Chapter 9
A Comparative Study of Feature Selection Methods for Wind Turbine Gearbox Bearing Fault Prognosis

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Abstract This paper focuses on comparing two main approaches for selecting input and target features for training a normal behavior model (NMB) using wind turbines' SCADA data. The NMB models aid in predicting gearbox failure in wind turbine structures. In the first approach, the target feature is excluded from the input features, and in the second approach, the NBM models are trained using lagged measurements of the target feature. Historical SCADA data from a wind farm are used in this study. The SCADA data are preprocessed and used to train four sequential artificial neural network long short-term memory (LSTM) models to predict the normal behavior of the target feature. The analysis of the errors between the predicted and measured output feature indicates that the first approach is more promising in failure prognosis, and the gearbox oil temperature is found to be the optimal target feature to foreshadow deterioration in components.

Keywords SCADA data · Wind Turbine · Prognosis

Introduction

The continuous monitoring of wind turbine (WT) components is critical for the early detection of potential failures. Operation and maintenance (O&M) of wind farms can account for a significant portion of their lifetime expenses, with some offshore projects reporting costs as high as 30% of the total expenditure [1]. To reduce these costs, condition-based maintenance

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systems are essential. These systems often require additional devices to measure and record the system behavior via various indicators, such as vibration response. In contrast, using Supervisory Control and Data Acquisition (SCADA) systems for WT condition monitoring is more cost-effective, as the manufacturer already integrates them into WTs.

Gearbox failures in WTs are particularly costly and result in the longest downtimes [2], making their prognosis highly critical. Previous research has focused on using SCADA data for WT fault prognosis. For instance, using high-frequency SCADA data, a neural network model combined with a one-class support vector machine classifier was employed by [3] to detect early gearbox faults. Their framework successfully predicted anomalies weeks in advance as it detected 80.9% of anomalies one week before failure. Another study investigated WT gearbox bearing failure prognosis using SCADA data alongside modeled data [4]. The authors trained and tested four algorithms and concluded that the LSTM model outperformed others in detecting faulty data during the month preceding failure. Previous research has also shown that failures of other turbine components, such as the main bearing, can be detected several months before a catastrophic breakdown [5].

When using neural networks to analyze SCADA data, one of the main challenges is selecting the most relevant features to ensure accurate predictions of the target feature. Additionally, it is crucial to identify the target feature that best reflects the deterioration of the component of interest when its behavior deviates from the norm. This study uses only SCADA data to compare two modeling strategies for predicting WT gearbox bearing failure. In one approach, the target feature is excluded from the input features, while in the other, the target feature is included as an input. The study also investigates which target feature is the most reliable indicator of impending WT gearbox bearing failure.

Methodology

The framework in this study consists of three main stages: 1) data preprocessing, 2) training and validating the normal behavior models (NBMs), and 3) testing the models on unseen data to compare the capacity of different approaches in performing gearbox bearing fault prognosis.

Data preprocessing

The data used in this study was collected by a research partner from a wind farm in the southern USA from December 1, 2008, to October 31, 2018. Table 1 details the available SCADA data per channel and unit. Only one WT was analyzed from the dataset. The selected WT experienced a high-speed shaft gearbox bearing failure. The gearbox was replaced on January 13, 2011, which is considered as the failure date in this study.

Table 1 SCADA channels for the available data.

SCADA channel	Units
Power	kW
Rotor speed	rpm
Wind speed	m/s
Wind direction (10 sec)	-
Wind direction (1 sec)	-
Gearbox oil temperature	°C
Gearbox bearing temperature	°C
Ambient temperature	°C
Nacelle temperature	°C

Since the impact of installing new components in the WT is not within the scope of this research, data collected after the gearbox replacement is omitted. Additionally, data recorded during low or extremely high wind speeds and during maintenance periods were excluded. Only data collected under normal running conditions were retained. Despite the discontinuity in the data, and given that the potential imputation methods may impact the comparison, no data imputation was performed.

The dataset was split into training, validation, and test sets, as shown in Figure 1. To ensure the model is trained only on healthy data, the last 9 months before the failure date (which may contain faulty data) were reserved for testing, while the remaining data was used for model training. Finally, the data was normalized to a [0, 1] range since the features have varying scales.

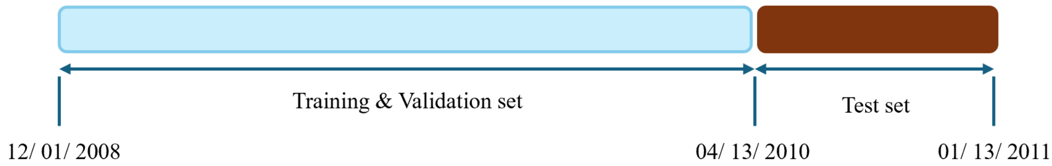

Fig. 1 Training, validation, and test data split for the studied WT.

Normal Behavior Model Development

Recurrent neural networks are designed for temporal data [6], preserving the running flow of information for their decision-making process. Long Short-Term Memory (LSTM), a type of recurrent neural network, is thus chosen to build four neural network architecture models to accommodate various features to be chosen as input and target features. The input and target features for each model are shown in Table 2. Gearbox oil and bearing temperatures, which are relevant to the component of interest, are selected as target features. Two models with different input features are built to predict each target feature. Models 1 and 2 predict future instances of the gearbox oil temperature from past measurements of the input features—*i.e.,* to predict the gearbox oil temperature at time *t*, observations of the input features at times *(t-1), (t-2)…, (t-n)* where $n = 144$, which is equivalent to the number of recorded measurements per day are fed to the model. Similarly, Models 3 and 4 are built to predict the gearbox-bearing temperature.

Table 2 Input and target features for each model.

Model 1		Model 2		Model 3		Model 4	
Input Features	**Target Feature**	**Input Feature**	**Target Feature**	**Input Features**	**Target Feature**	**Input Feature**	**Target Feature**
Power	Gearbox Oil Temperature	Gearbox Oil Temperature	Gearbox Oil Temperature	Power	Gearbox Bearing Temperature	Gearbox Bearing Temperature	Gearbox Bearing Temperature
Rotor Speed				Rotor Speed			
Wind Speed				Wind Speed			
Gearbox Bearing Temperature				Gearbox Oil Temperature			
Ambient Temperature				Ambient Temperature			
Nacelle Temperature				Nacelle Temperature			

Testing the NBMs and Gearbox Bearing Fault Prognosis

In the final stage, the trained models were tested on unseen data to evaluate their ability to predict gearbox bearing faults. The test data was used to assess the models' performance in identifying early signs of gearbox deterioration. The models' accuracy in forecasting abnormal behavior and potential failures was evaluated by comparing the predicted values to the actual SCADA measurements during the test period. The effectiveness of each model was determined based on how well it detected deviations from normal operating conditions leading up to the gearbox failure.

Results and Discussion

After training the four NBM models, they were used to predict the target features. Figures 2(a) and 2(b) show the predicted and measured target features over a specific period from the test set. The predictions closely align with the measured normal signals, demonstrating that the models learned the normal data patterns with a high degree of accuracy.

Table 3 presents the root mean squared errors (RMSEs) for comparing the predicted and actual target features during the last three months before the reported failure. All models show an increasing trend in the RMSE as the failure date

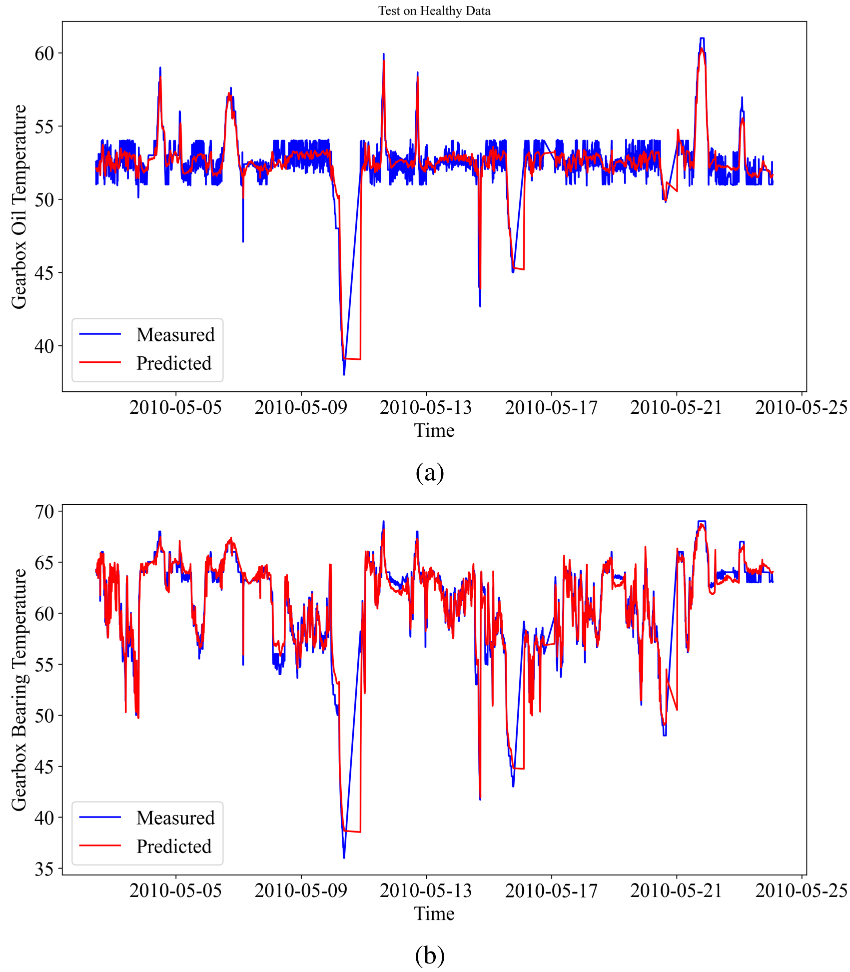

Fig. 2 Target feature prediction: (a) measured and predicted Gearbox Oil Temperature for a specific period in the test set, b): measured and predicted Gearbox Bearing Temperature for a specific period in the test set.

approaches, suggesting that the rising error is likely due to the progressive deterioration of the component before the actual failure occurs. For Model 1, which predicts gearbox oil temperature, the RMSE increased by 13% from the third-to- last month before failure to the second-to-last month, and 70% from the second-to-last month to the final month. Similarly, for Model 2, which also predicts gearbox oil temperature, the RMSE rose by 15% from the third-to-last month before failure to the second-to-last month, and 37% from the second-to-last month to the final month. For Models 3 and 4, which predict gearbox bearing temperature, the RMSE increased by 2.5% (Model 3) and 15% (Model 4) from the third-to-last month to the second-to-last month before failure. From the second-to-last month to the final month, the RMSE increased by 46% for Model 3 and 25% for Model 4. These results indicate that Models 1 and 3, which predict their target features using six input features, are more indicative of impending failure compared to Models 2 and 4, which use past measurements of the target feature as input. Furthermore, the changes in error between the predicted and actual gearbox oil temperature provide more reliable predictions of future failures than those between the predicted and actual gearbox bearing temperature.

Table 3 RMSE for the four models for the last month before gearbox bearing failure.

	Model 1	Model 2	Model 3	Model 4
Period of testing	RMSE			
Third last month before failure	0.0195	0.0159	0.0197	0.0164
Second last month before failure	0.0222	0.0183	0.0202	0.0189
Last month before failure	0.0378	0.0251	0.0295	0.0237

Conclusions

This paper investigated two alternative approaches for training NBMs for WT gearbox bearing fault prognosis and explored the optimal feature for detecting deterioration in the component of interest. The analysis of four different NBM models demonstrated that training the model using features that exclude the target feature is more effective for fault prognosis than the approach that utilizes past measurements of the target feature. Additionally, the results revealed that gearbox oil temperature is a more reliable indicator of gearbox bearing deterioration than gearbox bearing temperature.

Future work will employ generative models, such as Generative Adversarial Networks (GANs), for WT gearbox prognosis. Moreover, the potential of analyzing the frequency domain instead of the time domain will also be investigated.

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