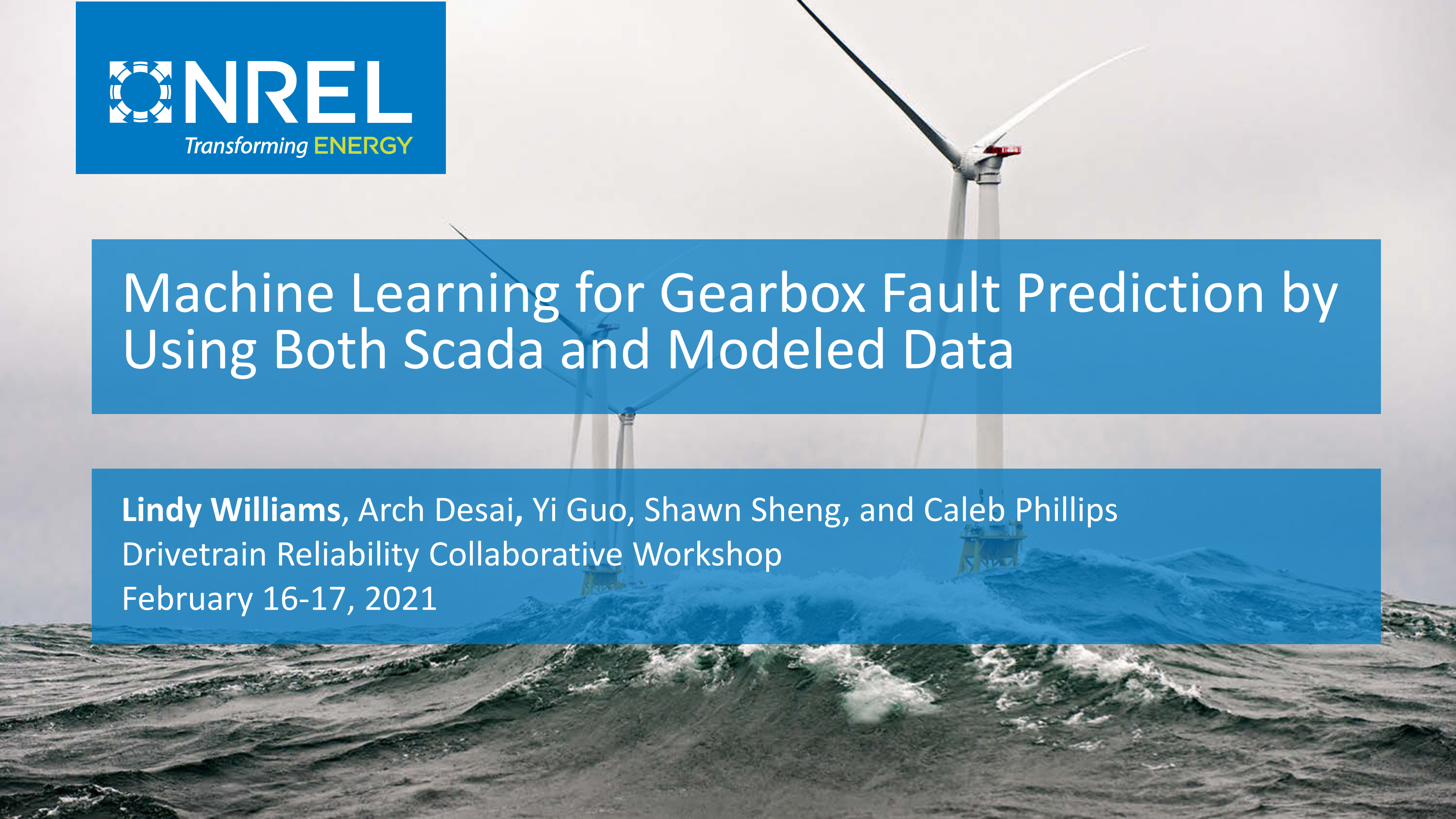

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Machine Learning for Gearbox Fault Prediction by Using Both Scada and Modeled Data

Lindy Williams, Arch Desai, Yi Guo, Shawn Sheng, and Caleb Phillips

Drivetrain Reliability Collaborative Workshop

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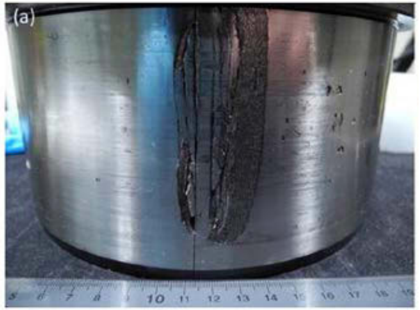
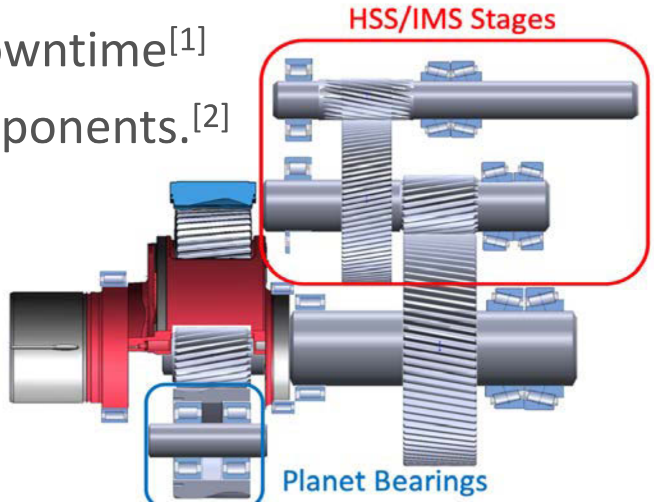
Background

1. Axial cracking in intermediate and high-speed-stage shaft bearings (white etching cracks: WECs)
2. Most common failure mode in WT gearboxes[1]
3. Possibly resulting in costly repairs and high downtime[1]
4. Failed bearings also damage surrounding components.[2]

Axial Crack



Source: Gould, B., Greco, A. The Influence of Sliding and Contact Severity on the Generation of White Etching Cracks. *Tribol Lett* 60, 29 (2015).



HSS = high-speed shaft; IMS = intermediate shaft

Source: Yi Guo, NREL

Approach

Existing systems use SCADA (supervisory control and data acquisition) data.

- SCADA data capture the overall condition of a wind turbine.
- Data do not allow the investigation of a specific bearing's health.

Additional data are calculated using physics-based models and gearbox design to enrich bearing fault signatures.[3][4]

- These models are developed by the NREL team with major contributions by Yi Guo, and this study is incorporating these models.

Data Description

December 2008 to October 2018

Thirteen 1.5-MW wind turbines

- Axial cracking (bearing A [rotor side] or bearing B [generator side, upwind] of intermediate or high-speed-stage shaft

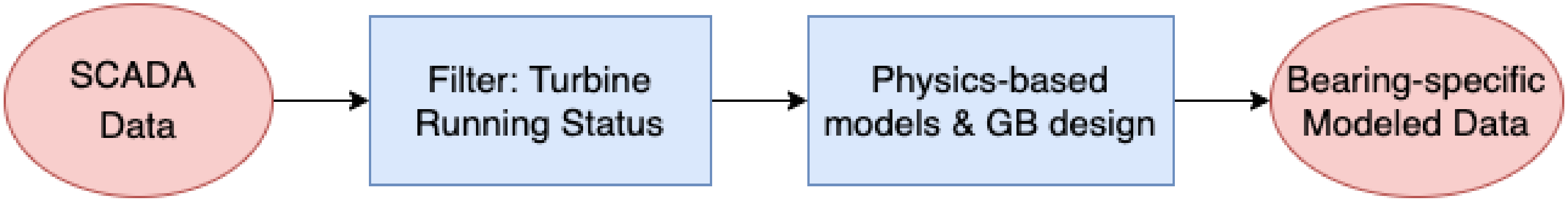
SCADA data: 10-minute averaged measurements of various sensors

- Power, wind speed, bearing temperature, oil temperature, ambient temperature, nacelle temperature, status code, and other data.

A total of 144 (6 per hour × 24 hours) rows of data are recorded per day by a single turbine in the SCADA system.

Modeled Data

1. Consider the data only when a turbine is in running condition and power is produced
2. To represent bearing's health, additional data are calculated using various models and gearbox configuration:
   - Bearing load, roller load, roller deflection, frictional energy, slide-to-roll ratio, and other data.



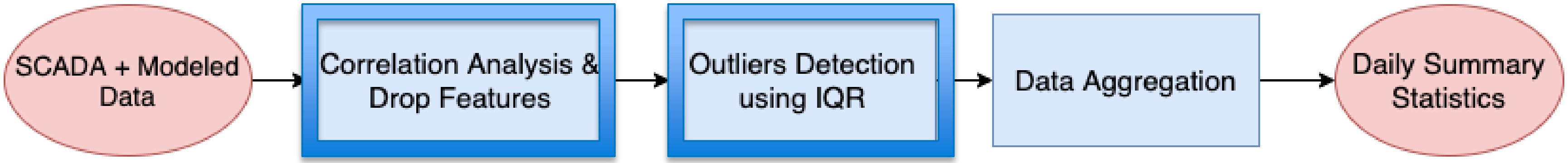
GB = Gearbox

Data Preprocessing

1. Perform correlation analysis (Pearson correlation coefficient) and drop features considering collinearity threshold as 0.9, including:
   – Ambient temperature, bearing roller load, roller deflection, and other features
2. Detect outliers using interquartile range (IQR)[5] method and replace them with median values:

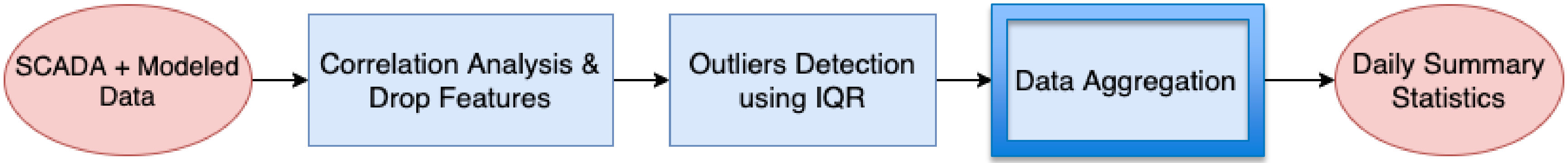
   [Q1 – 1.5 x IQR, Q3 + 1.5 x IQR]

   – *Outliers are few and random, with no correlation found with bearing failure*



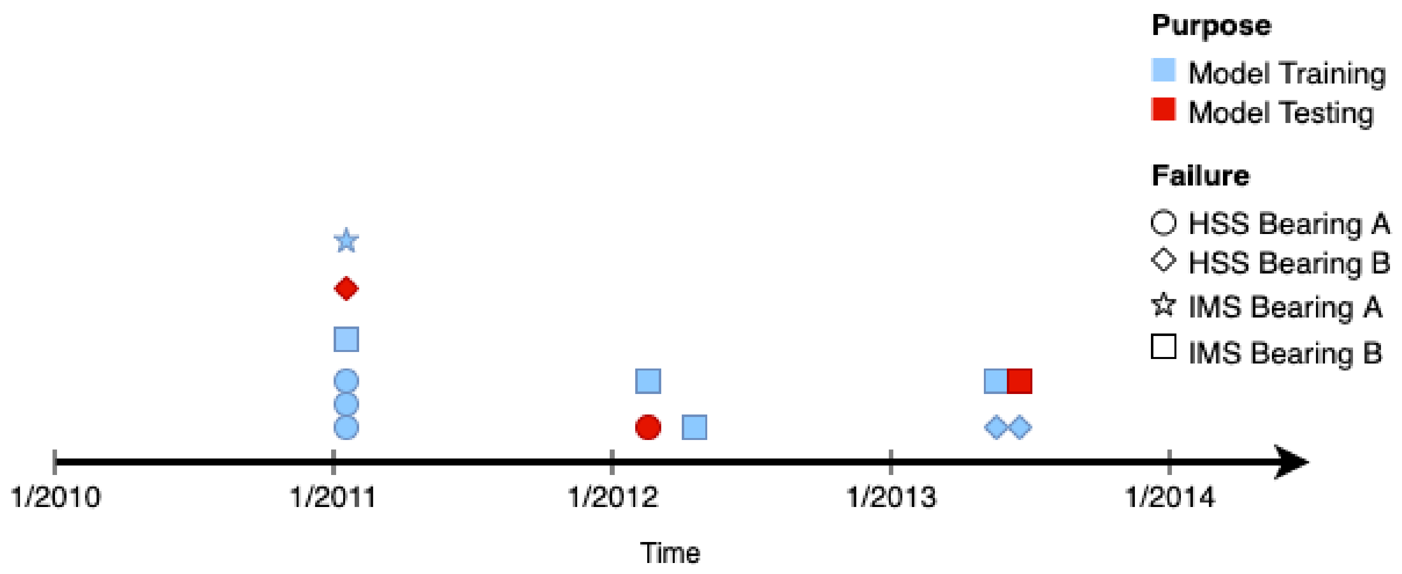
Data Preprocessing

3. Data aggregation and daily summary statistics are found:
   - Minimum, maximum, and length of data
   - Mean, standard deviation, and root mean square
   - Skewness and kurtosis.



Methodology

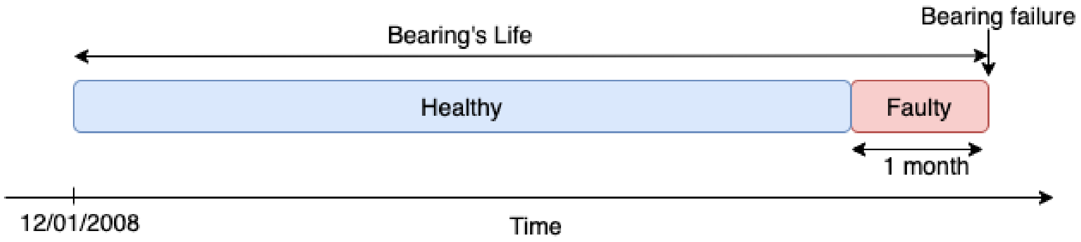
Train-Test Split



Methodology

Data Labeling

- Predicting failure 30 days ahead of its time
- **Hypothesis**: Data from last month before failure contains strong signal of bearing fault



Data show strong *seasonality* and distributions that vary month to month

Methodology

Class imbalance as we mark only last month of data as “faulty”

Note: Algorithms are biased toward majority class.

Two techniques to address class imbalance:

1. SMOTE (synthetic minority oversampling technique)[6]
2. Cost-sensitive learning

Methodology

Four algorithms are selected for bearing failure prediction:

1. Logistic regression[7]
2. Random forest[8]
3. XGBoost (Extreme Gradient Boosting)[9]
4. LSTM (Long Short-Term Memory) networks.[10]

Libraries

- Logistics regression, random forest: scikit-learn library[11]
- XGBoost: XGBoost library[12]
- LSTM: Keras library[13]

- SMOTE cannot consider temporal structure of multivariate sequential data.
  - SMOTE is used with logistic regression, random forest, and XGBoost.
  - We do not use SMOTE with LSTM, as it handles imbalanced data well.
- Cost-sensitive learning is used on all four algorithms.

Methodology

Recent historical data are helpful for prognostics, as axial cracking in bearings does not happen instantaneously.

- Add 1–30 days of lagging variables of SCADA channels while training logistic regression, random forest, and XGBoost
- LSTM handles a sequence of past observations as input.

All four algorithms are trained and tested on **two sets of data:**

1. SCADA data
2. SCADA data and modeled data.

We are interested in knowing how models perform when we add bearing-specific model data to capture a bearing’s health.

Evaluation

- We evaluate model performance using Precision, Recall, F1 score, and AUC (area under ROC [receiver operating characteristic] curve).
- ROC[14] is a probabilistic curve that shows the model performance at various classification thresholds.

		Prediction	
		Healthy	Faulty
Actual	Healthy	True Negatives (TN)	False Positives (FP)
	Faulty	False Negatives (FN)	True Positives (TP)

Metric	Formula
Precision	TP/(TP + FP)
Recall or TPR	TP/(TP + FN)
F1 score	2 × Precision × Recall/(Precision + Recall)
FPR	FP/(FP + TN)

TPR = true positive rate; FPR = false positive rate

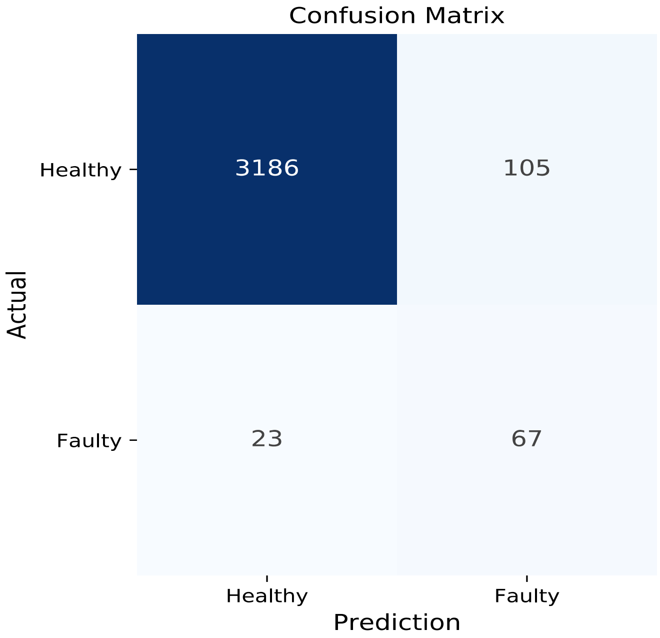
Results

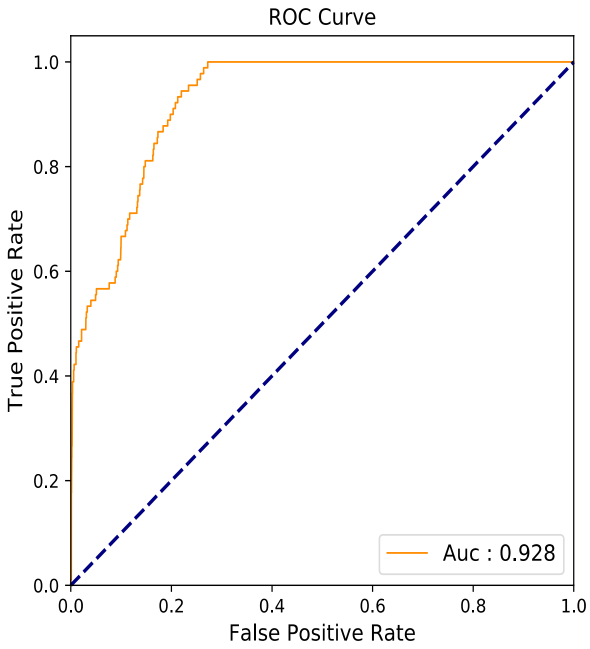
Cost-sensitive learning performs slightly better than SMOTE for logistic regression, random forest, and XGBoost models.

When we add modeled data to SCADA data, model performance increases in terms of F1 score and AUC.

- Precision increases, which improves overall F1, as it is a harmonic mean of precision and recall.
- LSTM models perform the best.

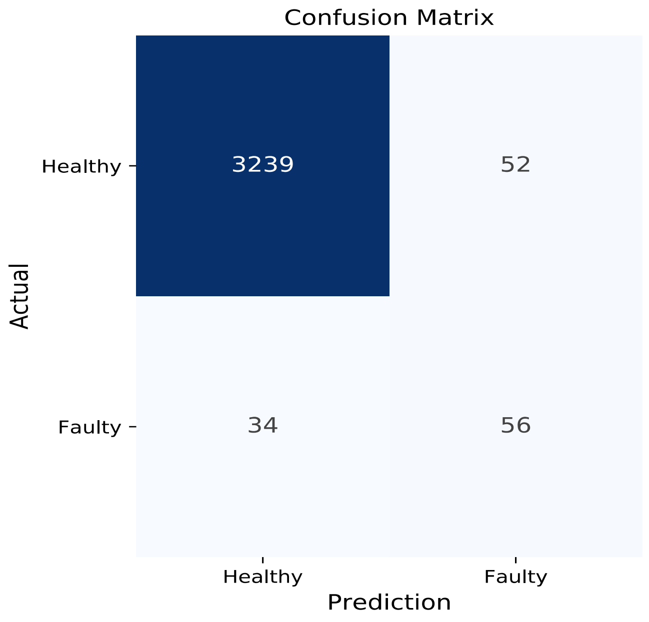
Results

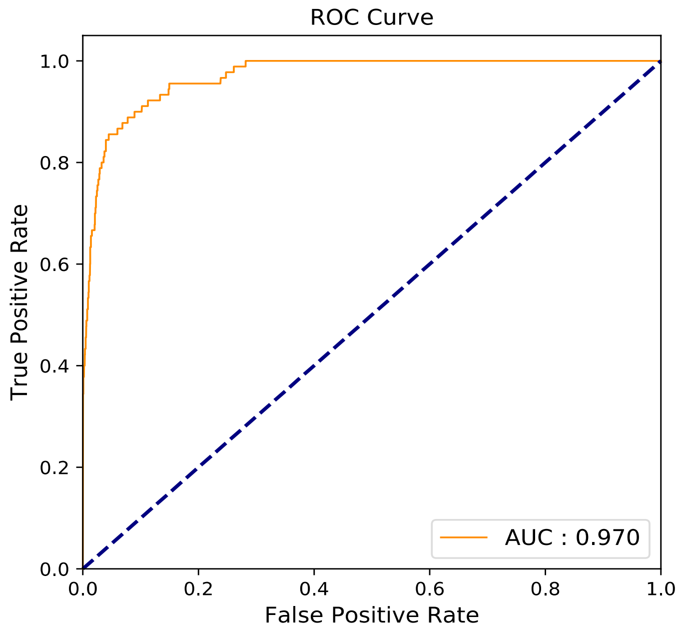




Performance of LSTM model built using **SCADA data**

Results: Modeled Data





- 50% reduction in false alarms
- F1 score is improved by 12%
- Overall AUC is increased by 6%

Performance of LSTM model built using **SCADA and modeled data**

Conclusion and Future Work

- Study shows the potential of bearing-specific modeled data, and they should be explored further.
- Optimum classification threshold can be optimized using ROC curve and considering false alarms and missed detections cost.
- Overall performance can be improved if machine learning models for individual bearings are developed.
- We do not know when the cracks start developing until they are visually detectable.
  - Further work would be to find the maximum lead time (assumed to be the last 30 days in this study) to predict bearing axial cracking

Additional Information

Prognosis of Wind Turbine Gearbox Bearing Failures using SCADA and Modeled Data

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Abstract

Predictive maintenance and condition monitoring systems for wind turbines have seen increased adoption to minimize downtime, reducing operation and maintenance costs. On today's wind power plants, the integrated supervisory control and data acquisition (SCADA) system provides low-frequency operational data that can be leveraged to quantify a wind turbine's health. The aim of this study is to utilize machine-learning techniques to predict axial cracking failures in wind turbine gearbox bearings up to 1 month ahead of time. The failures are assumed to have occurred when the investigated bearing was replaced. While current SCADA systems show the overall condition of a wind turbine, often they do not allow for the investigation of specific gearbox bearings' health. To enrich bearing fault signatures, additional data are computed through physics-based models using gearbox design information. Based on SCADA data, modeled data, and bearing failure log data from an actual wind plant, the performances of different machine-learning models on unseen data are then evaluated using industry-standard metrics, such as precision, recall, F1 score, and area under receiver operating characteristic curve (AUC). Results show the overall system performance enhancement in predicting bearing failure when modeled data are included with SCADA data. The reduction in terms of false alarms is about 50%, and improvement in terms of precision, F1 score, and AUC is about 33%, 12%, and 6%, respectively, based on the best performing modeling case in this study.

1. Introduction

Wind energy has been advancing rapidly as it plays a very significant part in clean-energy-based electric power generation (Kusiak & Li, 2011). However, the operation and maintenance (O&M) cost of a wind farm accounts for up to 30% of total energy cost (Fischer, Besnard, & Bertling, 2012), which can be reduced through continuous monitoring and successfully detecting incipient wind turbine failures. For this reason, predictive maintenance and condition monitoring systems are being implemented for O&M decision-making in the wind industry (Lau, Ma, & Pecht, 2012; Feng, Qiu, Crabtree, Long, & Tavner, 2013; Qiao, & Lu, 2015). These systems utilize a combination of statistics, data mining, and machine-learning-based techniques for fault diagnostics and prognostics, to assess wind turbine performance abnormalities and predict time to failure. The performance of these systems is improving with advances in data acquisition and signal processing technologies (Qiao, Zhang, & Chow, 2015; Zaher, McArthur, Infield, & Patel, 2009; Colone, Reder, Tautz-Weinert, Melero, Natarajan, & Watson, 2017).

Wind turbines operate in adverse weather conditions and their drivetrains undergo severe variable loading because of emergency shutdowns, varying wind speed, and fluctuations in energy demand (Yang, Tavner, Crabtree, Feng, & Qiu, 2013). One of the most important parts of a geared wind turbine drivetrain system is a gearbox that comprises various bearings, gears, and shafts. Most of the gearbox failures are related to the shaft bearings and result in very costly repairs and high downtime (Saidi, Ben Ali, Bechhoefer, & Benbouzid, 2017). Research has shown that cracks can develop in the gearbox bearings only within 3 years of a wind turbine's operation (Stadler & Stubenrauch, 2013). The failed bearings can damage surrounding components of the

1

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Prognosis of Wind Turbine Gearbox Bearing Failures Using SCADA and Modeled Data

Authors: Arch Desai, Yi Guo, Shawn Sheng, Caleb Phillips, and Lindy Williams

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