Hands-On Predictive Maintenance Kit for Manufacturing Education: An Accessible Experiential Learning Approach

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Abstract

Predictive maintenance (PdM) is a cornerstone of smart manufacturing systems due to its role in identifying potential machine failures before they occur, which allows strategic maintenance scheduling, maximizing operational uptime. Despite its importance in industry, traditional engineering education still lacks the tools required to give students a hands-on PdM experience. Current educational methods rely on mock PdM datasets, which disconnect students from the practical educational experiences built on sensor implementation, real-time data acquisition, and analytics using Machine Learning (ML). To bridge this gap, this research focused on the development of a low-cost educational PdM Add-On kit for FrED, a low-cost educational desktop-scale manufacturing system, developed at MIT, based on industrial fiber draw that serves as an experimental platform for data collection and analysis. The kit, consisting of a modular sensor suite and companion software, makes hands-on PdM education more accessible through realistic and interactive applications. This work aims to demonstrate that FrED, equipped with the PdM Add-On kit, provides an effective and scalable platform for data-centric PdM education. The kit was deployed in a classroom environment, where students collected process data, applied preprocessing and feature extraction methods, and developed ML models. The augmented FrED platform enabled students to engage with the full PdM workflow using a setup that mimics a real-world industrial scenario while growing their advanced analytics skill set. To validate the pedagogical effectiveness of this intervention, the study employed a mixed-methods assessment framework grounded in Self-Determination Theory (SDT). Student outcomes were evaluated using three distinct instruments: a technical Concept Inventory (CI) to measure objective learning gains, the Perceived Competence Scale (PCS) to quantify shifts in self-efficacy, and the Intrinsic Motivation Inventory (IMI) to assess student engagement and intrinsic motivation. Moreover, reflective questions were used to understand the student learning changes shown in the quantitative instruments.

1. Introduction

The accelerated adoption of Industry 4.0, enabled by the convergence of Big Data, the Internet of Things (IoT), and Artificial Intelligence (AI), has fundamentally transformed the manufacturing landscape [1]. Well-grounded frameworks such as Total Productive Maintenance (TPM) are expected to adapt to these changes through updated workflows and upskilled labor [2]. Within this paradigm predictive maintenance (PdM) has emerged as the transition of classical maintenance activities towards data-informed strategies. A cornerstone of operational efficiency, PdM allows for strategic maintenance scheduling that maximizes operational uptime and drastically reduces costs compared to traditional reactive or preventive strategies [3]. However, this rapid technological acceleration has created a skill gap in industry. As manufacturing and maintenance systems become increasingly data-centric, there is an urgent demand for manufacturing professionals who possess both mechanical and digital competencies [4].

In response to this demand, engineering programs are beginning to adapt; however, this research has identified a limitation within current curricula. While emphasis on machine learning (ML) and data analytics education has increased, these subjects are often taught in isolation from physical mechanics, leaving practical disconnect in the integration of these fields [5]. A primary deficiency in bridging this gap is the reliance on pre-packaged, "clean" datasets that fail to reflect the complexities of an actual factory floor [6]. In real-world scenarios, engineers must navigate challenges such as signal heterogeneity and irregular data acquisition. When students are restricted to mock datasets, they remain disconnected from the practical realities of sensor implementation, real-time data acquisition, and the "messy" nature of raw physical signals [7]. To address this educational gap, hands-on experimentation with physical machinery is required to simulate real-world faults. While some industrial-grade testbeds and data acquisition platforms exist, they are often prohibitively expensive or complex, prompting recent research into low-cost alternatives [8]. Consequently, there is a distinct need for an accessible, low-cost platform that can replicate real-world industrial scenarios and enable hands-on student participation.

This research focuses on the development and evaluation of an accessible, low-cost educational PdM Add-On kit for the FrED. FrED is a desktop-scale fiber extrusion device developed at Massachusetts Institute of Technology (MIT) and serving as an experimental platform for hands-on engineering education [9], [10]. The specific contributions of this paper are threefold:

1. **Development of a Low-Cost Instructional Kit:** Design of an accessible modular sensor suite for hands-on data collection and real-time data monitoring, specifically targeting gearbox fault diagnosis.
2. **Integrated Workflow:** Development and deployment of a companion software and curriculum that guide students through the complete PdM pipeline going from raw signal acquisition and feature extraction to the training and deployment of ML models.
3. **Classroom Implementation and Assessment:** Evaluation of educational impact through a mixed-methods approach deployed in a graduate-level workshop.

2. Background and Theoretical Framework

2.1 Total Productive Maintenance and Education

TPM is a holistic philosophy aiming for 'perfect production' by pursuing zero breakdowns and zero defects. Figure 1 illustrates the functional dependency required to achieve this in Industry 4.0, specifically mapping the transition from workforce preparation to operational reliability. As shown in the diagram's 'Input' block, modern maintenance relies on the integration of Autonomous Maintenance (Pillar 1), where operators monitor their own equipment, and Education and Training (Pillar 6). These pillars provide the necessary foundation for Planned Maintenance (Pillar 3), which houses predictive strategies. The diagram highlights the FrED PdM kit as the pedagogical bridge between these domains. While Pillar 3 represents the technological goal (uptime and reliability), it relies entirely on the competencies developed in Pillars 1 and 6. Consequently, education must evolve from teaching manual procedures to fostering the 'TPM 4.0' skills required to sustain modern Planned Maintenance strategies [11].

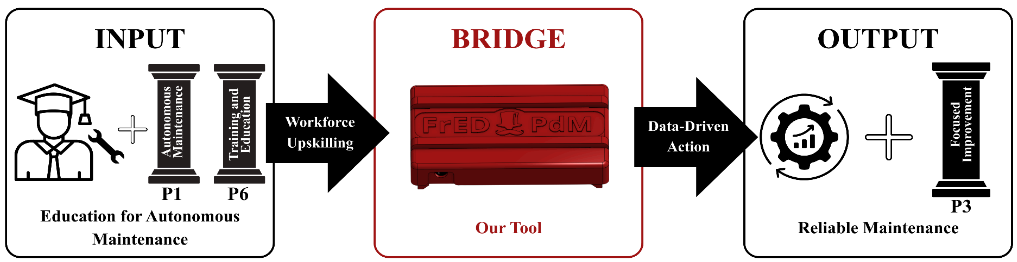

Figure 1: Operational framework linking TPM pillars to the proposed educational intervention.

2.2 Advancing from Preventing to Predictive Strategies

To achieve the efficiency promised by TPM 4.0, organizations must transition from reactive to proactive strategies. Historically, maintenance relied on corrective methods (fixing failures after they occur) or preventive methods (replacing parts on a fixed schedule), both of which can lead to unnecessary downtime or resource waste. PdM optimizes this by integrating ML and advanced data analytics with Condition-Based Monitoring to detect potential failures ("P-point") early in the degradation curve. Unlike traditional monitoring, which often relies on simple thresholds, these data-driven models can identify complex signal patterns indicative of developing faults [12]. By automating the analysis of real-time machine condition data, PdM shifts detection earlier in the lifecycle, effectively extending the actionable P-F Interval. (the time between a potential failure detection and functional failure) allowing for strategic intervention only when necessary, thereby significantly reducing costs compared to traditional approaches.

2.3 The Essential Skills for the PdM Workflow

Successfully implementing PdM requires a "hybrid" workforce capable of bridging the gap between mechanical domain knowledge and digital competency. Specifically, engineers must master a complete data-driven workflow:

- Data Acquisition (capturing physical signals)
- Feature Engineering (extracting meaningful features via techniques such as FFT)
- Machine Learning Training and Deployment (training models for live fault detection).

However, current engineering curricula often treat mechanics and ML as isolated silos, creating a "skill disruption" where students lack the ability to integrate these fields [13]. Furthermore, reliance on sanitized, pre-packaged datasets shields learners from the "messiness" of real industrial data, such as signal heterogeneity, highlighting a critical need for hardware-based educational tools that replicate the friction of real-world PdM deployment.

3. Educational Approach and Platform Design

3.1 Experimental Setup: Fiber Extrusion Device Overview

The development of the educational PdM kit is anchored around the FrED platform. As illustrated in Figure 2a, FrED is divided into five subsystems. Among these, the spooling subsystem is selected as the focal component for the development of the PdM kit due to its mechanical complexity and its suitability for simulating realistic fault conditions. In particular, the spooling subsystem incorporates a 3D-printed gearbox, shown in Figure 2b, which consists of 7 gears that sequentially transmit power to generate both linear and rotational motion at the spool through a scotch-yoke mechanism. To simulate common gearbox degradation scenarios within this system, three faulted gears were intentionally fabricated: chipped-tooth, vertical wear, and offset center, as presented in Figure 2c. These faults are intentionally introduced in the crank gear, as it experiences high mechanical load, and are designed to be both accessible and meaningful, enabling engineering students from diverse backgrounds to distinguish the differences between each scenario.

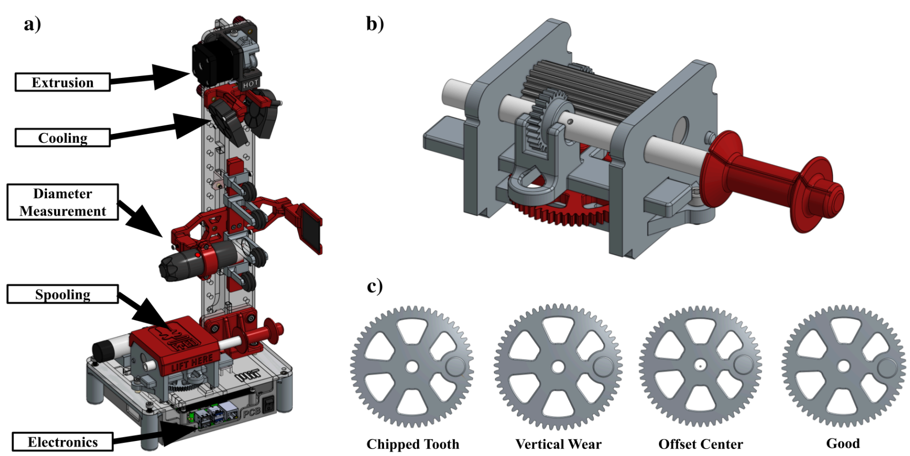

Figure 2: (a) FrED subsystems. (b) Spooling subsystem gearbox. (c) Induced gear faults

The FrED spooling gearbox is primarily a mechanical system with inherent natural frequencies. These frequencies are continuously stimulated during operation through gear meshing, load transmission, and intermittent contact within the scotch-yoke mechanism. These dynamic interactions generate measurable physical responses not only in the form of mechanical vibrations transmitted through the structure, but also sound waves propagating through both air and contact surfaces. These types of responses carry information about the mechanical state of the system. For example, under healthy operating conditions, these signals exhibit stable and repeatable frequency patterns; however, the presence of faults alter stiffness, contact forces, and excitation mechanisms within the gearbox. As a result, fault conditions present observable changes in signal amplitude, spectral content, and modulation behavior, particularly around gear mesh frequencies (rate at which the teeth from a driving gear come into contact with the teeth of a driven gear) and their harmonics [12]. To address these scenarios, an acoustic-based PdM strategy is adopted due to its ability to capture rich frequency-domain information while maintaining both a non-intrusive and low-cost approach.

3.2 PdM Add-On Kit Hardware: FrED Predictive Analysis and Learning Kit

The FrED Predictive Analysis and Learning (PAAL) kit integrates two core components: an electronics assembly and a sensor housing, each designed to support acoustic signal acquisition from the FrED gearbox. In order to simulate the high-noise conditions found in production facilities, contact microphones, in the form of piezoelectric sensors, are selected as the main sensing component of the kit. Their ability to capture sound via solid conduction effectively eliminates interference from environmental noise, room acoustics, and sensor positioning, while also providing a cost-efficient solution for the kit. The piezoelectric sensors are integrated with an AD828 pre-amplifier and a TRRS module, following Figure 3b schematic. Furthermore, the sensor housing is designed for the electronics to be fixed while maximizing contact surface area by being mounted on the gearbox lid; this is accomplished by dividing the housing into three components: a flat sensor base, a lid, and two clips, as shown in Figure 3a. In the end, the fabrication cost of a FrED PAL kit is approximately 26.00 USD, as summarized in Table 1, which represents an accessible price point for an educational engineering device designed to simulate a PdM environment.

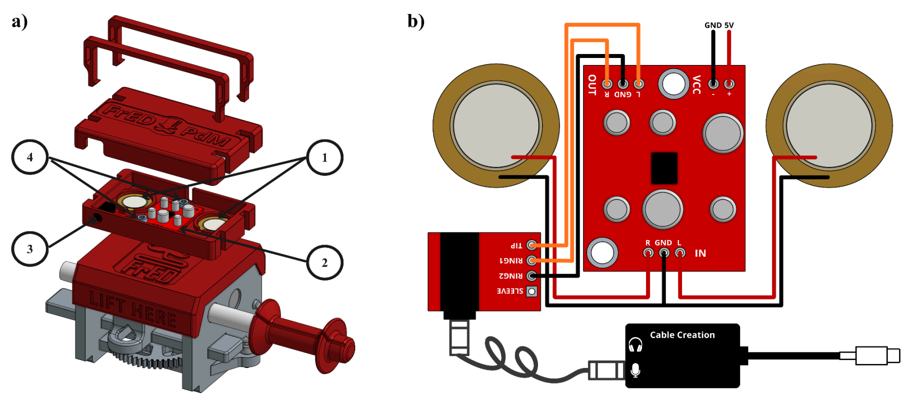

Figure 3: (a) FrED PAL exploded view. (b) Electric Schematic Diagram

Table 1: FrED PAL cost

Element	Description	Manufacturer	Quantity	Cost x Unit (USD)	Total (USD)
1	0.787 in piezoelectric sensor	Cheerock	2	0.53	1.07
2	AD828 pre amplifier board	HiLetgo	1	2.50	2.50
3	TRRS board module	Onyehn	1	2.56	2.56
4	Socket Head Screw M3x0.5x5	-	2	0.07	0.14
5	M3-4mm heat insert	-	2	0.10	0.20
6	Jumpers	-	4	0.06	0.23

7	57 grs of Sparkle Crimson PLA	Bambu Lab	57	0.02	1.43
8	TRS cable	AILKIN	1	2.50	2.50
9	Auxiliary to USB-C adapter	Cable Creation	1	14.99	14.99
				Total:	**25.62**

The kit workflow begins by assembling the components, mounting the sensor module on the gearbox lid, and powering the electronics through the FrED PCB 5 V supply and ground. A TRS cable is then connected from the TRRS module to a USB-C audio adapter through the microphone port. This configuration is selected to ensure reliable signal acquisition and cross-platform compatibility. Direct TRRS microphone connections rely on internally provided bias voltages and headset-detection mechanisms that vary across operating systems. In contrast, the USB-C audio adapter provides a standardized audio codec with an internal ADC and biasing scheme, enabling consistent signal capture across computing platforms. During gearbox operation, acoustic signals from the left and right sides are captured by the piezoelectric sensors at a sampling rate of 40 kHz, forming a stereo signal that is amplified by the AD828 and transmitted through the TRRS module. The auxiliary cable then carries the signal to the adapter, where it is converted to a mono stream and stored on the computer in Waveform Audio File Format (WAV).

3.3 Companion Software and ML Workflow

The FrED PAL kit serves as the physical platform for hands-on acoustic data collection from the FrED gearbox. A complementary Python notebook processes the collected WAV audios for fault classification using ML algorithms, following the pipeline shown in Figure 4 and initiated once the data from healthy and faulty gearboxes are acquired. After the data is imported into the virtual environment and labeled, each audio file is denoised using a 2nd order low-pass filter with a 1 kHz cutoff frequency, where the cutoff frequency is determined by the gear mesh frequencies of the gearbox. This filtering removes the high-frequency components associated with the DC motor while preserving the gear meshing and sliding frequency content. Moreover, the filtered signal is split into training and testing datasets with an 80%-20% ratio to evaluate the model performance on unseen data. Additionally, to avoid data leakage between training and testing data, a 1 second portion of audio is removed in between sets. Afterwards, each dataset is time-based split into 5 second segments in order to have a time change of information between segments when extracting features. Furthermore, each segment is divided into frames with 50% overlap to preserve contextual continuity and increase the amount of usable training and testing data, enabling the model to detect fault signals occurring at the beginning, middle, or end of a frame. Concluding the data preprocessing workflow, feature extraction is performed using three levels of complexity: Raw, Time domain, and Time & Frequency domain.

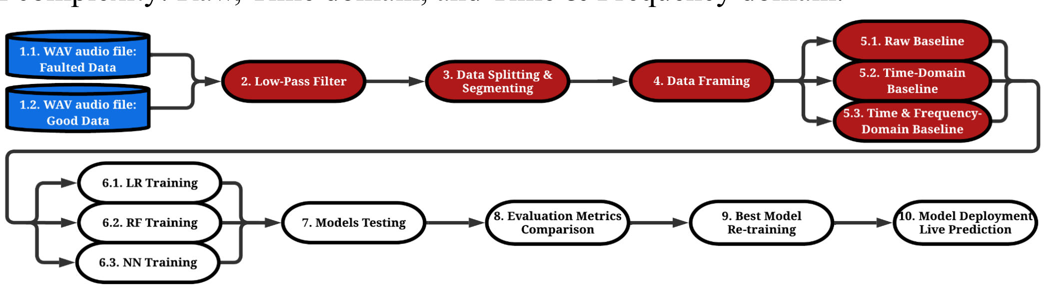

Figure 4: ML pipeline for data analytics

First, the *raw baseline* downsamples each time-domain frame by computing its average, consequently using raw signal values as model inputs and enabling direct comparison with feature-based approaches. Next, the *time-domain baseline* extracts per frame the 14 time-domain features shown in Table 2; these features capture changes in amplitude, variability, impulsiveness, and energy associated with transient and nonstationary behavior in early-stage mechanical faults. Finally, the *time & frequency baseline* involves using the time-domain features and extracting frequency-domain ones by applying the Fourier Transform (FT). The 29 frequency-domain features shown in Table 2 are extracted. These baselines were designed to assess the performance of identical machine learning models trained on different input data.

Table 2: Time and frequency-domain features

	Feature	Description	Feature	Description
Time Domain	Mean	Average amplitude of the audio segment; indicates DC/level.	Energy	Sum of squared amplitudes over the segment; total signal energy.
	Std	Standard deviation of amplitudes; measures overall variability.	ZCR	Zero-Crossing Rate; frequency of sign changes, higher for noisy or high-frequency signals.
	Var	Variance of the amplitudes; the square of std.	Skewness	Asymmetry of amplitude distribution; positive skew means longer right tail.
	Median	Middle amplitude value when samples are sorted; robust center measure.	Kurtosis	"Tailedness" of distribution; high kurtosis indicates sharp peaks/impulses.
	Min	Minimum sample amplitude; useful for detecting negative peaks or noise.	Quantile 25	25th percentile amplitude (lower quartile), robust dispersion info.
	Max	Maximum sample amplitude; useful for detecting peaks or impulses.	Quantile 50	50th percentile amplitude (same as median).
	RMS	Root Mean Square of amplitudes; indicates signal power (energy-like).	Quantile 75	75th percentile amplitude (upper quartile).
Frequency Domain	**Feature**	**Description**		
	Spectral Centroid Mean & Std	Center of mass of the magnitude spectrum; perceptual "brightness".		
	Bandwidth Mean & Std	Spread of the spectrum around the centroid; broader bandwidth = more high-frequency content.		
	Spectral Rolloff Mean & Std	Frequency below which a specified proportion (e.g., 85%) of spectral energy resides; indicates spectral shape.		
	Spectral Flatness Mean & Std	Ratio indicating how noise-like vs. tonal the spectrum is (higher = more noise-like).		
	Spectral Contrast b{i} Mean & Std	Contrast between peaks and valleys in spectral band i (typically several bands, e.g., 7); useful to distinguish tonal vs. noisy components.		
	MFCC 0-12	Mel Frequency Cepstrum Coefficient is a feature extraction technique used in several applications (medical, industry, etc) that uses 13 coefficients to represent a signal in the way human ears perceive sound. [15]		
	Chroma Mean & Std	Energy distribution across pitch classes (12 chroma bins); captures harmonic/tonal content and periodicities.		
	Onset Strength Mean	Average onset (event) strength across frames; higher when there are many or strong transients.		
	Tempo	Estimated beats-per-minute (BPM) or dominant rhythm estimate		
	Dominant Freq	Frequency with maximum power in the spectrum (peak frequency).		
	Spectral Entropy	Entropy of the normalized spectral power distribution; higher values indicate more uniform (noise-like) spectra.		

The ML pipeline's next step consists of using the features extracted in the 3 baselines to train ML models. *Logistic regression* (LR), *random forest* (RF), and *neural network* (NN) are the selected ML algorithms since it has been proved that they perform with great accuracy in similar applications [8], [12], [16]. The models are trained using the training data only; they are evaluated using the unseen testing dataset, and the evaluation metrics listed in Table 3 are calculated to assess each algorithm's performance. Once the best-performing model is selected, it is subsequently retrained using the full dataset; this is only done to add robustness to the algorithm for the model deployment assessment. The retrained ML model is saved to finally be deployed into a live prediction application.

Table 3: Multiclass Evaluation Metrics

Metric	Description
Accuracy	Ratio of the number of the correct predictions (either positive or negative) to the total number of predictions.
Macro Precision	Multiclass evaluation metric that calculates precision (proportion of correctly predicted faulty samples among all samples predicted as faulty) for each class independently and obtains the unweighted average across all classes. Average of all faulty predictions (either true or false), how many are true.
Macro Recall	Multiclass evaluation metric that calculates recall (proportion of correctly predicted faulty samples among all actual faulty samples) for each class independently and then takes the unweighted average across all classes. Average of all faulty true positive predictions, how many are caught or actually true.
Macro F1-score	Multiclass evaluation metric that calculates the unweighted average of the F1-scores calculated independently for each class. Provides a balance in between precision and recall while treating all classes equally.
Training time	Computational time required to train the machine learning algorithm.

3.4 Workshop Structure and Learning Objectives

In order to test the educational impact FrED PAL has on engineering students, a predictive maintenance workshop is developed. The experience immerses students in the complete PdM workflow, allowing them to execute a functional PdM pipeline by diagnosing the four possible operating conditions on the crank gear of FrED gearbox. The workshop agenda, shown in Figure 5, consists of 1 theoretical background and 3 hands-on sessions. During the first day, the students are introduced to the theoretical concepts required to understand the outcomes of the next 3 sessions. Subsequently, day 2 is dedicated to hands-on data collection; a total of 12 FrED units and FrED PAL kits are prepared to acquire data from both healthy and faulty gearboxes, enabling an evaluation of sensor and device variability. Students work in pairs, and each team submits two 3-minute audio recordings, resulting in 24 total recordings, where 12 are from healthy gearboxes and 12 from faulty ones (4 recordings per fault condition).

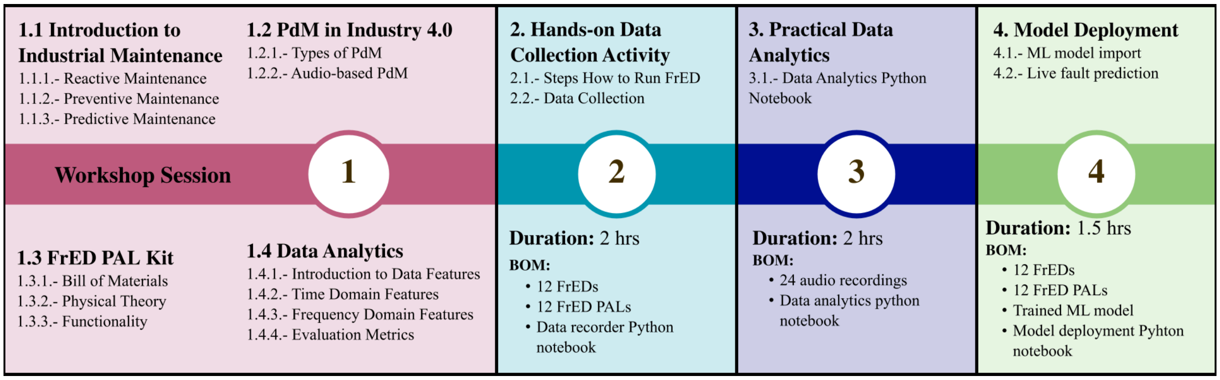

Figure 5: Workshop agenda

The third session consists of using the kit's python notebook to analyze the data recorded during session 2. In addition to the ML pipeline, a data visualization section is included in the notebook for students to perceive the differences on the 4 types of gearbox conditions. These plots include amplitude and time-frequency spectrograms, basic and standard features plots, and FFT spectrums. Together, they allow students to understand not only the variations between the different scenarios, but also the theoretical foundation of gearboxes. By the end of session 3, students deliver their best trained ML model. Finally, the fourth session consists of deploying the downloaded ML model in a live prediction scenario. A total of 4 FrEDs and FrED PAL kits are prepared considering the 4 scenarios for each team to predict the scenario present in each gearbox.

By the end of this workshop, students should be able to:

1. Translate a PdM problem into a full ML workflow.
2. Allow students to design data preparation pipelines, visualize and inspect time-series signals, and extract meaningful features.
3. Compare and refine multiple ML models using multiclass evaluation metrics and running inference on new data to evaluate real-world effectiveness.

4. Workshop Educational Evaluation and Outcomes

The workshop was deployed for the first time in the graduate-level course, "Introduction to Manufacturing Systems", at MIT in the Fall 2025 semester. All students are required to participate as one of the lab components of the course. The experience impact was evaluated through pre- and post-workshop surveys following a mixed-evaluation methodology (quantitative and qualitative data) grounded in Self-Determination Theory (SDT). A total of 25 students participated in the course and workshop, of these, n = 14 consented to research participation and provided complete survey responses, which were analyzed to generate deeper insights into the trends of the educational impact of the predictive maintenance workshop. The study is IRB exempt.

4.1 Quantitative Evaluation

The quantitative section of the pre- and post-workshop surveys was designed to assess the intervention's impact across three key dimensions: technical understanding, self-efficacy, and intrinsic motivation. Data from the pre- and post-workshop surveys were analyzed using descriptive statistics, specifically the Mean (*M*) to determine central tendencies and Standard Deviation (*SD*) to assess the variability of student responses. Additionally, a transition analysis was conducted on the technical assessment to track individual knowledge retention and correction patterns.

4.1.1 Concept Inventory Outcomes

A Concept Inventory (CI) served as the primary instrument for measuring objective learning gains. This assessment comprised 10 technical questions, listed in Table 4, addressing core PdM topics that span the complete workflow: From Physical Sound to Digital Data, Feature Engineering, Model Training & Evaluation, and Application. To capture the nuance of student progress, a transition analysis was performed to categorize response shifts from pre- to post-test.

Table 4: Concept inventory technical pre- and post-workshop test

ID	Topic	Questions	Mean Pre-	Mean Post-
CI 1	From Physical Sound to Digital Data	A microphone records a machine's sound wave. How is that continuous, physical wave digitized and represented in code (e.g., in a NumPy array)?	57.143%	78.571%
CI 2		In signal processing, what is the primary purpose of applying a Fast Fourier Transform (FFT) to create an Amplitude Spectrum?	85.714%	92.857%
CI 3	Feature Engineering	Conceptually, what are "features" in the context of machine learning?	85.714%	92.857%
CI 4		Why is "feature extraction" necessary when using complex data like raw audio for ML?	100.000%	92.857%
CI 5		In many machine learning pipelines, a process called "feature scaling" (e.g., using a StandardScaler) is applied. Why is this step important for some models (like NN)?	64.286%	78.571%
CI 6	Model Training & Evaluation	If your goal is to build a model that identifies a sound signal of a gearbox as "normal" or "faulty," which type of machine learning problem is this?	78.571%	85.714%
CI 7		What is the primary reason for splitting data into a "training set" and a "testing set"?	85.714%	78.571%
CI 8		When evaluating a machine learning model, it often misclassifies the rare "faulty" sounds. Which performance metric would be more important to analyze?	28.571%	50.000%
CI 9		When building a predictive maintenance system, why is it common practice to train and compare different models (e.g., Logistic Regression vs. Random Forest)?	57.143%	71.429%
CI 10	Application	What does it mean to "run inference" with a trained machine learning model?	64.286%	64.286%

As presented in Figure 6, the results indicated a marked improvement in foundational concepts. Marked "Learning Gains" (Green: Wrong to Right) were observed, particularly in CI 1 (Signal Representation) and CI 8 (Performance Metrics), where a large proportion of the cohort successfully corrected initial misconceptions. While some persistent knowledge gaps remained in advanced topics (Gray: Wrong to Wrong), the overall trend confirms that the hands-on data collection process effectively clarified abstract theoretical concepts.

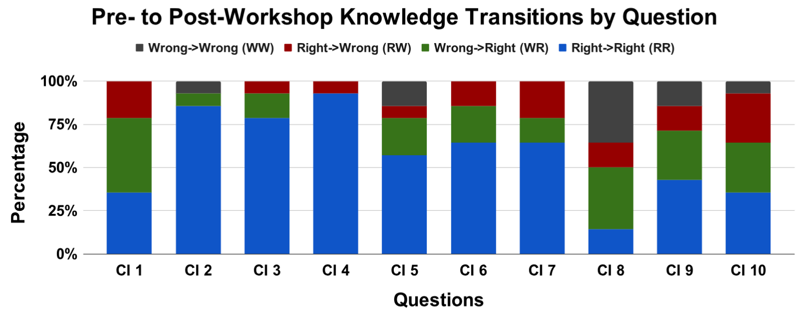

Figure 6: Transition analysis of student responses on the Technical Concept Inventory.

4.1.2 Perceived Competence Scale Outcomes

To measure shifts in self-efficacy, a Perceived Competence Scale (PCS) [17], [18] was administered before and after the workshop. The survey consisted of 4 items, listed in Table 5, designed to assess students' confidence in executing specific PdM tasks, such as implementing signal processing pipelines and carrying out condition monitoring. Responses were recorded on a 7-point Likert scale.

As summarized in Table 5, the results demonstrated a notable increase in self-efficacy. Prior to the workshop, the overall mean confidence level was 2.339, indicating a "Beginner" status, with notable variability across the cohort (SD range = 1.424 – 1.637). Following the session, the overall mean rose to 4.250, representing a net increase of 1.911 points and shifting the class toward "Competent" and "Advanced" classifications. Crucially, the standard deviation of the students' composite scores decreased from 1.540 (Pre) to 1.250 (Post). This reduction in variability indicated a convergence in student confidence, suggesting that the physical interaction with the FrED PAL kit provided effective scaffolding that narrowed the skill gap between novice and experienced students.

Table 5: Perceived Competence Scale pre- and post-workshop survey results.

ID	**PCS Test Questions:** **Not at All True (1) – Somewhat True (4) – Very True (7)**	**Mean Pre-** **(SD)**	**Mean Post-** **(SD)**	**Delta Mean** **(Delta SD)**
PCS 1	I feel confident in my ability to implement signal processing and a machine learning pipeline for PdM applications.	2.429 (1.604)	4.430 (1.342)	2.001 (-0.262)
PCS 2	I am capable of applying signal processing and machine learning pipelines for PdM applications.	2.429 (1.604)	3.700 (1.383)	1.271 (-0.221)
PCS 3	I am able to carry out condition monitoring techniques for PdM.	2.214 (1.424)	4.230 (1.267)	2.016 (-0.157)
PCS 4	I feel able to meet the challenge of executing a PdM project.	2.286 (1.637)	4.640 (1.447)	2.354 (-0.190)
	Overall Mean PCS Scores	**2.339** **(1.540)**	**4.250** **(1.250)**	**1.911** **(-0.290)**

4.1.3 Intrinsic Motivation Inventory Outcomes

Student engagement was evaluated using the Intrinsic Motivation Inventory (IMI) [19], [20]. This instrument utilized the 16 items presented in Table 6 to measure four subscales: Interest/Enjoyment, Value/Usefulness, Perceived Competence, and Effort/Importance. Descriptive statistics were calculated for each subscale to identify specific drivers of student motivation.

As detailed in Table 6, the results validated the pedagogical approach with high consistency across all four dimensions. Students reported the highest engagement in the Interest/Enjoyment category (M subscale = 6.232), indicating that the hands-on nature of the workshop was intrinsically motivating. This engagement was further evidenced by the already inverted high score on the reverse-coded item IMI 3 ("I thought this was a boring workshop," M = 6.429, SD = 0.756), confirming that students actively rejected the notion that the content was uninteresting. Similarly, the perception of professional relevance in the Value/Usefulness subscale was equally high (M = 6.054, SD = 1.253). The item IMI 7 ("beneficial to me") received the highest individual endorsement in this category (M = 6.214, SD = 1.188), confirming that students recognized the direct applicability of the FrED PAL kit to their future engineering careers.

Regarding the learning dynamics, students reported a strong sense of competence (M = 5.232, SD = 1.265), which corroborated the self-efficacy gains observed in the PCS analysis and suggested that the workshop successfully empowered them to handle complex PdM tasks. Finally, scores in the Effort/Importance category remained moderate-to-high (M = 4.964, SD = 1.200), suggesting the workshop achieved a "desirable difficulty." The tasks were challenging enough to require significant energy, yet the high competence scores implied that the scaffolding was sufficient to prevent frustration, keeping students in an optimal learning zone.

Table 6: Intrinsic Motivation Inventory (IMI) post-workshop survey questions and results.

ID	IMI Questions: Not at All True (1) – Somewhat True (4) – Very True (7) Note: Items marked with (R) are reverse-coded. The values shown have already been inverted.	Mean (SD)
Interest / Enjoyment		**6.232 (0.988)**
IMI 1	I enjoyed doing this workshop very much.	6.071 (1.207)
IMI 2	This workshop was fun to do.	6.214 (1.188)
IMI 3	I thought this was a boring workshop. (R)	6.429 (0.756)
IMI 4	I would describe this workshop as very interesting.	6.214 (1.188)
Value / Usefulness		**6.054 (1.253)**
IMI 5	I believe this workshop could be of some value to me.	6.143 (1.231)
IMI 6	I think that doing this workshop was useful for my future studies.	5.714 (1.684)
IMI 7	I believe doing this workshop was beneficial to me.	6.214 (1.188)
IMI 8	I think this is an important workshop.	6.143 (1.099)
Perceived Competence		**5.232 (1.265)**
IMI 9	I think I did pretty good at this workshop.	5.143 (1.460)

IMI 10	After participating in this workshop, I feel pretty competent.	5.071 (1.592)
IMI 11	I am satisfied with my performance in this workshop.	5.071 (1.269)
IMI 12	This was a workshop that I couldn't do very well. (R)	5.643 (1.447)
Effort / Importance		**4.964 (1.200)**
IMI 13	I put a lot of effort into this workshop.	4.571 (1.284)
IMI 14	I tried very hard in this workshop.	4.929 (1.542)
IMI 15	It was important to me to do well at this workshop.	4.857 (1.460)
IMI 16	I didn't put much energy into this workshop. (R)	5.500 (1.286)

4.2 Qualitative Evaluation

To complement the quantitative measures, qualitative data was integrated into the curriculum through structured reflection questions, shown in Table 7. These questions were analyzed using a thematic analysis methodology, in which responses were systematically organized, cleaned, and examined through multiple stages to extract meaningful patterns and insights. This process included data familiarization, initial coding of meaningful text segments, grouping and refinement of codes into preliminary themes, and iterative theme review to ensure coherence and evidentiary support. By triangulating the CI results with PCS and IMI scores and conducting thematic analysis of the qualitative responses of questions, the study captured the "engagement gap" between theoretical instruction and physical implementation. This pre/post assessment approach enabled the evaluation of not only final learning outcomes but also the shifts in self-efficacy that emerge as students move from working with 'clean' theoretical data to interacting with 'messy' real-world hardware.

Table 7: Post-workshop survey reflective questions

ID	Questions
RQ 1	What was the most valuable or interesting part of this workshop for you, and why?
RQ 2	Looking back at the Perceived Competence Survey (Part A), which topic (e.g., feature engineering, training models, model comparison) did you find most challenging or least clear? Please explain why.
RQ 3	Thinking about your responses in the Workshop Experience (Part B), what specific part of the workshop (e.g., the coding, the data, the final challenge) made you feel the most (or least) interested and engaged?
RQ 4	Do you have any other comments or suggestions for how we could improve this workshop?

4.2.1 Thematic Analysis Outcomes

The thematic analysis identified five primary themes: (1) hands-on, real-world learning increases engagement; (2) feature engineering and signal processing represent key learning challenges; (3) the pacing and scaffolding of the coding component require adjustment; (4) students value understanding the full ML pipeline rather than merely executing code; and (5) an overall positive perception and high motivation. As shown in Figure 7a, the most frequent theme was overall positive perception, with students expressing strong motivation through comments such as "I loved this module" and "Excited to see it grow." Hands-on engagement emerged as the second most cited theme, with students highlighting data collection and model deployment as particularly relevant and engaging, indicating that direct interaction with the FrED and FrED

PAL hardware supports understanding of ML applications in PdM. However, eight students identified feature engineering as the most challenging topic, citing limited prior experience and insufficient time, revealing an opportunity for improvement in the data analytics notebook. Consistent with these findings, Figure 7b shows that hands-on data collection was the most frequently referenced source of engagement, followed by the coding session and the final challenge. This distribution suggests that engagement was highest when the workshop balanced physical experimentation with guided coding and culminated in an integrated, real-world application, aligning with prior research on embodied learning in engineering education.

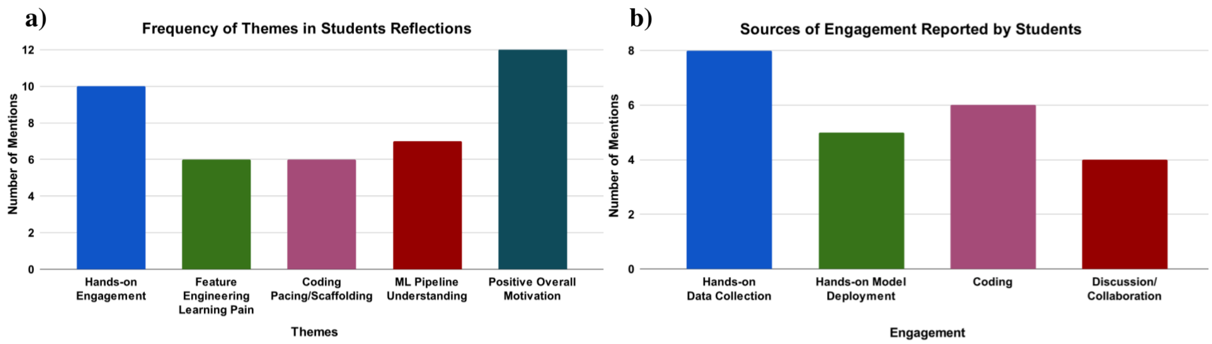

Figure 7: (a) Frequency of themes in students reflection. (b) Sources of engagement reported by student during the workshop

4.3 Discussion of Learning Impact

The integration of the FrED PAL kit facilitated a distinct shift from theoretical abstraction to practical competency. As evidenced by the CI transition analysis, the most significant learning gains occurred in foundational concepts such as digital signal representation (CI 1) and model evaluation (CI 8). This suggests that the "friction" introduced by real hardware, connecting sensors, and witnessing signal heterogeneity, proved to be a valuable pedagogical feature rather than a detriment. Unlike pre-packaged datasets that mask the complexities of the factory floor, the raw signals generated by the FrED gearbox forced students to confront the messy intersection of physical mechanics and digital processing, aligning with the "hybrid" competency needs described by Hernandez-de-Menendez et al. [13]

Despite the technical demands, the motivational impact measured via the IMI contradicts the assumption that difficulty leads to disengagement. Students reported high scores on the Effort/Importance subscale alongside high Interest/Enjoyment and Perceived Competence. In the context of SDT [17], this suggests the workshop created a condition of "optimal challenge," where the difficulty of tasks like feature extraction was matched by the scaffolding provided by the kit. While qualitative feedback indicated that some students struggled with feature extraction (highlighting a need for a more graduated introduction to feature selection and pipeline design in future iterations), the high Value/Usefulness scores confirm that students recognized the direct relevance of these skills to their future careers.

However, the study is subject to limitations, primarily the sample size (n=14) and the short duration, which prevented a longitudinal assessment of skill retention. Nevertheless, the success of the intervention demonstrates that low-cost, transparent hardware can effectively bridge the gap between mechanical theory and machine learning application [5]. By moving away from overly-complicated commercial tools, engineering programs can cultivate the "hybrid" professionals described by Assante et al. [12] who are capable of navigating the complex cyber-physical systems of the future. Future work will focus on scaling this intervention to multi-institution deployments to verify these findings across diverse student populations.

5. Conclusion and Future Work

This study evaluated the trends in the educational impact of the FrED Predictive Analysis and Learning kit, a low-cost, hands-on platform designed to support learning in PdM and ML. The kit was deployed as a workshop in a graduate-level class at MIT, integrating hardware-based data collection, guided coding, and a final challenge to bridge theory and practice. Twenty-five students participated, with fourteen providing complete quantitative and qualitative data. The workshop targeted three outcomes: translating PdM problems into full ML workflows, developing data preparation and feature extraction pipelines, and training and comparing ML models. Results indicate these objectives were met, with CI analysis showing notable conceptual gains, PCS scores increasing by 81%, and high IMI ratings confirming strong engagement. Qualitative reflections further highlighted the value of hands-on experimentation and real-world data. Nevertheless, the study presents certain limitations. The relatively small number of complete responses constrains the generalizability of the results, and the absence of a controlled comparison group limits the ability to isolate the effects of prior student experience on observed learning gains. Despite these limitations, the findings suggest that combining physical systems with structured analytical tasks can meaningfully enhance learning, confidence, and motivation in graduate-level PdM and ML education.

Future work will focus on expanding the technical depth and evaluative rigor of the FrED PAL kit. Additional sensors, such as temperature, vibration, and current monitoring, can be integrated to enrich data collection, improve fault classification accuracy, and introduce remaining useful life (RUL) prediction as an advanced learning objective. The feature engineering component of the workshop can also be strengthened through more hands-on activities that require students to implement and justify their own feature extraction strategies. Finally, future deployments should involve larger cohorts and controlled group designs that account for participants' prior backgrounds, enabling to validate statistical generalizability supporting the development of a scalable PdM educational framework.

Supplementary Materials

The supporting materials used for the example presented in the paper in the version as of the publication date can be found in the link below. The repository contains the CAD, BOM, schematics, sample dataset, code, notebook, and workshop slides for the FrED PAL kit.
https://github.com/mit-fredfactory/FrED-PAL-Kit/

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