Wireless Instant Fault Detection through Finite-Element Trained Machine Learning

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***Abstract*—The rapid development of Industry 4.0 technologies has brought predictive maintenance into focus, particularly for small and medium-sized enterprises (SMEs) where cost and complexity are major barriers. In this paper, we present an innovative approach to vibration analysis, a key component for fault detection in mechanical systems and the creation of digital twins. Utilizing MatLab, we generated synthetic data points to simulate various vibration scenarios. These synthetic data points served as the training set for our machine learning model. The trained model was then integrated with a low-cost, Bluetooth-enabled accelerometer for real-time monitoring. Our system successfully identified fault conditions, specifically lump mass irregularities, through real-time sensor data. Our findings show promising capabilities for offering a cost-effective and straightforward solution for predictive maintenance. This research not only advances the field of vibration analysis but also opens doors for SMEs to embrace the benefits of digital twin technologies.**

***Index Terms*—Wireless Communication, Vibration Analysis, Predictive Maintenance, Machine Learning, Synthetic Dataset**

I. Introduction

Vibration analysis is a cornerstone technique in the realm of predictive maintenance, serving as a powerful diagnostic tool for assessing the operational health of various mechanical systems, from industrial machinery to automotive components [2]. By analyzing the vibration patterns and frequencies emitted by these systems, it is possible to identify a wide range of mechanical faults and anomalies, such as misalignments, imbalances, and wear and tear, well before they escalate into catastrophic failures.

Despite the critical importance of vibration analysis, its adoption has been hindered by several barriers, most notably the high costs associated with specialized equipment and the technical expertise required to interpret complex vibration data [7]. These challenges are particularly apparent for small and medium-sized enterprises (SMEs), which often lack the resources to invest in sophisticated predictive maintenance solutions. Accelerometers are the sensors predominantly used for capturing vibration signals in rotating machinery applications, capable of capturing signals in frequency ranges from 1 Hz to 10 kHz [8].

The Fourier-based analysis, including Fast Fourier Transform (FFT), is the most traditional approach to identify the specific harmonic constituents, which are often indicative of mechanical faults and failures . Additionally, advancements in machine learning algorithms like Support Vector Machines (SVMs) and Neural Networks have introduced an additional layer of predictive power and accuracy [10].

Serial communication serves as a foundational element in the realm of hardware-software interfacing. Unlike parallel communication, where multiple bits are sent simultaneously over multiple channels, serial communication transmits data sequentially, bit-by-bit, over a single channel. This makes it a more straightforward and cost-effective solution for long-distance data transmission. Serial communication is effective when signal integrity is prioritized over bandwidth [12].

Given the focus of our study on capturing low-bandwidth data—specifically z-axis acceleration—serial communication's emphasis on signal integrity aligns well with our needs.

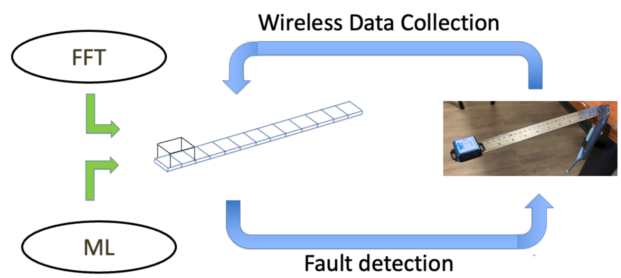

Fig. 1. System and operation

In light of these challenges, the primary aim of our research is to democratize access to vibration analysis technologies by developing an affordable and efficient monitoring system. At the heart of our system is a Bluetooth-enabled accelerometer, affixed to cantilever beams to facilitate straightforward and wireless data acquisition. This hardware setup is complemented by a machine learning model trained on synthetic data [13], which we generate using MatLab . This approach eliminates the need for expensive and time-consuming experimental setups, thereby accelerating the model training phase and reducing overall costs.

In our system, the Bluetooth accelerometer captures raw vibration data from the physical setup. This data is wirelessly transmitted to MATLAB via serial communication, where the primary task is to analyze and identify the vibrational frequencies using FFT. After extracting these frequencies, MATLAB interfaces with a Python-based ML module. This module, pre-trained on a synthetic dataset generated through FEM simulations, now receives real-world frequency data as input. The ML model processes this input to predict the mass and its precise location on the beam. The final step is the display of these predictions in MATLAB. While the ML model's initial training occurs on synthetic data, its real-world application involves making predictions based on actual data collected from the accelerometer.

Our proposed solution is engineered to be not only cost-effective but also highly precise, capable of real-time fault detection and diagnosis.

Moreover, our work lays the groundwork for the broader adoption of digital twin technology in the field of predictive maintenance [3]. Digital twins, or virtual replicas of physical systems, offer a transformative paradigm that can significantly enhance the accuracy and efficiency of maintenance strategies [13].

In this particular study, FEM is applied to analyze the natural frequencies of a cantilever beam system constructed in MATLAB. Eigenvalue analysis is subsequently conducted on this system to extract the natural frequencies. These first two natural frequencies serve as the two primary features for training our ML model. By leveraging the concept of FEM, we are able to create a robust synthetic dataset [6] to train the ML model, without the need for costly or difficult experiments to gather raw real-world data.

This paper provides a detailed account of the development, experimental validation, and potential impact of our vibration analysis system. Moreover, our work lays the groundwork for the broader adoption of digital twin technology in the field of predictive maintenance [7].

This research aims to address several key objectives:

1) Design a cost-effective and efficient vibration analysis solution specifically tailored for small and medium-sized enterprises (SMEs).
2) Employ machine learning techniques to automate fault detection in mechanical systems using vibrational data.
3) Create synthetic datasets via MatLab to train machine learning models, thus circumventing the need for costly and labor-intensive experiments.
4) Integrate a Bluetooth-enabled accelerometer for seamless real-time monitoring and data collection, negating the need for wired systems.

II. Advanced Machine Learning Approaches with XGBoost

The Extreme Gradient Boosting (XGBoost) algorithm serves as the foundation of the machine learning component in this research. Originating as an extension of the Gradient Boosting Machine, XGBoost is an ensemble learning method that aims to optimize a differentiable loss function. It employs a set of weak learners, typically decision trees, and boosts their performance in an iterative manner.

One of the key features that sets XGBoost apart from other machine learning algorithms is its regularization component. Specifically, XGBoost incorporates both L1 (Lasso) and L2 (Ridge) regularization terms in its cost function. This not only helps in controlling the complexity of the individual trees but also effectively mitigates the risk of model overfitting, effectively enhancing the model's generalization capability.

The algorithm is efficiency is further increased as a result of its parallelization techniques [9]. These features make XGBoost not only fast but also scalable, capable of handling large datasets and high-dimensional feature spaces [4].

Given its high predictive accuracy and computational efficiency, XGBoost is an ideal choice for our study.

III. Synthetic Data Generation

A. Finite Element Method

The necessity for a robust training dataset is paramount for the success of any machine learning model. In this research, we generate synthetic data by leveraging the Finite Element Method (FEM) to simulate vibrational behavior for various configurations of cantilever beams with a randomized lumped mass being placed at a random location along the beam.

The assumptions at this stage include constant physical dimensions and material of the cantilever beam. Variability is introduced through the mass and location of the lumped element, both of which are randomly generated from a uniform distribution within to ensure a comprehensive range of scenarios. The range for this random distribution is outlined in TABLE II.

The governing equation for the dynamics of the cantilever beam is the Euler-Bernoulli beam equation.

To accomplish this, we use Matlab to construct a digital twin of our system. Eigenvalue analysis is subsequently conducted on this system to extract the natural frequencies. These first two natural frequencies serve as the two primary features for training our ML model.

In this study, the beam is assumed to be made of stainless steel, characterized by a density ($\rho = 7800\,\mathrm{kg/m^3}$) and Young's Modulus ($E = 198 \times 10^9\,\mathrm{Pa}$). These matrices are assembled using for loops.

TABLE I
CANTILEVER BEAM PARAMETERS

Parameter	Symbol	Value
Length	L	$0.3\,\mathrm{m}$
Width	W	$0.03\,\mathrm{m}$
Thickness	T	$0.001\,\mathrm{m}$
Cross-sectional Area	A	$W \times T$
Moment of Inertia	I	$\frac{W \times T^3}{12}$
Young's Modulus	E	$198 \times 10^9\,\mathrm{Pa}$
Density	ρ	$7800\,\mathrm{kg/m^3}$

We initiate the simulation by randomizing key physical parameters of the cantilever beam. The following table summarizes the randomized parameters and their ranges.

In the Finite Element Method (FEM), the cantilever beam is discretized into a number of smaller elements. The stiffness

TABLE II
RANDOMIZED PARAMETERS

Parameter	Range	Description
mass-location	$0.1 - 0.9$	Position along the beam as a fraction of its length.
lumped-mass	$0 - 1$ kg	Additional mass added at the randomized location.

and mass matrices for these elements are assembled to solve for the natural frequencies of the beam. Here, we describe the formulation of these matrices.

The boundary conditions describe both the free and fixed end of the cantilever beam and are then applied to these matrices to yield the natural frequencies of the system.

A constant mass of 20 g is added at the free end of the beam to simulate the constant weight of our Bluetooth module, which will be affixed to the free end of the beam. For our simulations, we model the sensor as a singular point mass.

This mass matrix is then added to the global mass matrix.

An additional mass is randomly placed along the length of the beam.

B. Data Collection and Storage

A dataset composed of 50,000 unique simulations is generated, each with randomized mass and location. To ensure the reproducibility of the data, a consistent random seed of 42 is utilized in MATLAB.

The dataset is archived in a structured CSV file. This file contains four columns:

- First natural frequency (f_1)
- Second natural frequency (f_2)
- Additional lumped mass (m_{random})
- Location of the additional lumped mass (l_{random})

C. Machine Learning Models

The recorded natural frequencies, f_1 and f_2, serve as features for training two separate machine learning models. Conversely, the additional lumped mass (m_{random}) and its location (l_{random}) will serve as target variables for the respective models.

IV. BLUETOOTH ACCELEROMETER DATA ACQUISITION

The efficacy of any Machine Learning model in a real-world scenario hinges on the quality of the input data. Even a model of impeccable accuracy can yield inaccurate predictions if fed with inaccurate data. In essence, the principle of "garbage in, garbage out" applies; accurate predictions require precise data acquisition. This section delves into the specifics of our Bluetooth-enabled accelerometer, detailing the methodology employed to capture precise natural frequencies from vibrational data, thereby ensuring the reliability of our predictive models.

A wireless setup was essential due to our experimental configuration; the accelerometer was attached to a beam's free end, where wires could have introduced extraneous variables, such as physical interference from wire entanglement or measurement bias from wire tension. Because of the low cost and modest 200Hz transmission capability of our accelerometer, it was crucial to minimize potential signal distortion, which necessitated the wireless setup to preserve the integrity of the data.

A. Hardware Components

To conduct the experiment, a high-precision and low-cost WT-901 Bluetooth accelerometer was used, available for $47.99 online. This cost-effective choice compares favorably to traditional accelerometers used in fault detection, which can cost thousands of dollars. The components are as follows:

- **Accelerometer:** WT-901 Bluetooth IMU Module
  - 3-Axis acceleration measurement
  - Range: ± 16g
  - Data rate: 200Hz

B. Serial Connection and Data Acquisition

1) Serial Initialization: In the first step of our data acquisition procedure, MATLAB clears any existing serial connections. A new serial connection is then established, setting parameters like the serial port and baud rate. Should this serial connection attempt fail, an error message alerts the user and the code terminates.

2) Data Collection: Z-axis acceleration data are continuously monitored and collected from the accelerometer. When a sufficient amount of data becomes available in the serial buffer, the Z axis acceleration is extracted and stored. In this experiment, a total of 2300 Z-axis readings are collected and validated to ensure data integrity, representing a real-world sampling window of 11.5 seconds.

3) Data Preprocessing: To improve data accuracy, the first 300 samples are discarded as they are considered transient. Then a high-pass filter is applied to the remaining data to remove low-frequency noise. The cut-off frequency for this filter is set at 1.5 Hz, which was determined empirically.

4) Time Array: A time array is generated that aligns with the duration and number of Z-axis data samples, at a sampling rate of 200 Hz (Limited by the accelerometer's sampling rate). This array provides the time context for each data point, which is necessary to perform FFT. In this stage, FFT (Fast Fourier Transform) is applied in MATLAB to shift the time-domain acceleration data to the frequency domain. The frequency range is set between 1 and 100 Hz due to the nyquist frequency, determined by the accelerometer's 200 Hz sampling rate.

MATLAB's built-in `findpeaks` function is subsequently used to identify natural frequencies in the FFT spectrum, observed as local peaks in the frequency-domain plot. Parameters for this function are fine-tuned for optimal peak detection, with values determined empirically.

The first two natural frequencies are then extracted, to serve as input features for the predictive models.

V. Machine Learning

A. Algorithm Selection

We chose the eXtreme Gradient Boosting (XGBoost) algorithm for its balance of accuracy with computational efficiency. XGBoost is especially suited for Small and Medium-sized Enterprises (SMEs) because it is resource-efficient, supports parallel computing, and scales well with large datasets [5].

Additionaly, Our empirical tests showed that XGBoost outperformed alternatives like Random Forest and Support Vector Machines in predictive accuracy, as measured by R^2 scores and Mean Squared Error (MSE). Therefore, XGBoost was selected as the algorithm for both models.

B. Feature Engineering and Data Preprocessing

We initially use `frequency1` and `frequency2` as primary features for training the machine learning model. We augment this with `freq_ratio` and `freq_product`, calculated as the ratio and product of the two natural frequencies. These additional features were incorporated due to XGBoost being highly effective with large feature spaces [5]. This four-feature set is standardized using scikit-learn's StandardScaler to ensure zero mean and unit variance.

C. Model Training and Evaluation

1) Data Partitioning: We allocate 80% of the dataset for training and 20% for testing to validate our model's predictive accuracy. The R^2 score serves as the principal evaluation metric, complemented by scatterplots for visual assessment.

2) Hyperparameter Tuning: We performed a grid search with three-fold cross-validation to optimize the model's hyperparameters, targeting the R^2 score as the objective function to maximize. Post-optimization, two sets of hyperparameters are identified and applied for the final model training, to enhance predictive accuracy.

TABLE III
Optimized Model Hyperparameters

Parameter	Mass Prediction	Location Prediction
learning_rate	0.3	0.1
max_depth	5	5
n_estimators	300	300

D. Performance Metrics and Results

1) Evaluation Metrics: The effectiveness of the models was evaluated using the R^2 score, a statistical measure that represents the proportion of the variance for a dependent variable that's explained by an independent variable or variables. An R^2 score of 1 implies an ideal fit between the model predictions and the actual outcomes.

2) Performance: The model developed for predicting the mass variable achieved a high R^2 score of 0.9995. Similarly, the model designated for predicting location recorded an R^2 score of 0.9984.

It is worth noting that R^2 scores approaching 1.00 often raise concerns of potential issues such as overfitting or data leakage, where the model could have inadvertent access to the target variable [11]. In our specific context, however, these near-perfect R^2 scores can be attributed to the inherent simplicity of the physical system under study. Our objective was to validate the efficacy of our modeling approach using a less complex case as a starting point. Additionally, the risk of overfitting is mitigated in our scenario, as the model is intentionally fine-tuned to represent a specific, well-defined physical system [1].

3) Graphical Evaluation: We employed graphical methods to offer additional insights into the performance of our models. Specifically, scatter plots were created to compare the predicted values with their corresponding actual values. A 45-degree reference line was superimposed on the graphs to improve interpretability. A tighter fit relative to this line represents a more accurate model.

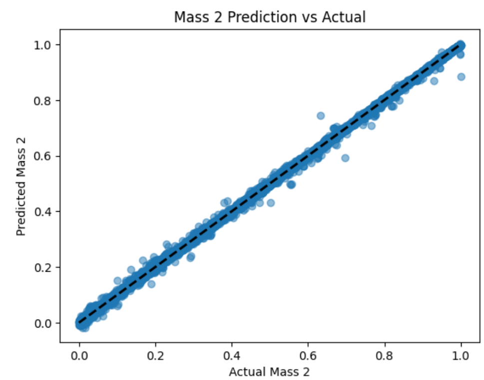

Fig. 2. Predicted vs. Actual Mass

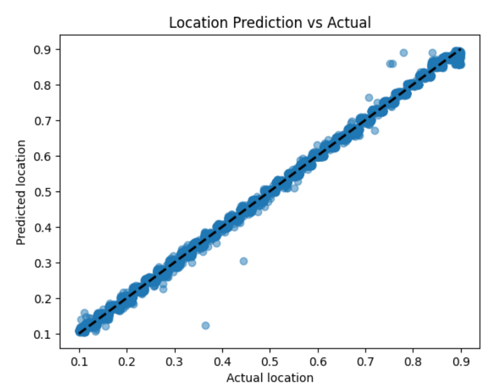

Fig. 3. Predicted vs. Actual Location

4) Real-World Validation: While our model exhibited high performance metrics in a controlled synthetic environment, as evidenced by near-perfect R2 scores and graphical evaluations, these measures alone do not guarantee real-world efficacy. It is critical to assess whether the model can be applied practically and yield reliable results outside of simulation.

To this end, following the initial training with FEM-generated data, we conducted real-world testing. To assess the model's accuracy, we placed a 50g mass at specific points on the beam and input the resulting vibration frequencies into the model. This allowed us to directly compare the model's predictions with the actual mass positions. The consistency between our model's predictions and the actual test results affirms its practical effectiveness in real-world settings, and extending its utility beyond simulated environments.

E. Results

We achieved successful integration of the accelerometer and machine learning models. Our system operates in a multi-step process as a) Time-Domain Data Acquisition b) Frequency Transformation c) Natural Frequency Identification d) Mass and Location Prediction.

Figures showcasing the various stages of this process are presented below. These include plots of the time-domain readings, frequency domain representations, and the predicted values for mass and location achieved by the machine learning models. As can be seen in the test cases, as the mass gets smaller or closer to the fixed end, the variations in frequencies are diminished so the model accuracy increases as the mass is placed further along the beam.

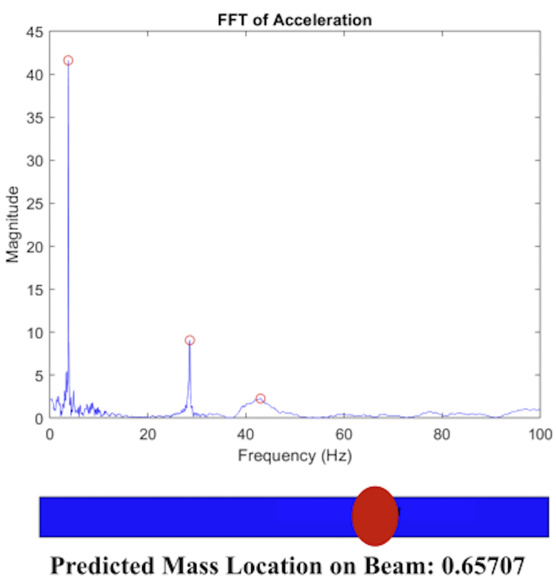

Fig. 4. Test 3 Results

TABLE IV
TEST SERIES

Test	Target	Predicted
Test 1	Mass: 0.2 Location: 0.33	Mass: 0.244836 Location: 0.282615
Test 2	Mass: 0.2 Location: 0.5	Mass: 0.193305 Location: 0.531582
Test 3	Mass: 0.2 Location: 0.67	Mass: 0.20474 Location: 0.657067

VI. CONCLUSION

This research has succeeded in developing a highly accurate and well-validated framework for the specific case of analyzing vibrational behavior in cantilever beams. Utilizing a approach that combines Finite Element Modeling, advanced machine learning techniques through XGBoost, and Bluetooth-enabled data acquisition, we have achieved remarkable predictive accuracy. This accomplishment is particularly noteworthy given the challenges associated with developing a cost-effective and user-friendly solution that is accessible to small and medium-sized enterprises.

Despite the significant strides made in this research, it is crucial to acknowledge its limitations. Our framework is tailored to a simplified model that focuses on cantilever beams with lumped masses. While this allows for high-precision predictions, it may not fully encapsulate the complexities and nuances of more diverse real-world mechanical systems. Therefore, the current model serves as a proof of concept and should be interpreted within the confines of its design parameters.

Looking ahead, there is considerable scope for extending this research. Future endeavors should aim to generalize the model to accommodate a wider range of mechanical systems, including those with varying boundary conditions, structural complexities, and different types of loadings. The high predictive accuracy achieved in this study serves as a promising indicator of the model's potential for scalability and adaptability [14]. We are optimistic that with further refinement, our framework can serve as a cornerstone for the development of more versatile and comprehensive predictive maintenance solutions.

VII. ACKNOWLEDGMENTS

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VIII. REFERENCES

REFERENCES

[1] Qaisar Abbas, Ayyaz Hussain, and Abdul Rauf Baig. "cad-alz: A blockwise fine-tuning strategy on convolutional model and random forest classifier for recognition of multistage alzheimer's disease". *Diagnostics*, 13(1):pp. 167, 2023.

[2] Mona Amer, Joerg Wallaschek, and Joerg R Seume. "operational modal analysis of an axial compressor rotor and casing system for the online identification of a digital twin". *Applied Mechanics*, 3(1):pp. 244–258, 2022.

[3] Kaikang Chen, Yanwei Yuan, Bo Zhao, Liming Zhou, Kang Niu, Xin Jin, Shengbo Gao, Ruoshi Li, Hao Guo, and Yongjun Zheng. "digital twins and data-driven in plant factory: An online monitoring method for vibration evaluation and transplanting quality analysis". *Agriculture*, 13(6):pp. 1165, 2023.

[4] Tianqi Chen and Carlos Guestrin. "xgboost: A scalable tree boosting system". In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining*, pages pp. 785–794, 2016.

[5] Dimitrios Effrosynidis, Athanassios Tsikliras, Avi Arampatzis, and Georgios Sylaios. "species distribution modelling via feature engineering and machine learning for pelagic fishes in the mediterranean sea". *Applied Sciences*, 10(24):pp. 8900, 2020.

[6] Yohei Hirano, Keito Shinmoto, Yohei Okada, Kazuhiro Suga, Jeffrey Bombard, Shogo Murahata, Manoj Shrestha, Patrick Ocheja, and Aiko Tanaka. "machine learning approach to predict positive screening of methicillin-resistant staphylococcus aureus during mechanical ventilation using synthetic dataset from mimic-iv database". *Frontiers in medicine*, 8:pp. 694520, 2021.

[7] Aurelien Teguede Keleko, Bernard Kamsu-Foguem, Raymond Houe Ngouna, and Amèvi Tongne. ”artificial intelligence and real-time predictive maintenance in industry 4.0: a bibliometric analysis”. *AI and Ethics*, 2(4):pp. 553–577, 2022.

[8] Zhixiong Li, Yu Jiang, Zhihe Duan, and Zhongxiao Peng. ”a new swarm intelligence optimized multiclass multi-kernel relevant vector machine: An experimental analysis in failure diagnostics of diesel engines”. *Structural Health Monitoring*, 17(6):pp. 1503–1519, 2018.

[9] Manoharan Prabukumar, Shrutika Sawant, Sathishkumar Samiappan, and Loganathan Agilandeeswari. ”three-dimensional discrete cosine transform-based feature extraction for hyperspectral image classification”. *Journal of Applied Remote Sensing*, 12(4):pp. 046010–046010, 2018.

[10] Riccardo Rosati, Luca Romeo, Gianalberto Cecchini, Flavio Tonetto, Paolo Viti, Adriano Mancini, and Emanuele Frontoni. ”from knowledge-based to big data analytic model: a novel iot and machine learning based decision support system for predictive maintenance in industry 4.0”. *Journal of Intelligent Manufacturing*, 34(1):pp. 107–121, 2023.

[11] Miseon Shim, Seung-Hwan Lee, and Han-Jeong Hwang. ”inflated prediction accuracy of neuropsychiatric biomarkers caused by data leakage in feature selection”. *Scientific Reports*, 11(1):pp. 7980, 2021.

[12] Uzairue Stanley, Victor Matthews Olu, Charles Ochonogor, Peter Amaize, and Anyasi Francis. ”experimental analysis of cable distance effect on signal attenuation in single and multimode fiber optics”. *International Journal of Electrical and Computer Engineering*, 8(3):pp. 1577, 2018.

[13] Lintao Wang, Yuchong Liu, Hang Yin, and Wei Sun. ”fault diagnosis and predictive maintenance for hydraulic system based on digital twin model”. *AIP Advances*, 12(6), 2022.

[14] Hao Zhang, Qiang Zhang, Siyu Shao, Tianlin Niu, and Xinyu Yang. ”attention-based lstm network for rotatory machine remaining useful life prediction”. *Ieee Access*, 8:pp. 132188–132199, 2020.