International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 3 Volume No.7 May - June – 2023
DOI:10.46647/ijetms.2023.v07i04.034 ISSN: 2581-4621

Predictive Maintenance and Preventive Measures forCalibration Devices: A Mobile Application Approach

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ABSTRACT
In the field of artificial intelligence, ensuring timely maintenance of mechanical devices like bikes, cars, air conditioners, etc., is crucial. This research paper proposes the designof a user-friendly Mobile Application that seamlessly connects with Calibration devices and utilizes advanced algorithms to predict system failure dates, assess device health, and provide proactive service and failure information. The application offers proactive service recommendations and alerts by analysing data from pressure controllers and considering factors such as calibration, aging, subsystem failures, and component failures. It optimizesmaintenance schedules and minimizes downtime through state-of-the-art predictive maintenance algorithms. This research aims to significantly enhance the reliability and efficiency of mechanical devices by accurately predicting issues and providing preventive measures.
Keywords – Health-Monitoring, predictive analysis

1. Introduction

In the realm of calibration, a wide range of devices exists, including hydraulic, pneumatic, thermocouple, and temperature calibration instruments. These devices incorporate calibrated sensors and mechanical components. Timely calibrationand maintenance of these instruments are essential to ensure accurate measurements and reliable performance.

This research aims to develop a mobile standalone ap- plication that can receive and analyze data from pressure controllers. The application will consider crucial factors such as calibration, aging, sub-system failures, and component failures. By leveraging intelligent algorithms, the application will provide predictive maintenance capabilities and offer preventive service and failure information to the users. The ultimate goal is to estimate maintenance dates and predictsystem failures for the instruments.

To achieve this, a unique identity will be assigned to each instrument, allowing users, whether individuals or large companies, to manage multiple devices efficiently. The applicationwill adapt to the usage patterns of different instruments, accommodating various scenarios and optimizing maintenancerecommendations.

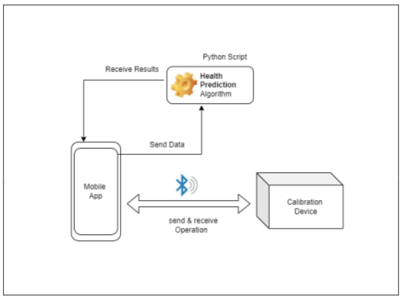


Figure 1 Structure of The System

2. Literature Survey:

Singh and Kumar provide an overview of the state-of-the-art techniques in predictive maintenance. The paper discusses the challenges associated with implementing predictive maintenance strategies, such as data acquisition, fault detection, and prognostics. The research highlights the importance of intelligent algorithms for accurate predictions and preventive measures. [1] Li, Liu, and Chen present an in-depth analysis of predictive maintenance methods and their applications in industrial systems. The paper reviews various algorithms, including machine learning and deep learning techniques, for predicting system failures and optimizing maintenance schedules. The research emphasizes the benefits of predictive maintenance in terms of reducing downtime and improving operational efficiency. [2] Rao, Rao, and Venkatachalam focus specifically on predictive maintenance techniques for electro-mechanical systems. The paper discusses different approaches, such as statistical analysis, machine learning, and expert systems, for predicting failures in electromechanical devices. The review emphasizes the significance of accurate failure prediction and preventive measures to enhance system reliability and reduce maintenance costs. [3] Khoshnoudian and Yau propose an intelligent predictive maintenance framework for industrial control systems. The framework integrates real-time data analysis, fault detection, and machine learning algorithms to predict failures and optimize maintenance activities. The research highlights the effectiveness of predictive maintenance in prolonging the lifespan of control systems and improving their performance. [4]

3. Methodology

3.1 Dataset

1) Calibration Points -The term "calibration point" refers to the specific relationship between an instrument’s measured value and its corresponding calibration value. It represents the accuracy of the calibration function, which is typically polynomial and highly precise at these designated points. The instrument firmware directly stores the calibration details, ensuring continued calibration regardless of the specific device used for data entry.

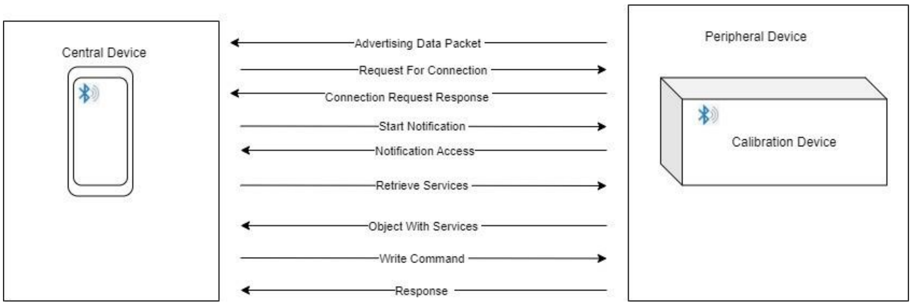
2) Date and time- The date and time information corresponding to the specific moment when the calibration point was calibrated. Each calibration point is associated with its own distinct date and time, reflecting the precise moment when the calibration process took place.

3.2 Method used to develop BLE application

Bluetooth Low Energy- BLE uses the same radio wavebands as Bluetooth and allows two devices to exchange data in many of the same ways.

3.4 Algorithm for BLE

1) Start: Begin the process of initiating the BLE connection.



2) Scan: Conduct a scan to discover nearby BLE devices.
3) Device Selection: Enable the user to select the desired BLE device from the list of scanned devices.
4) Connect: Establish a connection with the chosen BLE device using its unique MAC address.
5) Service Discovery: Discover the services offered by the connected BLE device by utilizing service UUIDs.
6) Characteristic Discovery: Explore the characteristics within the identified services by utilizing characteristic UUIDs.

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7) Enable Notifications: Activate notifications for a specific characteristic to receive data updates from the device.
8) Read/Write Operations: Perform read/write operations on the relevant characteristics to retrieve or send data to the device.
9) Data Processing: Process the received data and utilize it within the application as per the specific requirements
10) Disconnect: Gracefully disconnect from the BLE device when the task is complete or upon user interaction.
11) End: Terminate the BLE connection process.

For my project, I developed a React Native mobile application for BLE communication, implementing the aforementioned steps. It is important to note that while multiple devices may have the same service UUID and characteristic UUID, their MAC IDs are unique. BLE utilizes two keys, namely the Long-Term Key (LTK) and Short Term Key (STK), for integration and optimized operation. When a new device is created, an STK is generated for the initial pairing. Subsequently, upon successful pairing, an LTK is generated to remember the device, eliminating the need for repeated pairing with the same device.

3.5 Methods used for health prediction algorithm

3.5.1 Linear Regression:

The Linear Regression analysis is used to predict the effect of one variable over another one. In the health prediction analysis for the usage time of the screw, I need to find out the date when the screw traveled 1 kilometer, for this I had two parameters "DATE-TIME" and "USAGE TIME OF SCREW/ CALIBRATION POINT". here date-time is the independent variable and usage time is the dependent variable. By taking the cumulative sum of the Calibration point column we can apply the Linear regression to it The equation for the linear line can be represented as follows:

$$Y = a + bx \qquad (1)$$

where: - Y is the dependent variable (Usage Time of the Screw). - a is the Y-intercept of the line. - b is the slope of the line. - x is the independent variable (Date - time).

$$b = \frac{n\sum xy \quad (\sum x)(-\sum y)}{n\sum x^2 - (\sum x)^2} \qquad (2)$$

$$a = \frac{\sum y - b(\sum x)}{n} \qquad (3)$$

After extrapolating the regression line, the next estimated value can be obtained using the equation:

$$y = w[i] \cdot x + w[i+1] \qquad (4)$$

Please note that equation (4) is used for extrapolation, where w[i] and w[i+1] represent the regression coefficients.

3.6 LSTM:

The Long Short-Term Memory (LSTM) model is a recurrent neural network (RNN) architecture that has gained significant attention in effectively modeling sequential data, addressing the challenge of capturing long-term dependencies. LSTM incorporates a set of mathematical equations that govern the information flow within the network, allowing it to selectively retain or discard the information. The first key component of LSTM is the forget gate, which determines the information to be discarded from the previous time step. By applying a sigmoid activation function to the concatenation of the previous hidden state, h(t-1), and the current input, x(t), the forget gate output, f(t), is obtained.

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This output signifies the degree of forgetting and is computed as follows:

$$f(t) = \sigma(W_f \cdot [h(t-1), x(t)] + b_f) \quad (1)$$

Next, the input gate regulates the amount of new information to be stored in the memory cell. Similar to the forget gate,it applies a sigmoid activation function to the concatenationof h(t-1) and x(t). Additionally, a tanh activation function is applied to the same inputs, generating a candidate cell state,C (t). The input gate and candidate cell state are computed as:

$$i(t) = \sigma(W_i \cdot [h(t-1), x(t)] + b_i) \quad (2)$$

$$C\ (t) = \tanh(W_c \cdot [h(t-1), x(t)] + b_c) \quad (3)$$

To update the memory cell, the forget gate output is element-wise multiplied by the previous memory cell, C(t-1), and theinput gate output is element-wise multiplied by the candidatecell state, C (t). The resulting values are summed, yielding the updated memory cell:

$$C(t) = f(t) \cdot C(t-1) + i(t) \cdot \tilde{C}(t) \quad (4)$$

Finally, the output gate determines the information to be passed to the next hidden state, h(t). The output gate applies a sigmoid activation function to the concatenation of h(t-1) and x(t). Additionally, a tanh activation function is applied to the updated memory cell, C(t), squashing the values withinthe range of -1 to 1. The output gate and hidden state are computed as:

$$o(t) = \sigma(W_o \cdot [h(t-1), x(t)] + b_o) \quad (5)$$

$$h(t) = o(t) \cdot \tanh(C(t)) \quad (6)$$

By adjusting the trainable weights (W) and biases (b) during the model training, the LSTM can effectively learn to capture temporal dependencies and make accurate predictions basedon the input sequence.

4. Conclusion

In this research, we proposed the design of a mobile application that connects to calibration devices and utilizes advanced algorithms to predict system failure dates, assess device health, and provide preventive service and failure information. By analyzing data from pressure controllers and considering factors such as calibration, aging, subsystem fail- ures, and component failures, the application offers proactive service recommendations and alerts, optimizing maintenance schedules and minimizing downtime.

Through the implementation of the mobile application, we aimed to enhance the reliability and efficiency of mechanical devices by accurately predicting maintenance dates and systemfailures. By leveraging artificial intelligence techniques, such as predictive maintenance algorithms, the application can provide valuable insights and enable users to take proactive measures to prevent potential failures.

Additionally, the application addresses the challenge of managing multiple calibration devices by providing a unique identity for each instrument. This ensures that the algorithms can adapt to different usage patterns and provide accuratepredictions and service recommendations for each device.

The research highlights the importance of timely servicing in mechanical devices and the potential benefits of utilizing advanced algorithms and mobile applications in predictivemaintenance. By employing the proposed solution, users can optimize maintenance schedules, reduce downtime, and en- hance the overall reliability and efficiency of their mechanicaldevices.

However, further research and development are requiredto refine and validate the proposed algorithms and mobileapplication. Conducting experiments and gathering real-worlddata will be essential to assess the accuracy and effectiveness of the predictive maintenance algorithms in different scenariosand with various types of mechanical devices.

Overall, this research contributes to the field of artificial intelligence and predictive maintenance by offering a comprehensive solution for the timely servicing of mechanicaldevices through accurate prediction, preventive measures, and proactive service recommendations provided by a mobile application. It paves the way for further advancements in optimizing maintenance processes and improving the reliability of mechanical systems in various industries.

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