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An Industry-driven, Project-based Learning Activity: System Identification based on Vibration Signals using Machine Learning

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Abstract

This paper highlights an industry-driven Project-Based Learning (PBL) activity focusing on the development of Machine Learning algorithms for Anomaly Detection to be used in vibration diagnostics centered around the analysis of aircraft equipment. Students worked alongside a Boeing Subject Matter Expert and a university Team Advisor to develop an engineering solution for a current industry problem. Periodic meetings and presentations are conducted in which project progress and deliverables are evaluated, challenges are discussed, goals are adapted, and deadlines are negotiated, all to mimic the industrial project development workflow. An experimental set-up is designed and implemented to generate data representative of the type utilized in industrial settings. A real-time Anomaly Detection solution for vibration signals is created utilizing time and frequency domain features alongside an LSTM Auto-Encoder which achieves a best performance of 72%, 100%, and 82% for precision, recall, and F1-score respectively. This report documents the PBL methodology tailored to engineering activities along with the engineering innovation, outcomes and lessons learned.

Keywords

Project-Based Learning, Subject Matter Expert, Anomaly Detection, Machine Learning, Engineering Innovation.

Introduction

The airline industry incurs heavy financial costs yearly from the downtime required for equipment maintenance[1]. With the advent of embedded electronics and with advances in computing hardware, airlines and aircraft manufacturers have access to large amounts of data pertaining to aircraft equipment and the physical environment in which aircraft operate. This data offers valuable insight into an aircraft's operation, both historically and in real-time. With the recent advancement and popularity of Data Science and Machine Learning (ML), it became apparent that methods from those fields could be applied to the data gathered in the airline industry for predictive maintenance, leading to significantly increased airline operational efficiency and aircraft equipment lifespan. This would lead to significant financial savings for the airline industry, with some estimated savings in excess of $5 billion per year[2].

A commonly utilized type of machinery in aircraft is rotary machinery. Due to its non-destructive nature and rich background, vibration analysis is often the primary tool used for both predictive maintenance and diagnostics across a broad range of rotary machinery[3]. The primary method of collecting vibration data is via an accelerometer sensor. The quality of vibration data collected and therefore the effectiveness of vibration analysis is highly dependent on the proximity of the accelerometer sensor to the location of interest. However, in aerospace applications of rotary machinery, optimal sensor placement is often not possible, creating unique challenges for vibration analysis. (e.g., difficulty of large and sophisticated hardware placement) which are not commonly present in other applications.

Using a Project-Based Learning (PBL) course as a vehicle, and in collaboration with Boeing and their Subject Matter Expert (SME), a project was proposed to address the challenges encountered with vibration analysis in the aerospace industry. The project was assigned to a team of graduate students to devise an engineering solution while advised by a faculty. Due to the difficulty and expense required in obtaining commercial aircraft equipment and working in a commercial aerospace setting, the project was distilled to a simpler version in which the object of analysis was a simple cantilever beam. This allowed the students to navigate the same fundamental challenges present in traditional aerospace settings on a much more manageable scale. The process and skills required in completing the project can be directly transferred to industry. To accomplish this project, the following phases were implemented:

- *Experimentation*: The experimental set-up included a simple cantilever beam as the structure of vibration analysis. The cantilever beam model was chosen because its motion can be modeled with relative ease mathematically and has a closed form solution. This allows for verification of the vibration data accuracy by comparison to a simulation of the same model.

- *Design and Implementation*: The team designed and implemented an embedded, edge-analytics system that successfully captures, processes, and stores vibration data to build a nominal model of the cantilever beam, which quantifies its deflection and response as a function of excitation frequency.

- *Machine Learning for Anomaly Detection*: Anomalies, which are vibration responses that deviate from the nominal model, were injected into the experimental set-up and vibration data was captured. Utilizing ML techniques, the team worked on isolating the anomalies from the nominal model and implemented the anomaly detection algorithms on an embedded system to achieve real-time edge-analytics based anomaly detection, similar to a practical system which may function in an aircraft or in some other industrial setting. Detecting these anomalies as quickly and accurately as possible is a core part of predictive maintenance discussed above, which airlines could greatly benefit from.

The PBL activity spanned two semesters, following the sequence of two project-based learning courses. In the first semester (Spring 2022), the team of 6 students conducted research and literature review into vibration analysis and anomaly detection to understand both fundamental and modern solutions. With the help of a Boeing SME, the team devised the experimental set-up discussed above on which they could apply their unique solution. A simulation of the experimental set-up was implemented to begin collecting data, and algorithms were designed to detect anomalies present in the simulated data. In the second semester (Fall 2022), the team comprising 3 students (participated in Spring 2022 as well) worked on a physical model of the experimental set-up, and the team implemented their solution to capture high quality vibration data from the physical model. The team applied the algorithms developed on the simulated data from the first semester to the real data and refined or changed the algorithms as needed to improve detection performance on the real data. The algorithms were then ported to an embedded system to allow for real-time edge-analytics based anomaly detection on the physical cantilever beam model. The results were periodically presented to the SME and the system was modified as required. The aim was to develop a final system which addresses the challenges faced with vibration analysis in aerospace applications.

The rest of the paper is organized as follows: initially, the Project-Based Learning methodology followed in this project is described. It is important to point out that the PBL methodology is adapted to the nature of engineering to help students meet the project goals. Next, the Engineering Design Methodology along with Evaluation, Results and Scientific Contributions are discussed. Challenges and Lessons Learned are also an integral part of this paper. Finally, Conclusions and Future work are given.

Project-Based Learning Methodology in Engineering

Project-based Learning courses allow students to apply their knowledge to devise engineering solutions which address current challenges and solve practical problems such as the one presented by Boeing. Additionally, collaboration with industry offers a unique opportunity to set-up an environment in which young future engineers can flourish and transform. Special rules of engagement and actions were implemented towards this goal.

Rules of Engagement, Actions and Benefits

- The team meets with the SME every two weeks to discuss findings, challenges and next steps. SME’s feedback is incorporated into project activities. SME’s feedback is communicated with the advisor as needed. This helps the team to take responsibility for its actions. A great benefit from these meetings is that students understand the professional language and terminology of their engineering domain.

- The team meets with the advisor every two weeks to share project progress. This helps students to differentiate the educational activity (e.g., the need to describe “problem statement”, learn about anomaly detection in Machine Learning or try professional presentations) from the (simulated) working environment (e.g., meet sharp deadlines, how to deal when data is not available on time). At the same time, it ensures the project progress and the achievement of learning outcomes in this educational activity.

- Team presents to SME every 4 weeks. This is a formal technical presentation in which students sharpen their communication skills, learn to listen, accept and address feedback, learn from SME how to be agile with comments and questions. To address this, “Presentation to Boeing SME” has been incorporated in the Syllabus.

- In the first week of the project, team members agree on their project roles. While initially working as a group to formalize project scope, address initial questions and tasks, in Week 3 they work on their specific predefined tasks, and deliverables as per the established agreement. They learn to work autonomously and be accountable; they experience partner reliability and professional responsibility. There are characteristics and skills required in real-world professional environments.

- Real-world problems and collaborations also have challenges: deadlines are real, data might not be available on time, and equipment might not be working properly. The team faced all these cases, and learned to be patient, to keep on trying and even fail in some experiments.

To achieve the above and assess student learning, the following steps were taken:

- The syllabus was adapted to the engineering nature as fallbacks might happen (e.g., data not available, equipment fails, SME approval on specific tasks not graded. For this, time was assigned as a safety net to allow the team to address these issues.
- "Check points with Industry" were agreed and incorporated in the syllabus (Week 1, 4, 12, 18, 24) for SME's meetings with the students.
- A detailed rubric to evaluate (a) engineering tasks, part and whole (b) communication skills (c) writing skills (d) function as a team members (e) communication with SME was made available to the students early on. The detailed rubric was based on the work of the Center for Project-Based Learning, Worcester Polytechnic Institute[4].

An excerpt of the PBL syllabus is presented in Table 1.

Week	Topic / Subtopic	Actions and Tasks
Semester One		
Week 0	**Project Analysis**	Team meeting with Advisor - Rules of engagement - Expectations Communication with Boeing SME
Week 1	**Requirements Analysis**	Problem Statement – Timeline - Literature Review - Best Practices Team meeting with Boeing SME
Week 4	**Simulation Design & Data Collection**	Design Beam Simulation - Verify Simulation Accuracy Present to Boeing SME and get feedback - Address SME comments
Week 8	**Model Design** **Feature Engineering**	Research ML models Perform feature engineering to collect relevant feature data Design and train task specific ML model Debrief with course instructor and get feedback
Week 12	**Model Tuning & Evaluation**	Perform Hyper parameter tuning and refine model Evaluate ML model using relevant metrics Present to Boeing SME and get feedback - Address SME comments
Week 14	**Project Presentation**	Deliverables: Final Report, Code, artifacts (e.g., datasets, algorithms)
Semester Two		
Week 16	**Lab Set-up**	Acquire lab Equipment - Organize physical lab setup space
Week 18	**Data Capture and Collection**	Implement Vibration Data Capture Apparatus Start collecting data Present to Boeing SME and get feedback - Address SME comments
Week 20	**Model Design - Feature Engineering**	Perform feature engineering to collect relevant feature data
Week 21	**Data Training**	Design and train task specific ML model
Week 24	**Model Tuning & Evaluation**	Perform Hyper parameter tuning and refine model Evaluate ML model using relevant metrics Present to Boeing SME and get feedback - Address SME comments
Week 26	**Documentation**	Debrief with course instructor and get feedback First Draft of project report
Week 29-30	**Project Presentation**	Final Report, Code, artifacts (e.g., datasets, algorithms)

Table 1: Excerpt of the Project-Based Learning Syllabus

Student Roles

Taimoor Qamar: experimental set-up, vibration analysis, embedded design, logistics manager, communication with SME and Advisor.
Ayush Dhar: lab letup, data collection, vibration analysis, model design, communication with SME and Advisor.
Sindhu Chava: model selection, preprocessing, experimentations, feature engineering, training models, hyperparameter tuning.

Engineering Design Methodology

The students developed an engineering design approach which was divided into five distinct phases: Data Collection, Feature Engineering, Model Design, Training, and Evaluation.

Data Collection

The first semester involved implementing a simulation of the cantilever beam model such that simulated data could be generated quickly for anomaly detection algorithm development. The well-established mathematical equations from Euler-Bernoulli beam theory[5] were used to simulate a vibrating cantilever beam and the outputs derived from solving said equations of motion for a cantilever beam were used to build an initial dataset.

In the second semester, a physical model of the experimental set-up was built to capture real-world vibration data. A steel beam was clamped to a table at one end. An electromagnetic shaker with an extended arm was attached to the beam towards its fixed end. The electromagnetic shaker was driven via a function generator to induce an excitation force on the beam. Four piezoelectric accelerometers were placed on the beam, equidistant from each other. The accelerometers were fed into a Data Acquisition System (DAQ) which captured their analog output signals at 44 KHz, filtered them, and converted them to processed digital signals, ensuring high quality data. The DAQ was connected to two raspberry pi microcontrollers which further processed and stored the vibration data simultaneously, one pi each for two accelerometers. Figures 1 and 2 below display the physical lab setup (including the electromagnetic shaker, the beam, and the accelerometers) and the vibration capture apparatus (including the DAQ and the microcontrollers). Figure 3 below depicts an illustration of the physical set-up.

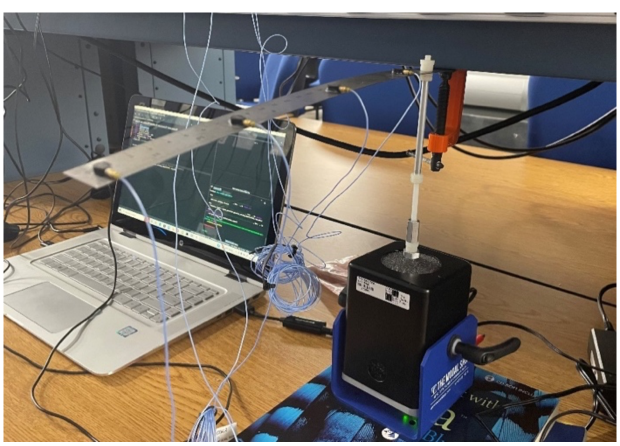

Figure 1: Physical Lab Setup

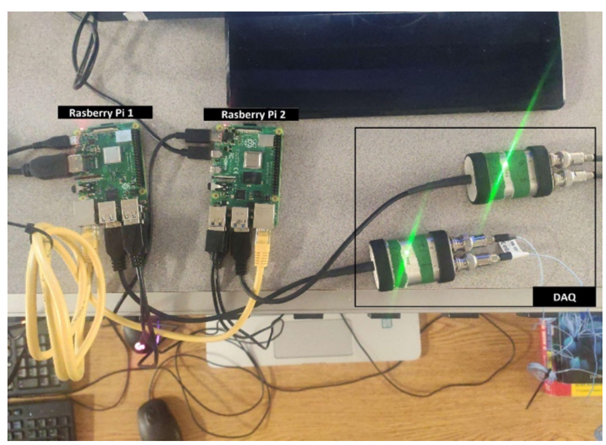

Figure 2: Vibration Capture Apparatus

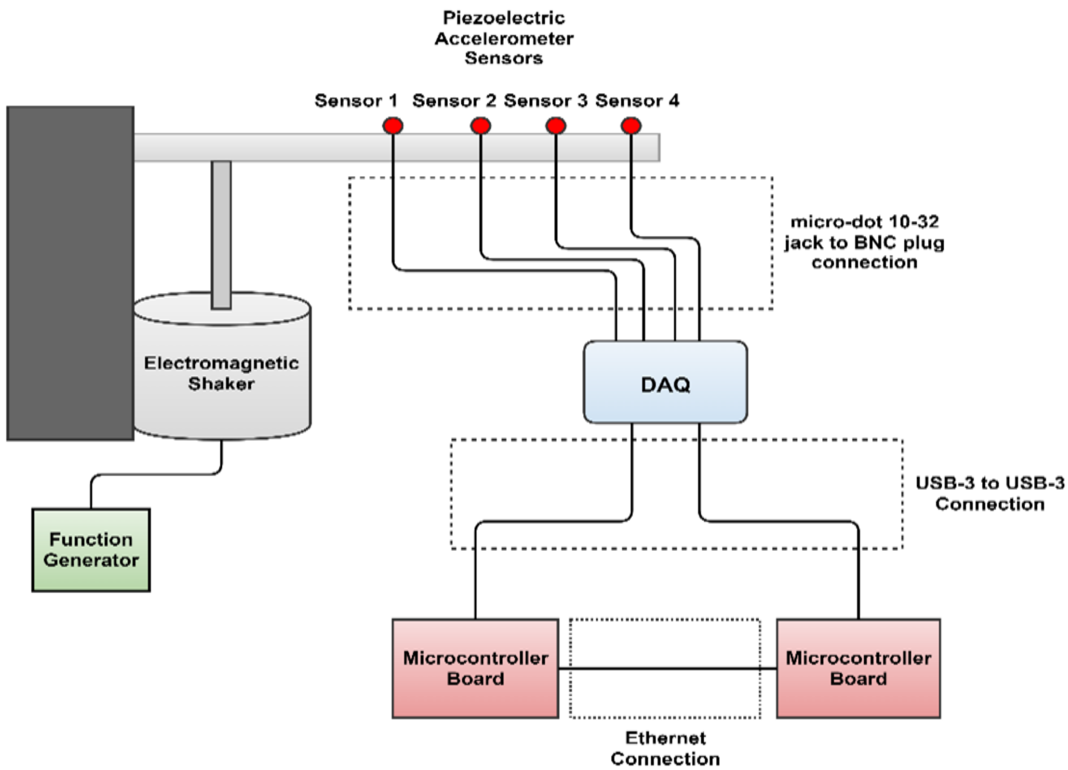

Figure 3: Physical Lab Setup Diagram

Feature Engineering

Utilizing raw vibration data for training anomaly detection models is not an efficient method. Therefore, useful features need to be extracted from the raw vibration signals which can be utilized to train models effectively. Literature review of traditional vibration analysis solutions revealed that the first four statistical moments of mean, variance, kurtosis, and skewness, along with signal root-mean-square (RMS), were commonly utilized features[6]. In order to extract these features from the raw vibration data, the vibration signals were split into window-sizes of x seconds (with various window-sizes used to create different datasets and find the optimal window size for anomaly detection model training) in which x number of samples were processed to obtain these features. These features are simply referred to as the regular time-domain features.

Initial results with the regular time-domain features showed relatively poor model performance. The students determined the model failed to detect the more subtle anomalies injected into the data. After discussion of the initial results with the SME, it was determined that relative acceleration (the difference in values between accelerometers) may be a useful feature to improve model performance.

The features discussed above only contain time-domain information of the vibration signal, leaving frequency components unutilized. In order to compensate for that, the Continuous Wavelet Transform (CTF) was applied to the signal. The CTF is applied with the transform kernel, known as the wavelet, both shifted and scaled during convolution allowing for the extraction of multi-resolution (time and frequency domain) information from the signal[7].

Model Design

With high quality vibration signals (both simulated and real) captured and corresponding datasets built using rich and informative features, machine learning techniques can be implemented to develop an algorithm which utilizes the vibration data to "learn" a nominal model of the cantilever beam vibration response. Thorough literature review from the first semester along with a few initial comparisons between various ML models on the simulated data determined that an LSTM Auto-Encoder was the best suited model for the task of anomaly detection within vibration signals in the context of this project.[8] Figure 4 below depicts the standard architecture and dataflow of an LSTM Auto-encoder model.

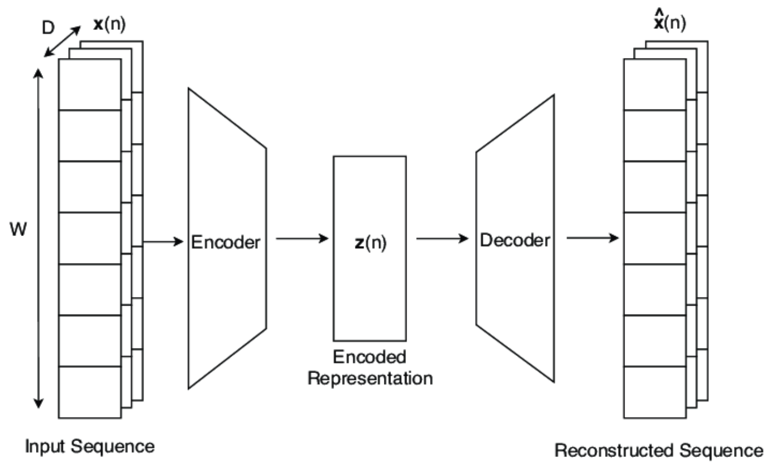

Figure 4: LSTM Auto-Encoder model diagram[9]

Training

In order to train the model to learn a representation of the beam's vibration response under normal conditions, train and validation datasets were created utilizing the features discussed in the Feature Engineering section of the paper. The model was trained on the training dataset and a validation set (5% the size of the training dataset) was used to assess the model's prediction accuracy during training. A separate test dataset was built which consisted of multiple experimental runs in which both subtle and non-subtle anomalies were introduced into the system at various times. To train the algorithm a standard Adam optimizer along with the Mean Absolute Error (MAE) objective function was used[10,11]. Model performance during training is assessed via metrics such as Precision, Recall, and F1-Score.

Evaluation, Results and Scientific Contributions

The model's performance was evaluated on the test dataset discussed in the previous section. Figure 5 below shows the plot of one simulated test signal sample which was used for model evaluation and visualization. Figure 6 below shows the plot of the Mean Average Error (MAE) values between the predicted values from the LSTM Auto-Encoder and the values of the signal in Figure 5. Any value above the red threshold line is classified as anomalous by the model and the ground truth anomalous regions are highlighted in red.

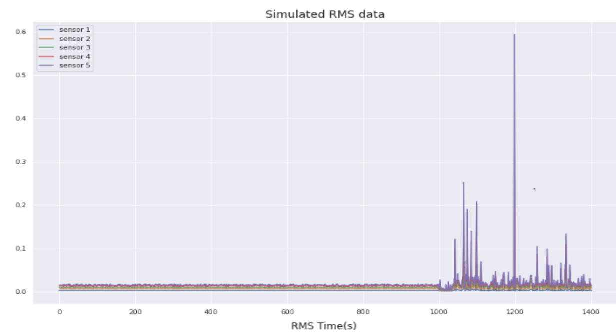

Figure 5: Vibration signal. Anomalies at ~1000 mark.

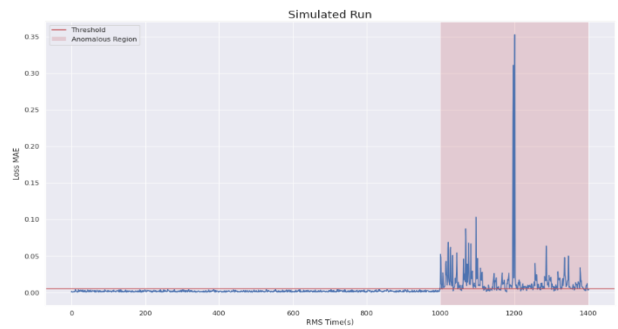

Figure 6: Ground truth vs predicted MAE

The three key metrics used to evaluate the performance of the anomaly detection algorithm were Precision, Recall and F1-score. The three equations below define these metrics. True positive is when an anomaly is correctly detected by the model. False positive is when an anomaly is incorrectly detected by the model. False negative is an anomaly that the model fails to detect.

- $Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$
- $Recall = \frac{True\ Positives}{True\ Positives + False\ negatives}$
- $F1 - score = \frac{2 * Precision * Recall}{Precision + Recall}$

Tables 2 and 3 below contain the performance metrics for the anomaly detection algorithm implemented on the simulated and real data respectively.

Features	Precision	Recall	F1-score
Time-Domain + Wavelet	98%	99%	98.6%

Table 2: LSTM AE Results for Simulation data

Features	Precision	Recall	F1-score
Time-Domain	72%	52%	55%
Relative Accelerat.	61%	92%	66%
Wavelet Coeff.	72%	100%	82%

Table 3: LSTM AE Results for Real Data

The values displayed in the tables above are the mean values of the model's performance on all the test datasets created to assess model performance. Model performance on the simulated data was significantly better than on the real data, as was expected. The simulated data modeled the structural dynamics and vibration response of the beam under ideal conditions. The physical setup introduces many factors present in the physical world which affect the structural dynamics and vibration response of the beam, which cannot be simulated accurately. As such, model performance between the two types of datasets cannot be compared fairly, but the model performance on the simulated data can be viewed very loosely as an ideal benchmark.

The addition of the relative acceleration feature significantly improved the model's recall at the detriment of the precision. Which parameter is more important is dependent upon the application for which anomaly detection is being implemented. F1-score is the harmonic mean of precision and recall. An improvement in the F1-score is generally the most favorable result. The addition of relative acceleration significantly improved the F1-score, confirming the students' and SME's intuition on its utility.

The addition of wavelet coefficients alongside the regular time-domain features and relative acceleration further improved the model's recall and F1-score. As discussed in the Feature Engineering section, the wavelet coefficients offer insight into the frequency response of the vibration signals that the time-domain features lack. This allows the LSTM model to better encode the beam's vibration response, and thus, detect anomalies more accurately.

Project Challenges and Lessons Learned

The field of vibration analysis and the motion of physical structures was a new domain to the students involved in the project, all of whom had a traditional electrical engineering or computer engineering background. Getting up to speed on the fundamental concepts of this domain while working on this project was a significant challenge. Successful capture and real-time processing of analog signals itself is an extensive field which, although somewhat familiar to the students, took significant effort to refresh on and learn as the vibration signal capture and processing hardware/software was implemented. This required knowledge from the domains of Electrical Engineering, Computer Engineering, Embedded Design and Digital Signal Processing. Formulating an experimental set-up with the limited hardware to mimic the challenges faced in the real-world scenario of vibration analysis in aerospace applications required creativity and careful consideration. Input from SME and faculty advisor was valuable.

Communication between team members required to understand their individual strengths and weaknesses and schedule appropriate tasks to progress project development and meet important deadlines was a crucial challenge in this project. Additionally, communicating with the SME and advisor to define requirements, explain limitations, present results, and refine or adapt core portions of the project as needed, iteratively, was another unique challenge which professional engineers face daily when working on and/or leading sophisticated engineering projects.

Conclusions and Future Work

This project was designed for students to apply their knowledge and devise an engineering solution to a complex problem currently present within industry. The SME was present to both guide students and behave as a client offering feedback and requests throughout the project lifespan. The faculty advisor made sure that educational procedures are in place and learning outcomes are met. Working alongside their peers with the SME, the students experienced the setting of an industry-based engineering project in which deadlines, failures/setbacks, project revisions, client requested modifications, regular presentations/meetings, and other challenges are encountered. Through this experience, the students learned to plan, schedule, design, and implement non-academic engineering solutions effectively.

In doing so, the students also devised a unique solution for the vibration analysis problem discussed in the beginning of the paper. The solution can potentially help identify faults or detect future failures in rotating machinery on a real-time edge-analytics based system. This can be useful in a wide variety of applications, such as those relevant to human safety, those in which the maintenance downtime for the equipment of interest is very long, and those in which cumbersome and sophisticated analysis equipment cannot be utilized. Future work includes applying the solution devised on real machinery operating in real industrial settings along with testing and evaluation.

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