Predictive Maintenance Strategies for Fan Motors: An Examination of Sensor Technologies and Machine Learning Approaches

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***Abstract*—Heating, Ventilation, and Air Conditioning (HVAC) systems are critical for maintaining comfort and air quality in buildings, but they are also prone to failures that can lead to costly downtime and inefficient energy usage. A key component of these systems is the fan, which plays a vital role in regulating airflow. Over time, wear and tear on fan components can cause system malfunctions. Predictive maintenance (PdM) aims to address these issues by detecting early-stage faults before they result in significant failures, helping to minimize unexpected breakdowns and reduce maintenance costs. This literature review aims to evaluate and discuss existing methods for fault detection in HVAC fan systems, addressing current challenges and limitations related to data collection and problem-solving approaches, in addition to proposing a novel solution that integrates hybrid methods with data fusion techniques and utilizes the Random Forest (RF) algorithm. By enhancing the accuracy and timeliness of fault detection, this review identifies gaps in existing research and lays the foundation for developing an innovative hybrid approach to advance predictive maintenance in HVAC systems.**

***Index Terms*—HVAC systems, Condition-Based Maintenance (CBM), fault detection, predictive maintenance, data fusion, Random Forest**

Abbreviations and Acronyms

List of Abbreviations

- CBM : Condition-Based Maintenance
- EDA : Exploratory Data Analysis
- ESN : Echo State Network
- FDD : Fault detection and diagnosis
- HVAC : Heating, Ventilation, and Air Conditioning
- ML : Machine Learning
- NRMSE : Normalized Root-Mean-Square Error
- PdM : Predictive Maintenance
- PHM: Prognostics and Health Management
- RF : Random Forest
- RMSE : Root Mean Square Error
- RNNs : Recurrent Neural Networks
- RUL : Remaining Useful Life

I. Introduction

With the rise of Industry 4.0, both physical and digital products have expanded more than ever before. This integration of physical and digital environments facilitates the collection of vast amounts of data from various pieces of equipment across different factory sectors [1]. Meanwhile, maintaining this equipment is crucial as it impacts operational uptime and efficiency. Thus, it is essential to detect and address equipment faults promptly to prevent interruptions in production processes, so-called predictive maintenance [2].

The building sector is respondible for 36% of the total global energy consumption. Of all the energy-consumer devices within a building, HVAC systems account for over 50% of the total energy consumed [6]. This makes HVAC systems a source of preventable and unexplored energy waste that can be tackled by incorporating intelligent operations. Meanwhile, malfunctioning of HVAC systems can endanger the lifespan of equipment, energy usage, and occupant thermal comfort. Therefore, it is crucial to find solutions that lower the energy consumption of HVAC systems while addressing their malfunctioning problem. FDD systems have the potential to address the issue by reducing equipment downtime, energy costs, and maintenance costs [3], [4].

There are three main categories of predictive maintenance: CBM, PHM and RUL. CBM focuses on monitoring the condition of equipment using real-time data to decide when maintenance should be performed. PHM, on the other hand, is a broader framework that includes predictive maintenance, diagnostics, and prognostics to manage the overall health of a system. While CBM is part of PHM, PHM also involves more sophisticated prognostic models that not only identify faults but also predict when a failure is likely to occur. RUL prediction goes a step further than CBM by predicting how much time remains before a failure occurs. RUL prediction takes this a step further by estimating the remaining operational time before a system failure happens. Regardless of the specific approach employed, predictive maintenance typically falls under one of three types: physical model-based, knowledge-based, or data-driven methods [1], [4]. Refer to the Figure 1 for a clearer understanding.

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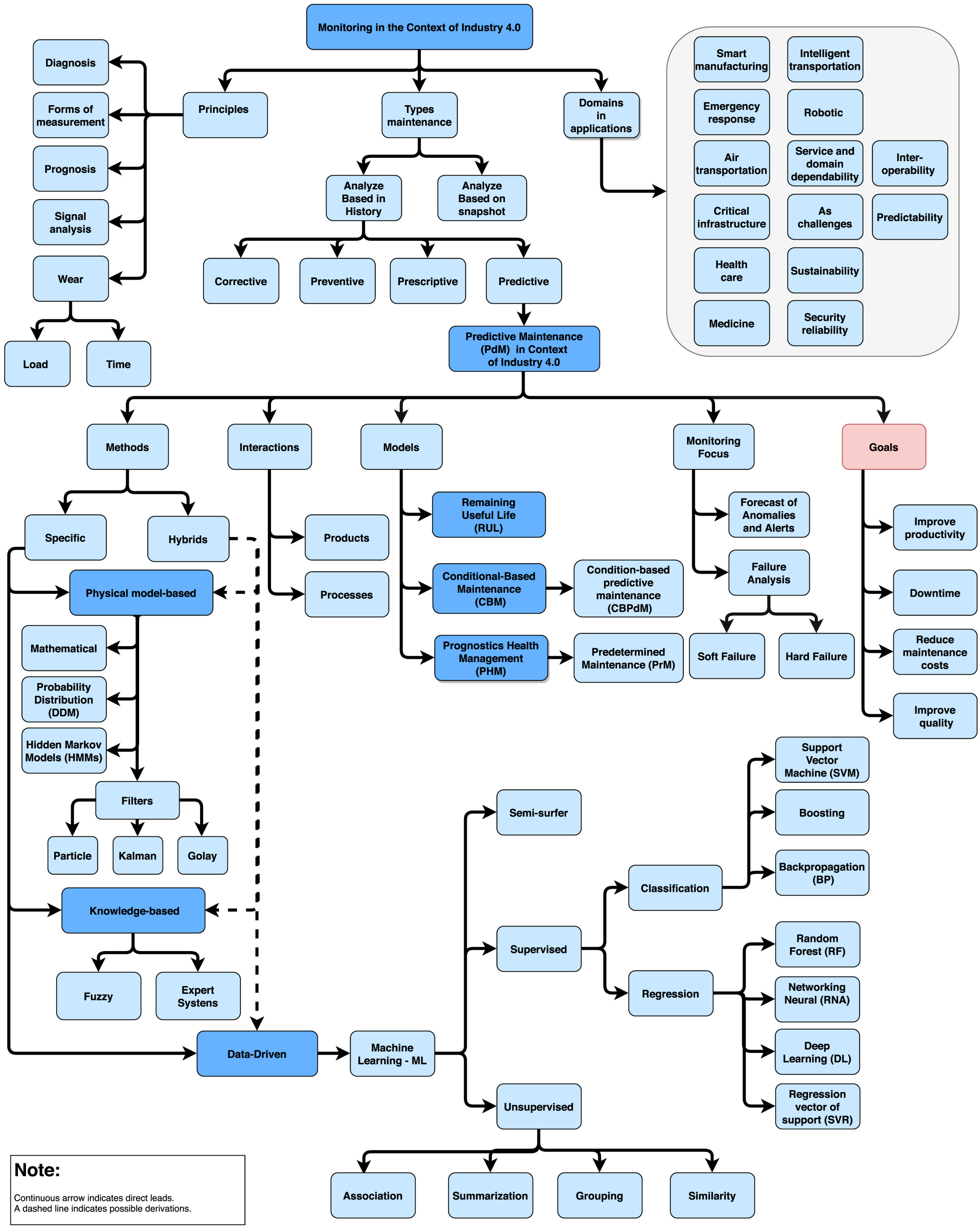

Fig. 1. Structure of Predictive Maintenance [7]

II. Literature Review

Several experiments have been conducted to predict failures in HVAC systems, in our interest research, focusing on fan systems. It is important to note that most tests applied in HVAC and predictive maintenance (PdM) rely on simulation environments as collecting real-world data presents significant challenges as well as just one source of sensor, which can be insufficient for analysis [1], [5], [7].One experiment [10] seeks to address the issue of frequent mill fan repairs in a power plant, where erosion leads to repairs every 2 to 2.5 months despite using high-resistance steels. Conducted at the Maritsa East 2 thermal power plant in Bulgaria, the study collected vibration data and key operational parameters (such as grinding productivity, fan productivity, and vibration state) through the Decentralized Control System (DCS) Historian system over an 8-month period in 2010. The researchers employed a hybrid method combining physics-based and knowledge-based models to analyze the vibration data for predictive maintenance purposes. They specifically focused on non-linear trends in the vibration data, utilizing MATLAB for regression analysis. The results showed that analyzing non-linear trends effectively predicts changes in the condition of the mill fan motor. To maximize the potential of the proposed diagnostic procedures, additional information on maintenance schedules and rotor replacement shutdowns is essential for interpreting vibration trends accurately. The study highlights the value of vibrosignals in diagnosing mill fan conditions, as they provide significant diagnostic insights that can isolate and clarify issues. Incorporating operational efficiency data into the analysis would enhance the overall understanding of the system's maintenance needs, ultimately optimizing predictive maintenance strategies by aligning vibration data with operational performance.

Another study [9] explored predictive maintenance for mill fan systems by using RNNs to predict potential failures based on performance degradation using data-driven method. Vibration data from bearings near the mill rotor were used to train two RNN types: the Elman Network and the ESN. The researchers aimed to assess these models' performance in terms of prediction accuracy and training time. Due to the presence of multiple vibration sources, wavelet de-noising was applied to filter the data. Results showed that the ESN significantly outperformed the Elman network, achieving a much lower NRMSE in both training and testing phases. Additionally, the ESN trained much faster, taking 20 minutes compared to over 10 hours for the Elman network. In a second experiment, the dataset was reduced by a factor of 10, with similar results favoring the ESN in both accuracy and speed. This study concluded that the ESN is particularly suitable for real-time predictive maintenance in scenarios requiring large datasets and quick response times.

In a recent study [8], the authors set out to predict faults or abnormalities in an industrial fan using a data-driven approach, specifically employing the RF algorithm. The data was collected through the MPU-6050 sensor, which measured both 3-axis accelerometer (vibration data) and temperature. The results showed that the RF algorithm performed exceptionally well, achieving an accuracy of 99%. Additionally, the regressor approach yielded a RMSE of 80, demonstrating the model's effectiveness. The authors also confirmed that overfitting was not an issue in the model.

While current solutions for detecting faults in fan systems within HVAC systems are effective, there are still areas where improvements can be made.

III. Approach Proposal

Firstly, the enhanced approach will integrate multiple data sensors through data fusion and utilize a hybrid method. This includes applying a data-driven approach using RF algorithms alongside a physical model-based method for simulation using Simulink to validate hypotheses and uncover new insights and findings.

A. Project Planning

For the project implementation , I aim to capture temperature data, vibration (accelerometer) data and audio signal data of the fan motor. Firstly, I will capture data of the normal-condition fan, then for the simulate fault scenarios

- Unbalanced Blades: Attach a small weight (e.g., tape or a small object) to one of the fan blades to simulate unbalance. This will increase vibrations.
- Bearing Failure: Temporarily obstruct the fan blades with an object to simulate increased friction. Observe changes in noise and movement.
- Overheating: Artificially increase the motor load by slowing the fan or obstructing airflow to simulate overheating. Monitor the temperature rise.
- Obstruction: Partially block the fan blades with an object to simulate reduced movement and changes in sound and vibration patterns.

After storing and processing the data, I implement a parallel approach by integrating outputs from separate models—a physics-based model using Simulink and a data-driven model using Random Forest. The outputs of these models are then combined to make the final prediction. The process is relatively straightforward. After obtaining predictions from both models, we combine these predictions using the `VotingClassifier`. Next, we evaluate the performance of the combined predictions and compare it to the performance of each individual model to determine whether the combination enhances accuracy, reliability, or robustness. Finally, the combined predictions are utilized for making the final decisions regarding the prediction of fan motor failure.

B. Hardware

To capture temperature, vibration, and sound from the motor for predicting potential failures, it is essential to incorporate specific sensors. Below is a list of sensors organized by their cost-effectiveness and their effectiveness in predicting failures I (they can be purchased at Core Electronics). Certainly, we will also require essential components such as wires, a

Sensor	Type	Cost (AUD)	Data Type
DHT22	Temperature Sensor	$3.85	Temperature Data
INMP441 MEMS High Precision Low Power	Microphone for ESP32	$1.47	Sound Data
Arduino Nano 33 IoT	Accelerometer Sensor	$44.60	Vibration Data
Arduino Nano 33 IoT	Development Board	$44.60	N/A

TABLE I
LIST OF SENSORS WITH COSTS AND DATA TYPES [11]

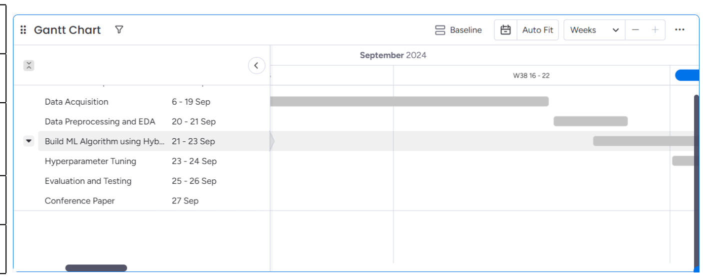

Fig. 2. Project Timeline

breadboard, and a laptop to connect the Arduino Nano 33 IoT for processing the sensor data. Additionally, we will need tape and scissors to simulate failure modes, as well as a screwdriver for the bearings.

C. Software

In addition to hardware, successfully implementing the project requires certain software packages:

1) **Arduino IDE**: This programming software is necessary to connect to the Arduino Nano.
   - `DHT.h` is needed to process data from the DHT22 sensor.
2) **Python**: This programming language will be used for data analysis and building machine learning algorithms.
3) **Packages**:
   - `pandas` and `numpy` for data manipulation and exploratory data analysis (EDA) as needed.
   - `matplotlib.pyplot` or `seaborn` for graphical representation and interpretation of results.
   - `sklearn` for developing algorithms and statistical models, specifically the Random Forest algorithm in this case.
   - `csv` for processing and storing CSV files.
   - `scipy.fft` to transform sound data into the frequency domain using the Fourier Transform.
   - `serial` for serial communication between two Arduinos: one for recording accelerometer data and the other for processing sensor data.
   - `datetime` for recording the Timestamp data.
4) **Simulink**: This software will be used for simulating the physical-based model.

D. Timeline

To successfully implement the project, adequate time is required for collecting data and configuring various components. The stages of this project will be illustrated through the following Gantt chart 2.

IV. ETHICAL CONSIDERATIONS

In predictive maintenance systems that use sensors like microphones, accelerometers, and temperature sensors, several ethical issues need to be considered. First, collecting data from these sensors can raise privacy concerns, especially in places where people are around. It is important to gather data openly and get permission from those affected. Additionally, potential biases in data analysis and machine learning models should be carefully examined, as these biases can lead to incorrect assessments of machine conditions and unnecessary maintenance actions. Researchers should also think about data security, making sure that sensitive information is protected from unauthorized access. Lastly, the environmental effects of using these technologies should be reviewed to promote sustainable practices and responsible use of resources in developing predictive maintenance solutions.

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