3 and Sensor-4 vibration data analysis has less importance. Hence, the diagnosis of the gearbox fault can be achieved with an exemption of Sensor-3 and Sensor-4 vibration data as these two sensors yield less Accuracy. Hence, the proposed model was tested only on Sensor-1 vibration data.

Table IV shows different test cases with varied numbers of features extracted at the bottleneck layer of the autoencoder with data frequency equal to 500 (number of time steps in each sample), tested with Sensor-1 vibration data. The results clearly show that at the bottleneck output of 350 time steps outperforms the model with respect to Accuracy and Training and Testing Times.

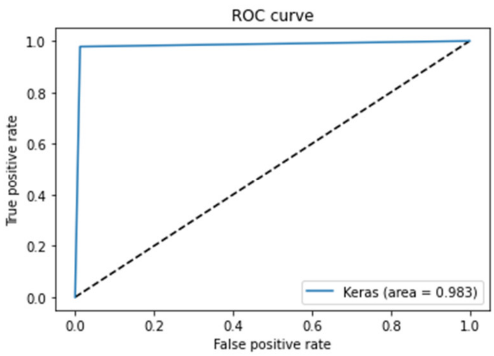


Fig. 2. ROC curve for vibration data from Sensor-1 with 80-20% split ratio BLSTM model.

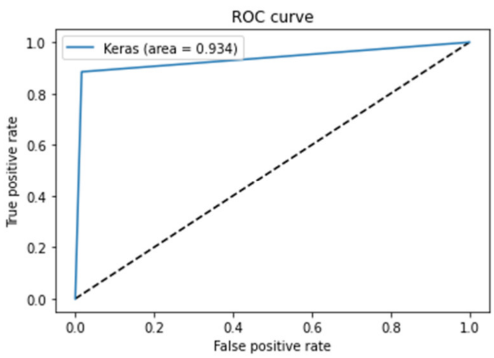


Fig. 3. ROC curve for vibration data from Sensor-2 with 80-20% split ratio BLSTM model.

The proposed method outperforms the BLTSM algorithm model in Classification Accuracy, Training Time, and Testing Time. Based on the experimental observations; the results indicate that the gearbox fault vibration data features can be learned to improve the generalization and the model's accuracy by fusing the undercomplete autoencoder and BLSTM models. However, the result comparison in Tables V-VI shows that the proposed model achieves 98.68% Accuracy with reduced features (350 time steps) in the samples, and the performance is increased by 71.73% in testing time and 65.61% in training time when compared to the BLSTM model. As a result, the fused model of autoencoder with BLSTM outperforms the conventional BLSTM.

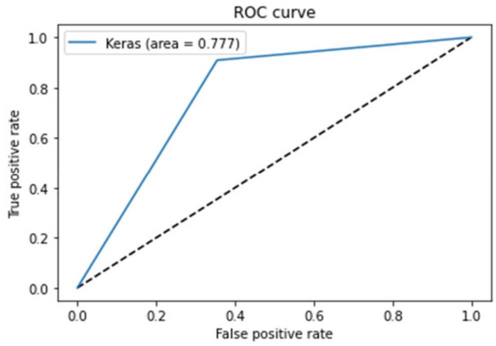


Fig. 4. ROC curve for vibration data from Sensor-3 with 80-20% split ratio BLSTM model.

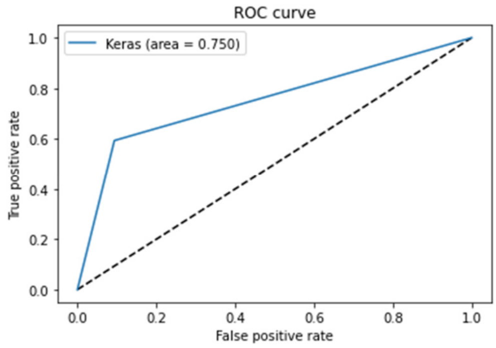


Fig. 5. ROC curve for vibration data from Sensor-4 with 80-20% split ratio BLSTM model.

TABLE V. PERFORMANCE COMPARISON OF THE PROPOSED MODEL WITH BLSTM

| Sensor | Conventional BLSTM model with 500 time steps per sample | | |
|---|---|---|---|
| | **Training Time (s)** | **Testing Time (s)** | **Classification Accuracy** |
| S-1 | 8697.74 | 9.76 | 98.28% |
| **Undercomplete autoencoder with BLSTM model with 350 time steps per sample** | | | |
| | **Training Time (s)** | **Testing Time (s)** | **Classification Accuracy** |
| S-1 | 2991.74 | 2.76 | 98.68% |

TABLE VI. GEARBOX HEALTH DIAGNOSIS METHOD COMPARISON

| **Ref.** | **Method** | **Accuracy** |
|---|---|---|
| [2] | WPT-PSO-KELM | 94.17% |
| [18] | Cos-LSTM | 98.55% with 550 samples |
| [19] | LSTM with firefly, cuckoo, PSO and ACO and relu activation function | 87.5% |
| [5] | Support vector machine model used to detect and isolate gear faults. It performs better than the Dynamic Principle Component Analysis (DPCA) using MLP | 91.24% |
| [24] | A technique for feature extraction based on CNN and LSTM for categorization was used to estimate gearbox faults using a better prediction method based on the early fusion of multisource sensing data | 97.9% |
| Proposed | Undercomplete autoencoder with BLSTM | 98.68% |

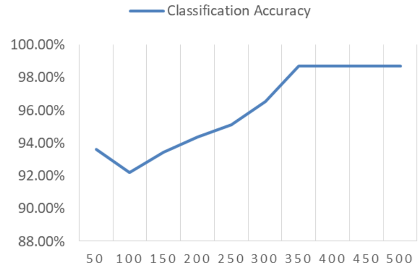


Fig. 6. Performance of the undercomplete autoencoder with BLSTM.

## V. CONCLUSION

This article provides the analysis of wind turbine gearbox vibration data for fault classification. The proposed hybrid model, combines the bidirectional LSTM neural network algorithm with the undercomplete autoencoder and is used for wind turbine gearbox fault detection and diagnosis. The experimental results demonstrate that the suggested model gives an Accuracy of 98.68% in wind turbine gearbox fault classification and improves the performance by 71.73% in the dataset testing samples and 65.61% in the dataset training samples, when compared to the traditional bidirectional LSTM model. With respect to Testing and Training Time, as well as Classification Accuracy, the proposed model outperforms the known models that was compared with.


## ACKNOWLEDGMENT

The authors would like to thank Dr. Yogesh Pandya, Symbiosis University of Applied Sciences, Indore for his help and for providing the dataset for public access.


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